AIRSI2022

Technologies 4.0
in Tourism, Services & Marketing

University of Zaragoza

Spain

11-13 July 2022

CONFERENCE PROCEEDINGS

PREFACE

This volume presents the proceedings of the 4th edition of AIRSI2022 held virtually by the METODO research group (University of Zaragoza; SPAIN) on 11-13 July 2022.

AIRSI2022 is an international conference focused on the application and effects of technologies that are part of the so called Industry 4.0 (artificial intelligence, robots, intelligent assistants, augmented reality, virtual reality, big data, blockchain, collaborative platforms, etc.). Specifically, the aim of this conference is to deepen and broaden the current understanding of the use of all these new technologies to offer all kind of products and a wide variety of services (e.g., tourism, hospitality, banking, education, health, etc.) by focusing on their effects on value creation, relationship outcomes (e.g., satisfaction, loyalty, engagement, profitability), customer perceptions (e.g. trust) and concerns (e.g. privacy, security, etc.), ethical issues and other related aspects..

Topics of interest for the Conference include, but are not limited to:

- **A**rtificial Intelligence, Service Automation, Machine Learning, Block Chain, Cybersecurity
- **I**mmersive Technologies, Smart Cities, Geomarketing, Omnichannel Strategies
- **R**obots, Chatbots, Intelligent Assistants, Data Driven Decision Making
- **S**ocial Networks, S-Commerce, UCG, Influencers, Sentiment Analysis, Big Data
- **I**nternet of Things, Digital Transformation, Collaborative Platforms, Cloud Computing, etc.

This conference is intended to be the germ that allows the developing of two special issues in two prestigious specialized research journals:

- *Psycology & Marketing*, Special Issue: “New horizons in customer experience: Exploring human embrace of Technologies 4.0 from a marketing perspective”.

We wish to thank all colleagues who contributed to the conference and to this volume. Thanks also to all members of the scientific committee and reviewers without whom the conference would not have taken place.

We hope that AIRSI2022 will serve as a forum for exchange of ideas, approaches, expertise and best practices between researchers and existing networks in the field, paving the ground for future standards of research in understanding the consumer’s perceptions and reactions when facing all the technological innovations included in what has been called Industry 4.0.

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Metaverse Conference Co-Chair of AIRSI2022

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AIRSI2022

Technologies 4.0
in Tourism, Services & Marketing

July 11-13, 2022

CONFERENCE PROGRAM

Monday July 11

12.30 – 13.00	Official Inauguration			
13.00 – 14.00	Plenary Session 1: Keynote Speaker ***Giampaolo Viglia (Editor-in-Chief of Psychology & Marketing. Professor of Marketing at the University of Portsmouth, UK and Universita della Valle d'Aosta, Italy)*** *What do we expect from Robots?*			
15.00 – 16.30	Competitive Papers 1.	Session 1A	Session 1B	Session 1C
16.45 – 18.15	Competitive Papers 2.	Session 2A	Session 2B	Session 2C

Tuesday July 12

09.30 – 11.15	Competitive Papers 3.	Session 3A	Session 3B	Session 3C
11.30 – 13.00	Competitive Papers 4.	Session 4A	Session 4B	Session 4C
15.30 – 16.30	Plenary Session 2: Keynote Speaker ***Martin Wetzels (Co-Editor of the Journal of Service Research. Professor of Marketing and service management at EDHEC Business School, France)*** *The Artificial Intelligence Narrative: A Meta-mining Approach for Mapping Literature*			
16.30 – 18:00…	Welcome session on the AIRSI2022 Metaverse			

Wednesday July 13 - METAVERSE

09.15 – 10.45	Competitive Papers 5.	Session 5A	Session 5B
11.00 – 12.00	Plenary Session 3: Keynote Speaker ***Jochen Wirtz (Recipient of the Christopher Lovelock Career Contributions to the Services Discipline Award. Professor of Marketing at the National University of Singapore)*** *Implications for Intelligent Automation, Robotics & AI on Marketing Strategy*		
12.00 – 13.30	Workshops on the Metaverse	Virtual Environments	Artificial Intelligence
15.00 – 16.30	Competitive Papers 6.	Session 6A	Session 6B
17.00 – 18:00…	Closing Ceremony		

Central European Time (CET)   Madrid, Brussels, Paris, Rome, Rome, Berlin, Budapest.

EXTENDED ACADEMIC PROGRAM

Central European Time (CET) Madrid, Brussels, Paris, Rome, Rome, Berlin, Budapest

Monday July 11

Official Inauguration. Monday, July 11. 12:30 – 13:00. https://bit.ly/3NS0XGK

Carlos Flavián	*Welcoming remarks and AIRSI2022 Special Issue*
Russell W. Belk (Distinguished Research Professor. York University, Canada)	*Opening speech*

Plenary Session 1. Monday, July 11. 13:00 – 14:00. Chair: Yogesh Dwivedi https://bit.ly/3NS0XGK

Giampaolo Viglia (Editor-in-Chief of Psychology & Marketing. Professor of Marketing at the University of Portsmouth, UK and Universita della Valle d'Aosta, Italy)	*What do we expect from Robots?*

Competitive Papers (1A). Monday, July 11. 15:00 – 16:30. Service Robots. Chair: Cristina Mele https://bit.ly/3OTTgBb

Cultured Robots: Social Imaginaries and Market Speeds	*Thomas Robinson*
Integrating robots into caregiving practices to reduce caregivers' burden	*Marialuisa Marzullo, Irene Di Bernardo, Stefano Paolo Russo, Cristina Mele, Tiziana Russo Spena and Alessandra La Salandra*
"Internal Service Error" – Threats to consumer well-being in human-robot service interactions	*Heiko Holz and Stefanie Paluch*
Impact of service robots on customer satisfaction: the moderating role of online review features	*Matteo Borghi and Marcello Mariani*
Rational thinking as a criterion for segmenting the acceptance of service robots?	*Ruben Huertas Garcia, Santiago Forgas-Coll, Antonio Andriella and Guillem Alenya*

Competitive Papers (1B). Monday, July 11. 15:00 – 16:30. Voice Assistants and Artificial Intelligence. Chair: Ana Maria Soares https://bit.ly/3bWdrzI

The use of artificial intelligence in the hospitality industry: understanding customer service interactions with smart speakers	*Daniel Ruiz-Equihua, Luis V. Casaló, Jaime Romero and Sandra Maria Correia Loureiro*
Exploring the essence of tourism experiences through artificial intelligence	*Sofía Blanco-Moreno, Ana M. González-Fernández and Pablo A. Muñoz-Gallego*
Feeling vulnerable with AI. How interaction modality influences consumers responses to interactions with AI digital assistants.	*Valentina Pitardi and Hannah Marriott*
Customer interactions between expert users and smart voice assistants: how experiences and love drive to long-term relationships	*Blanca Hernandez Ortega, Ivani Ferreira and Sara Lapresta Romero*
Exploring the role of Twitter communication flow in tourism demand forecasts	*Yuanming Qiu, Ewelina Lacka and Jake Ansell*

Competitive Papers (1C). Monday, July 11. 15:00 – 16:30. Social Media. Chair: Nikolaos Stylos https://bit.ly/3RncdNY

Attachment styles moderate applicant's responses to face-to-face vs asynchronous job interviews	*Valerio Deriu and Rumen Pozharliev*
Understanding how lenders' social presence in peer-to-peer platforms can boost consumers' prosocial behaviour	*Giovanni Pino, Marta Nieto Garcia, Giampaolo Viglia, Alessandro Peluso and Raffaele Filieri*
Exploring the effects of spectators' identification with esport players and the community on consumer behaviour	*Fernando Navarro-Lucena, Rafael Anaya-Sánchez and Sebastián Molinillo*
A Cross Cultural Analysis of Emoticon Utilization in Social Media Branding Communication	*Altug Tanaltay, Selcen Ozturkcan and Nihat Kasap*
Lexicon-based sentiment analysis of fake news on social media	*Bahareh Farhoudinia, Selcen Ozturkcan and Nihat Kasap*

Competitive Papers (2A). Monday, July 11. 16:45 – 18:15. Miscellaneous. Chair: Sandra Loureiro https://bit.ly/3OTTgBb

Development and Validation of a Technology Paternalism Scale	*Martin Rochi, Philipp Rauschnabel, Karl-Heinz Renner and Bjoern Ivens*
Does age matter in webrooming?	*Vaida Kaduškevičiūtė and Erika Pipiraitė*
Determinants of intention to use autonomous buses: A qualitative study	*Lidia Caballero-Galeote, Sebastian Molinillo, Francisco Liebana-Cabanillas and Miguel Ruiz-Montañez*
New horizons in customer resistance: Exploring consumer difficulties in adopting Autonomous Vehicles (AV) from a marketing perspective	*Fraser McLeay, Hossein Olya, Jessica Lichy and Ameet Pandit*
Consumer Responses to Private Versus Public Transportation Services By Autonomous Vehicles	*Rumen Pozharliev, Matteo De Angelis and Dario Rossi*

Competitive Papers (2B). Monday, July 11. 16:45 – 18:15. Chatbots and Voice Assistants. Chair: Raffaele Filieri https://bit.ly/3bWdrzI

Consumer willingness to disclose personal information to conversational agents (CAs): The double-edged sword of CAs' perceived intelligence	*Stefanie Sohn, Dominik Siemon and Stefan Morana*
Scared off by the joneses: Exploring the complex social nature of adoption of smart home technology for ageing consumers	*Brian T Hart, Graham Ferguson and Saadia Shabnam*
More than Just a Chat: A Classification of the Anthropomorphised AI – User Relationships	*Amani Alabed, Ana Javornik, Diana Gregory-Smith and Rebecca Casey*
The impact of voice assistants on flow: a comparison between virtual reality stores and websites	*Enrique Bigné, Carla Ruiz-Mafe and Rafael Curras*
Customer Perspectives on the Process of Co-Creation with Chatbots	*Daniela Castillo, Ana Canhoto and Emanuel Said*

Competitive Papers (2C). Monday, July 11. 16:45 – 18:15. New technologies in service and retailing. Chair: Eleonora Pantano https://bit.ly/3RncdNY

Personalized Technology Services for In-store Shopping: Impact on Customer Engagement and Shopping Satisfaction	*Youngdeok Lee and Sejin Ha*
Investigating consumers' hesitant adoption of medical artificial intelligence	*Elisa Konya-Baumbach, Miriam Biller and Sabine Kuester*
Generation Zers Engagement with Cryptocurrencies: A Behavioral Reasoning Theory Perspective	*Fulya Acikgoz, Nikolaos Stylos and Sophie Lythreatis*
Exploring Experts' Perceptions of Key Factors Favoring Successful Implementation of Chatbots in customer service encounters: the Case of the Canadian Financial Industry	*Massilva Dekkal, Manon Arcand, Sandrine Promtep, Lova Rajaobelina and Line Ricard*
Assessing the role of technology readiness in telemedicine adoption in an international context	*Anne Schmitz, Ana M. Díaz-Martín and María Jesús Yagüe Guillén*

Tuesday July 12

Competitive Papers (3A). Tuesday, July 12. 09:30 – 11:15. Miscellaneous. Chair: Park Thaichon https://bit.ly/3OTTgBb

Pay with your Face - Customer Decision-making Journey of Trialling Facial Recognition Payment Technologies	*Shasha Wang, Gary Mortimer, Laszlo Sajtos, Byron Keating and Stephanie Chen*
Collectives in Social Media: Predicting their brand engagement using deep learning methods	*Mohamed Zaki and David Solis Diaz*
Unpacking Emotion on Social Media Marketing in Global and Emerging Local Market Contexts with Evidence from Big Data	*Altug Tanaltay, Selcen Ozturkcan and Nihat Kasap*
Customer relationships formation and development in AI-based organisational frontlines	*Arezoo Fakhimi, Tony Garry and Sergio Biggemann*
Value-Attitude-Behaviour Model: Explore Consumer Emotions and Purchase Intentions in Live Streaming	*Xiaolan Xia, Park Thaichon and Wei Shao*
How customers' expectations and experiences towards global chain hotels be captured post-COVID-19? A netnographic perspective	*Anam Afaq, Loveleen Gaur and Gurmeet Singh*

Competitive Papers (3B). Tuesday, July 12. 09:30 – 11:15. Chabots and Digital Assistants. Chair: Sanjit Roy https://bit.ly/3bWdrzI

Emotional response of virtual assistants as an added value of an interactive product	*Álvaro Saavedra Montejo, Raquel Chocarro Eguaras, Mónica Cortiñas Ugalde and Natalia Rubio Benito*
Digital companions in marketing: the crucial roles of perceived similarity and perceived humanlikeness in driving of customer outcomes	*Katja Gelbrich, Alina Kerath and Helen Chun*
Teaming up with chatbots: Creating an effective collaboration between human employee and digital employee to enhance customer experience	*Khanh Le, Laszlo Sajtos, Werner Kunz and Karen Fernandez*
What's in a Name? Gender Suitability of Task-Specific Digital Assistants	*Stewart Palmer, Darius-Aurel Frank, Lina Fogt Jacobsen and Polymeros Chrysochou*
Psychological predictors of chatbots continuance intention: The role of subjective knowledge, innovativeness, and customer experience	*Raffaele Filieri, Lamberto Zollo, Riccardo Rialti and Sukki Yoon*
Does chatbots establish humanness in customer purchase journey?	*Janarthanan Balakrishnan, Abdullah Baabdullah, Raffaele Filieri and Yogesh Dwivedi*

Competitive Papers (3C). Tuesday, July 12. 09:30 – 11:15. Metaverse and Immersive Technologies. Chair: Enrique Bigné https://bit.ly/3RncdNY

The Effect of Autonomy Need Satisfaction and Escapism Motivation on Consumer's Variety-seeking Behavior in Metaverse	*Terry Haekyung Kim and Hyunjoo Im*
Psychological ownership of virtual store experiences: the role of control	*Ezgi Merdin Uygur, Gulen Sarial Abi and Aulona Ulqinaku*
Metaverse: A Bibliometric Analysis	*Yioula Melanthiou and Surat Teerakapibal*
A Process Model of Metaverse Immersion and Consumer Responses	*Christine Sung, Ohbyung Kwon and Kwonsang Sohn*
Psychological impacts of digital travel shaped via immersive technology	*Tseng-Lung Huang, Tong Xin Hong, Hsin-Yu Chen and Yi-Jyun Cai*

Competitive Papers (4A). Tuesday, July 12. 11:30 – 13:00. Artificial Intelligence & Service Robots. Chair: Marcello Mariani https://bit.ly/3OTTgBb

AI-informed Transformative Service Research – Deploying AI Agents to Empower Vulnerable Consumers	*Nika Mozafari, Maik Hammerschmidt and Welf H. Weiger*
Integrating AI into Customer Service: Improving the Actionability of Customer Feedback Analysis Using Machine Learning	*Joni Salminen, Mekhail Mustak, Nina Rizun, Aleksandra Revina, Anastasija Nikiforova, Hind Almerekhi, Soon-gyo Jung and Bernard J. Jansen*
Learning FinTech from AI Chatbot: Two Dimensions of Trust on Financial Self-efficacy on Consumer Adoption of a Wealth Management App.	*Chia-Yang Chang, Cong-Minh Dinh and Sungjun Steven Park*
The Interplay Between Robot Design, Customer Perceptions and Service Outcomes: A fsQCA Perspective	*Héctor González Jiménez and Sun Yang.*
The emerging "we" tribe of human-robot partners in consumption spaces	*Ezgi Merdin Uygur and Selcen Ozturkcan*

Competitive Papers (4B). Tuesday, July 12. 11:30 – 13:00. Technology-based Services. Chair: Yioula Melanthiou https://bit.ly/3bWdrzI

Traveling in the post-COVID era: The role of intelligent technologies in enhancing travelers' service experience	*Heiko Holz and Stefanie Paluch*
Marketing 5.0 and its business applications: a bet on the future	*María Pilar Martínez-Ruiz, María Ángeles García-Haro, Ricardo Martínez-Cañas and Juan José Nájera-Sánchez*
Does the cognitive style influence user experience? A comparative analysis of website and virtual reality in a hotel choice setting	*Enrique Bigné, Luisa Andreu and Isabel Sanchez-García*
Uses and gratifications of chatbots: their influence on consumer experience and purchase intention	*Paulo Ribeiro Cardoso, María D. Illescas Manzano, Cristina Segovia López and Sergio Martínez Puertas*

Competitive Papers (4C). Tuesday, July 12. 11:30 – 13:00. Social Media and Consumer Influence. Chair: Kim Willems https://bit.ly/3RncdNY

May I suggest these products to you?: Effects of recommender and product types on expected quality of product recommendations	*Hyunjoo Im and Garim Lee*
Understanding the impact of pre-existing online reviews upon customer intention to review the products on fashion e-commerce websites	*Harmanjit Singh*
Micro-level and cross-level moderating effects on customer satisfaction in social commerce platform: A multilevel analysis in the hospitality industry	*Xingting Ju and Xiaowei Cai*
Virtual influencers: generation of trust, loyalty and purchase intentions.	*Rafael Anaya-Sánchez, Carlota Aurora Mesas Ruiz, Sebastián Molinillo and Arnold Japutra*
Looking at embarrassment in consumer-technology interactions	*Maher Georges Elmashhara and Ana Maria Soares*

Plenary Session 2. Tuesday, July 12. 15:30 – 16:30. Chair: Wener Kunz https://bit.ly/3NS0XGK

Martin Wetzels (Co-Editor of the Journal of Service Research. Professor of Marketing and service management at EDHEC Business School, France)	*The Artificial Intelligence Narrative: A Meta-mining Approach for Mapping Literature*

Welcome session on the AIRSI2022 Metaverse. Tuesday, July 12. 16:30 – 18:00

Chairs: Carlos Orús, Sergio Ibáñez and Sergio Barta https://bit.ly/3NS0XGK

Wednesday July 13 – Metaverse

Competitive Papers (5A). Wednesday, July 13. 09:15 – 10:45. Artificial Intelligence & Service Robots. Chair: Stanislav Ivanov

Artificial Intelligence and Value Creation: Present Research Focus and Future Research Agenda	*Kunjan Rajguru*
To explain, or not to explain, that is the question. Do we need explainable artificial intelligence (XAI) in consumer neuroscience?	*José Paulo Marques dos Santos, José Diogo Marques dos Santos, José Luís Reis and Alexandre Sousa*
Relationship quality in customer-service robot interactions: An analysis of value recipes	*Sanjit K. Roy, Gaganpreet Singh, Richard Gruner, Saadia Shabnam, Mohammed Quaddus and Bidit De*
Citizen Science and Photovoice technique to assess Food Waste Perceptions: An AI-driven approach	*Kanwal Gul and Swapnil Morande*
Artificial Intelligence Applications. Challenges for Cultural Institutions	*Alicia Orea Giner, Ana Muñoz, Teresa Villace and Laura Fuentes*

Competitive Papers (5B). Wednesday, July 13. 09:15 – 10:45. Virtual Assistants & New Technologies. Chair: Sebastián Molinillo

What if we took a holiday? Enriching Advertising with Intelligent Voice Assistants	*Pedro Miguel Oliveira, João Guerreiro and Paulo Rita*
Chatbots as service recovery agent: the role of chatbot disclosure on perceived justice and forgiveness	*Kaiwen Xue, Sven Tuzovic and Udo Gottlieb*
Reshaping the Hospitality Industry by Technologies 4.0: The perspectives of top managers	*Hsuan Hsu*
Perception of avatar attitudes in Virtual Reality	*Elodie Etienne, Anne-Lise Leclercq, Angélique Remacle and Michaël Schyns*
Analysis of seller`s persuasive styles impact on audience participation in a multi-brand live-streaming shopping event	*Michele Girotto, Mel Solé Moro and Jordi Campo Fernández*

Plenary Session 3. Wednesday, July 13. 11:00 – 12:00. Chair: Valentina Pitardi

Jochen Wirtz (Recipient of the Christopher Lovelock Career Contributions to the Services Discipline Award. Professor of Marketing at the National University of Singapore)	*Implications for Intelligent Automation, Robotics & AI on Marketing Strategy*

Workshops on the AIRSI2022 Metaverse. Wednesday, July 13. 12:00 – 13:30.

Virtual Environments and Technologies 4.0	*Carlos Orús*
Artificial Intelligence and Technologies 4.0	*Daniel Belanche*

Competitive Papers (6A). Wednesday, July 13. 15:00 – 16:30. New Technologies & Virtual Reality. Chair: Philipp Rauschnabel

Privacy-Personalization Paradox in Adoption of Facial Recognition Technology at Business Events	*Olena Ciftci, Katerina Berezina and Inna Soifer*
Implications of new technologies on consumer engagement	*Samson Ajayi, Sandra Loureiro and Daniela Langaro*
Effects of Perceived Risks on Innovation of Tourism Industry: The Case of Contactless Airline and Hotel Services	*Mary Grace Burkett and Nuria Recuero Virto*
Virtual reality and other video types in destination marketing: Which one is more effective in attracting travelers?	*Katerina Berezina, Olena Ciftci and Cihan Cobanoglu*
Barriers to full-adoption of digital payment methods: the mediating role of barrier-breakers	*Irina Dimitrova and Peter Öhman*

Competitive Papers (6B). Wednesday, July 13. 15:00 – 16:30. Artificial Intelligence & Service Robots. Chair: Bart Larivière

Together or Alone: Should Service Robots and Frontline Employees Cooperate at the POS	*Kim Willems, Malaika Brengman, Laurens De Gauquier, Hoang-Long Cao and Bram Vanderborght*
Humans and/or robots? Tourists' preferences towards the humans-robots mix in the service delivery system	*Stanislav Ivanov, Craig Webster and Faruk Seyitoğlu*
When is artificial intelligence "too intelligent"? A critical thresholds approach in retail service	*Eleonora Pantano and Daniele Scarpi*
Anthropomorphic Service Robot Design: The Impact of Linguistic Human Cues on Customer Reaction	*Changxu Victor Li and Bart Lariviere*
Consumer experience with voice-based artificial intelligence: exploring voice love and its acoustic origins	*Alice Zoghaib and Jennifer Takhar*

Closing Ceremony. Wednesday, July 13. 17:00 – 18:00...

Carlos Flavián	*Closing remarks*
Werner Kunz (Director of the Digital Media Lab. University of Massachusetts, Boston)	*AIRSI2023 Special Issue*
Best Papers Awards Winners and Metaverse Awards	

Proceedings Index

Integrating robots into caregiving practices to reduce caregivers' burden

Marialuisa Marzullo[a], Irene Di Bernardo[b], Stefano Paolo Russo[c], Cristina Mele[d], Tiziana Russo Spena[e] and Alessandra La Salandra[f]

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Type of manuscript: Extended abstract

Keywords: caregivers' burden; caregiving practice; Hiro minimal design robot.

An increasing number of studies in service research focus on the roles of robots in caregiving activities and their effect on human-robot interaction (Caic et al., 2018; Henkel et al., 2020; Soraa et al., 2021). In addressing this interaction, service research tends to focus on customers. A few studies focus on employee experience, particularly on formal caregivers (Pfadenhauer & Dukat, 2015; Belanche et al., 2020). In service research, there aren't any works offering insights on the impact of such an interaction on caregiver burden as an aspect of the experience.

Studies in psychology and medicine address the role of caregiver burden (Miyamoto et al., 2010; Adelman et al., 2014) as a multidimensional construct, "addressing tension and anxiety (stress burden), changes in dyadic relationships (relationship burden), and time infringements (objective burden) resulting from caregiving" (Savundranayagam, et al., 2010).

The aim of this paper is to understand how the use of minimal design robotic solutions enhances service interactions and affects caregivers' burden. The study adopts an action research approach based on a process of planning, acting, observing and reflecting, in order to generate mutual understanding and positive changes in practice (Reason & Bradbury, 2001). This methodological choice refers to the active involvement of different actors in a combination of quantitative (e.g. validated scales) and qualitative (e.g. focus group) tools, (Onwuegbuzie & Johnson 2004; Gelo et al. 2008).

The experimental project aims at using the service robot Hiro, a Japanese minimal design service robot, in a daily care centre as a research setting settled in Italy. The research process follows three stages. The first stage concerns the Hiro robot pre-use analysis, i.e., the investigation of how minimal robots function. Semi-structured interviews with technology developers offered preliminary insights on the features of the HIRO minimal robot. The second stage concerned the burden identification (i.e., the identification of the burden and needs experienced by caregivers). The researchers administered to a group of caregivers semi-structured interviews that refer to a caregivers burden in Savundranayagam conception (Savundranayagam, et al., 2010). The third stage is the integration of Hiro into their caregiving practices. The authors observe if and how the integration of HIRO impacts the

caregiving practices for patients affected by dementia and how the robot can impact the three dimensions of caregiver burden: tension and anxiety (stress burden), changes in dyadic relationships (relationship burden), and time infringements (objective burden).
Finally, the aim of stage 4 is to deepen understanding of the caregivers' experiences and emotions after Hiro's implementation in their daily activities. Thus, the authors induced caregivers to share their viewpoints about feelings and the burden management. Operationally, the stage consisted of one focus group with caregivers and follow-up individual semi-structured interviews organized and conducted by the research group.
The results show that the introduction of service robots allows caregivers to improve relationships with patients and reduce the chances of conflicts with them. The implementation of service robots enables the constant monitoring of the parameters of the state of agitation by caregivers, giving the latter the opportunity to change the patient-caregivers interactions (relationship burden). This is the first step in reducing stress, tension and anxiety. Minimal design robots enable the reduction of caregivers' concerns about managing patients' aggressive and/or nervous behaviours resulting from their health status. In addition, they contributed to emotional regulation, which in turn resulted in responsive and conversational interaction (stress burden). Finally, the results also show that the introduction of Hiro helps caregivers to manage time better and increase the time they spend on additional recreational activities (objective burden).
This study contributes to research on employee experience by exploring the nascent literature on technologies and assistance burden (Halinski et al., 2020). It suggests an enhanced perspective on the integration of minimal design robots in caregiving practices. The research also illustrates a deeper understanding of new dynamics that enhance patient-caregiver interaction. New avenues for scholars and service providers are delineated.

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"Internal Service Error" – Threats to consumer well-being in human-robot service interactions

Heiko Holz[a] and Stefanie Paluch[b]

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Type of manuscript: Extended abstract

Keywords: humanoid service robots; customer experience; human-robot service interaction.

Relevance of research

Humanoid service robots (HSR) are on the rise. Designated by scholars and practitioners as the workforce of the future, their introduction into many service contexts and industries is fueled by advancing technological developments in artificial intelligence (AI) and automation (Rust & Huang, 2014). HSR are becoming an integral part of frontline service operations (FSO) to fulfill socially assistive positions across several service sectors such as healthcare (Holland et al., 2021), hospitality (Tuomi et al., 2021), and retail (Amelia et al., 2022). Here, they support or even replace frontline service employees. The increasing relevance of the topic in practice is also reflected in the remarkable increase in research in the field of service robots in recent years (Lu et al., 2020).

Nevertheless, prior studies on the interaction with and acceptance of humanoid service robots were conducted primarily with a focus on a HSR vs. human employee perspective by applying comparative (experimental/quantitative) methods. Thus, the current discussion of HSR in frontline service encounters lacks consideration of the fact that "human-robot interaction analysis requires a different approach that recognizes that humans' relationship with technologies is multifaceted and context-dependent" (De Keyser & Kunz, 2022, p.68).

This goes along with the identified lack of scholarly research on the ethical and moral considerations of de-humanizing service encounters by introducing HSR. These considerations range from privacy concerns and biased consumer outcomes to concerns related to loss of customer autonomy, social isolation and more (Mariani et al., 2022).

Research objectives and research question

Against the background of the blind spots regarding the impact of human-robot service interaction listed above, this research seeks to answer the following research question:

> *How can humanoid service robots in frontline service encounters put the customer experience and well-being in jeopardy?*

To narrow this research question down and make it more approachable and assessable during our empirical design, we further established two guiding questions for our two empirical studies (see "methodology" below) to facilitate the course of our two-study research. The guiding questions helped us collect the relevant insights and knowledge to successively answer the research question above.

These guiding questions were:
(1) What are the ethical concerns and negative outcomes experienced by customers interaction with HSR?
(2) How should service providers manage HSR in frontline service operations to account for customers' concerns and prevent threats to their well-being?

Research methodology
Our methodological approach acknowledges the lack of conceptual underpinnings regarding the contextual and relational character of human-robot service interaction (HRSI) and its impact on customers' service experience and well-being. We thus used an exploratory research design with two complimentary studies to (1) understand what constitutes the service experience for customers interacting with HSR and what factors negatively influence the service experience and (2) determine what service providers using HSR in FSO can do to actively address ethical concerns and threats to customer well-being.

The first study was designed as a problem-centered interview study with service customers (n=41, age range 19 to 71 years old) who had had either prior experience with HSR in a service setting themselves or were familiar with the technology through prior research or experience in other contexts. Thus, a purposive sampling approach was applied to account for the novelty and distinctness of the topic.

The second study was conducted as an exploratory study using expert interviews (n=27) with company representatives working for companies that either actively use HSR in their FSO already or manufacture HSR for service application. Service providers from various fields were integrated, among others hospitality, gastronomy, human care, and transportation.

All interviews were transcribed verbatim and checked for correctness and accuracy and then exported to atlas.ti 22, a qualitative data analysis software. We followed a systematic stepwise recursive process in the thematic analysis of the data (Boyatzis, 1998). Transcripts were coded independently by both members of the research team. A code system was established and built inductively, based on the in-depth textual analysis. New codes were created in an iterative fashion to capture the meaning of initial code groups (Thomas & Harden, 2008). Co-occurrence matrices in atlas.ti were applied to hierarchically organize individual codes in the shape of a coding tree. In an iterative process, the data material was merged, and the two members of the research team independently formed the main categories, discussed the content and labeling and, after several rounds, agreed on a final set of themes.

Preliminary findings
The preliminary findings (analysis ongoing) decode the major concerns faced by customers interacting with HSR across various service encounters. They reveal customer concerns addressing the personal (e.g., privacy, rapport), the social (e.g., fear of substituting human labor), or the interactive (e.g., service quality) level of the HRSI. As customers interact with a HSR in a specific service encounter, they form expectations about the performance level of the service. Their evaluation of the service experience is based on the perceived performance level in terms of contextual (type of service, i.e., information-processing vs. people-processing), transactional (i.e., task complexity, convenience), and relational (i.e., empathy, emotionality) performance.

Originality of the paper

This research is among the first to openly address critical components of customers' service experience with HSRs to assess ways in which they can put the customer experience and well-being in jeopardy. It presents negative consequences of unfavorable human-robot service interactions to pinpoint current boundaries of HSR-implementation in service settings.

Scholarly (re)search for determinants and interdependencies of emotionally and psychologically stimulating service experiences with HSR is still in its infancy. This research thus motivates scholars to strive for a better understanding of the ways in which HRSIs can cause negative impacts on customer well-being to inform technological development and contextual implementation in service settings. It reveals interdependencies of personal, technological, and contextual determinants to lead to concerns and threats to customer well-being, thereby creating awareness and leading service providers and managers towards a more customer-oriented design and application of HSR.

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Rational thinking as a criterion for segmenting the acceptance of service robots?

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Type of manuscript: Extended abstract

Keywords: social-robot acceptance; reasoning system; dual-process theory.

The emergence of Covid-19 and the resulting physical distancing measures have provided an opportunity to extend the use of social robots worldwide to cover customer service tasks in hospitals, nursing homes, stations and airports, etc. (Aymerich-Franch & Ferrer, 2020). Although new technologies (internet, computers and smartphones) had already transformed the service experience towards self-service to improve productivity, social robots represent a new paradigm as they try to replicate human skills to provide customer services with human quality (Van Doorn et al. al., 2017). Indeed, human-robot interaction has configured a multidisciplinary research field that combines knowledge from robotics, artificial intelligence (AI), cognitive science, psychology, ethology and sociology (Suchman, 2006).

A distinctive feature of robots is their ability to mimic humans. Therefore, robot designers attempt to replicate both human form (embodiment) and behaviour in their designs, so that they appear to be able to communicate, as well as display emotions and social skills (Suchman, 2006). However, while anthropomorphising is fairly easy (e.g. Harmony, the sex robot), replicating behaviour, communication skills and autonomy is tremendously difficult (Andriella et al., 2021). For example, to replicate the human way of communicating, robots are equipped with social intelligence protocols (Forgas-Coll et al., 2022). Furthermore, when consumers interact with a human-like robot, but it expresses itself in a clumsy way, this experience can lead to disappointment (Suchman, 2006). To mitigate these negative responses, designers have proposed using designs more in line with their true human abilities, showing their mechanical nature or outlining their human form (humanoid designs), to predispose consumers to expect simpler interactions (Mende et al., 2019).

Until recently, in social robotics it was usual to consider all people with similar tastes and, therefore, robots are designed with standard characteristics (Pinillos et al., 2016). However, recent work has started to consider different user characteristics, such as gender, personality, etc., as criteria for their segmentation, and for companies to design robots with skills adapted to their profiles (Forgas-Coll et al., 2022). On the other hand, some researchers have proposed other criteria that may be interesting as segmentation criteria, for example, the decision-making systems. According to the dual-process theory, people process information gathered from the environment through two mechanisms: one autonomous and intuitive, and the other more deliberative and analytical (Pennycook & Rand, 2019). The use of one system or the other can lead to different diagnoses of the same event. For example, the use of an analytical rather than an intuitive thinking system may cause people to increase their disbelief towards extraordinary or difficult-to-explain phenomena (Pennycook & Rand, 2019). We believe that dual-process theory may be a key factor in the acceptance of social robots, so we propose the following research question:

Does the dual-process system have a different impact on the technological acceptance of social robots, who, thanks to having a social intelligence protocol, can provide customer services?

Empirical study

This study uses a quasi-experiment to simulate a social robot delivering a front-office service, that is, providing information and giving advice, as well as expressing empathy and concern towards customers (Gelbrich et al., 2021). For this purpose, a stand was set up at a trade fair in Barcelona that is visited by thousands of people every year. The stand had two spaces: one with an open structure, to capture the attention of visitors and where they could fill in authorisations and questionnaires, and another, more enclosed, with a board game, headphones and a TIAGo robot. Visitors were invited to complete the board game that consists of forming the five-letter name of a Nobel laureate from 10 tokens and, to facilitate the task, they were assisted by a TIAGo robot, equipped with AI software, called SOCIABLE (Andriella et al., 2020). The protocol is structured in three parts: a) introduction, where the robot presents the game and the instructions to follow; b) a dialogue, with advice on where to locate the correct token, encouragement and empathy messages; c) a farewell message at the end of the game. In addition, the robot transmits these messages with two types of signals: non-verbal, through animation software that reproduce facial expressions on an LCD screen inserted in its head, and text-to-speech software to generate the voices.

A total of 219 visitors between 18 and 67 years of age (M_{age} =35 years, 106 women) participated in the experiment, where researchers controlled for gender and age (Mende et al., 2019). After completing the game (5 minutes), they answered a questionnaire consisting of 19 statements composing the five constructs (Intention to use, Perceived usefulness, Perceived ease of use, Perceived enjoyment, Social influence) that had to be evaluated on a five-point scale (1 = "strongly disagree" and 5 = "strongly agree"). The scales were adapted from the literature and derived from the UTAUT model (Heerink et al., 2010). Finally, they completed seven items of the Cognitive Reflection Test consisting of open-ended questions that have the characteristic of intuiting a simple but incorrect answer, with the correct answer being more complex and difficult to discover (Pennycook & Rand, 2019). Correct questions were counted, the median was estimated and the sample was divided into two: system 1 (S1) to those who followed a more intuitive or heuristic process (obtaining three or fewer correct answers) and system 2 (S2) to those who followed a more rational process (obtaining more than three correct answers). The psychometric characteristics of the constructs were validated and, from each subsample, a UTAUT model (Heerink et al., 2010) was estimated using Structural Equation Modeling, based on variance and covariance matrices by maximum likelihood with EQS 6.4 (Bentler, 2006).

Findings

The key findings of the analysis show that the dual-process system may be relevant in explaining the intention to use front-office robots. For S1 (intuitive) users the intention to use is mainly explained by the social acceptance they could achieve with it and, with less influence, perceived enjoyment and perceived usefulness. But, for S2 (rational) users, social acceptance and enjoyment have equivalent weights and, also playing a relevant role, ease of use and usefulness (Table 1).

Table 1. Causal relations in intuitive/rational

Independent variable	Dependent variable	System 1 (intuitive) Beta	T	R^2	System 2 (rational) Beta	T	R^2
PU	ITU	0.26	1.99	0.85	0.20	2.05	0.92
PEOU		0.05*	0.85		0.25	2.53	
PENJ		0.28	3.58		0.34	3.50	
SI		0.50	3.64		0.36	2.57	
PEOU	PU	0.32	3.09	0.15	0.38	2.20	0.10

$p<0.05$ *Not significant

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The use of artificial intelligence in the hospitality industry: understanding customer service interactions with smart speakers

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Type of manuscript: Extended abstract

Keywords: smart speakers; psychological ownership; customer responses.

Introduction

Artificial intelligence machines exhibit human aspects such as human voice, human physical appearance, or a degree of human intelligence, allowing companies to use it in services such the health care or hospitality ones (Huang and Rust, 2018). In this regard, the advent of artificial intelligence machines is changing customer frontline experiences in services such as the hospitality ones (e.g., Yoganathan et al., 2021). For example, customers can order food to a robot in a restaurant, ask for a drink to a voice assistant in a hotel, or converse with a chatbot in a company's website. Among all these initiatives, 78% of hotel companies consider that voice assistants devices would be in mass adoption for 2025 (Oracle, 2018). Specifically, voice assistants are "voice-controlled devices designed to provide personal assistance for users' daily activities" (Whang and Im, 2021, p.581), and the most known voice-assistant are the ones included in smart speakers such as Amazon Echo and Google Home. Smart speakers are devices provided with artificial intelligence which can perform several tasks such as reporting the weather forecast, switching off the light, or playing music (Romero *et al.*, 2021)g music (Romero *et al.*, 2021). These devices, employing artificial intelligence, are able to "converse" with people (Belanche *et al.*, 2020), arising perceptions of social interactions resulting in favorable customer responses (van Doorn *et al.*, 2017). Thus, this research aims to enhance the understanding of how and why customer-smart speaker interactions generates favorable customer responses in the hospitality industry. To do so, this research focuses on the influence of smart speakers in customers frontline experiences on the hospitality industry, specifically in hotels. Thus, we propose the following research questions:
RQ1: which positive aspects customers highlight in online reviews regarding their positive experiences using a smart speaker in hotels?
RQ2: which is the mechanism through which positive customer responses arise from the interaction with smart speakers in hotels?
RQ3: which are the actual behaviors from customers that interacts with smart speakers in hotels?
To answer these questions, this research conducts three studies that are detailed in the subsequent sections.

Methodology

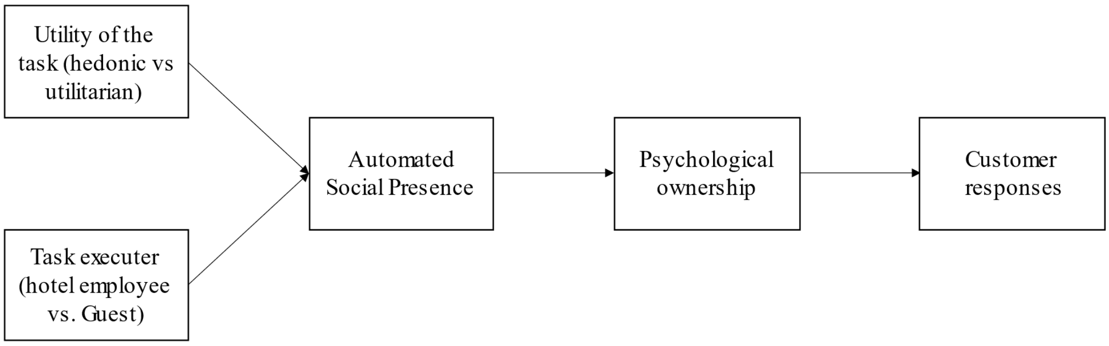
Study 1

This study aims to answer RQ1. To do so, focusing on hotels, we will download online reviews from TripAdvisor (English language) about hotels where interactions with smart speakers take place. Following, we will analyze whether such interactions are related to positive or negative feelings.

Study 2

This study aims to answer RQ2. To do so, using a 2 (hedonic vs. utilitarian) x 2 (guest task vs. employee task) experimental research design. We will present participants a situation where they enter an hotel room which has a smart speaker on it. Following, an audio will be reproduced presenting the smart speaker and explaining the tasks that can do for the customer. The audio will contain a hedonic/utilitarian list of tasks which, in the past, were attributed to be made by hotel customers/employees. We will present the same number of tasks in the four scenarios and randomly assigned the participants to each condition. Next, we will ask the participants to answer questions about social presence, psychological ownership, and customer responses such as word of mouth or revisiting intentions. Figure 1 shows study 2 research model. Additionally, we will include the Bagozzi et al. (2016) scale to measure the realism and credibility of our scenarios. The questionnaire will be implemented in Qualtrics and self-administrated by participants. The data will be analyzed by using Partial Least Squares (PLS). First, PLS is an appropriate method to develop theories in exploratory research, as in our case. Second, PLS can properly estimate type II reflective-formative second-order constructs, such as psychological ownership with the smart speaker in our research. Given that psychological ownership of the smart speaker is an endogenous construct in our research, we will estimate our model using a two-stage approach. (Hair *et al.*, 2017).

Figure 1. Proposed model.



Study 3

This study aims to answer RQ3. To do so, using an experimental research design, we will present participants a situation, employing virtual reality, where they are in a hotel room with a smart speaker on it. Following, while the participant is immersing in the virtual reality, the smart speaker, using the audios from study 2, will present itself and introduce the tasks that can do for the customer. Next, we will ask participants to answer questions regarding actual behaviors arising from the interaction with the smart speaker in the virtual reality. The questionnaire, as in study 2, will be implemented in Qualtrics and self-administrated by participants.

Expected contributions

This research aims to enhance the understanding of the influence of artificial intelligence, specifically smart speakers on customer responses in the hospitality industry. First, study 1 aims to identify from actual online reviews regarding customer’s use of smart speakers in hotels, the elements that contribute to generate positive customer responses. Second, study 2 focuses on developing a framework to understand how and why customer "social" interactions with smart speakers in hotels generates such positive responses. Specifically, study 2 aims to analyze how automated social presence influence customer psychological ownership regarding the smart speakers and the resultant customer responses. Additionally, this research aims to analyze if human substitution and task type are antecedents or not of social presence perceptions. Finally, study 3 aims to analyze actual customer behaviors regarding the use of smart speakers in hotels.

Originality of the paper
This research combines 3 studies using different methodologies (e.g., experiment design, online questionnaire, field study…) and measures (e.g., actual behaviors, customer perceptions…) to identify the influence of customer interactions with smart speakers on customers' responses in the hospitality industry. The aim is to explain how and why positive customer-smart speaker interactions in hotels generate positive customer responses.

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Exploring the essence of tourism experiences through artificial intelligence

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Type of manuscript: Extended abstract

Keywords: memorable tourism experience; Instagram; artificial intelligence; emotions.

Purpose

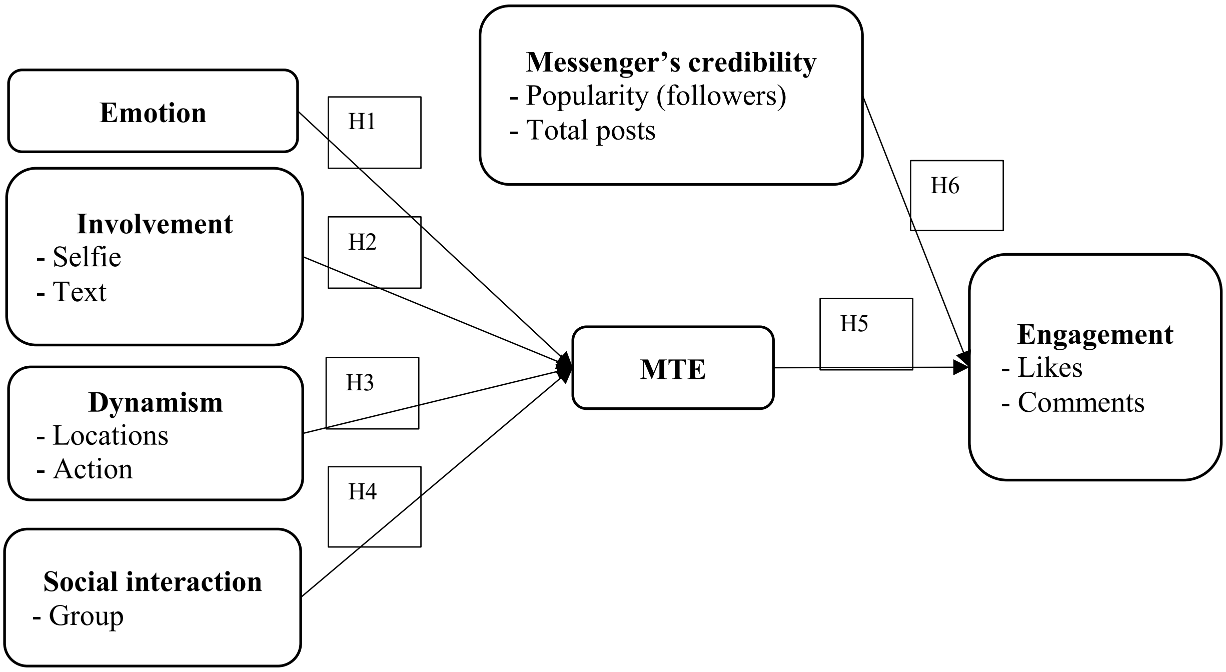
Tourism is about creating experiences, which are the core of travel (Cohen, 1979), and both consumer psychologists and experiential marketing scholars acknowledge the importance of experiences in people's daily lives (Hosany et al., 2022; Schmitt et al., 2015). Although there are numerous studies that have enriched the literature on customer experiences, few have explained the customer experience from a dynamic and holistic perspective (Li et al., 2022).

This research measures and explains the relationships between MTE (memorable tourism experience) and various antecedents such as emotions, dynamism, participation and socialization, as well as the effect of MTE on participation in social networks. The data analyzed is social network UGC (content generated by the user) from photos, texts and metadata extracted from Instagram posts through artificial intelligence techniques. This study is perhaps the first analysis of artificial intelligence applied to MTE.

A MTE has been defined as “a tourism experience remembered after the event has occurred” (J. H. Kim et al., 2012). There is more and more agreement between authors who show that tourist destinations should create MTE for tourists (Fan & Luo, 2022; Y. Kim et al., 2022; Li et al., 2022). This existing research has as its main limitation the use of self-report surveys based on a retrospective evaluation to measure MTEs (Hosany et al., 2022).

In light of this research gap, this study intends to fill by proposing research that allows measuring MTEs that tourists share on Instagram through an artificial intelligence model. Instagram offers the highest penetration rates among users between 18 and 50 years old and whose main motivation for use is the publication of tourist photographs (DataReportal, 2022). Furthermore, this research on MTEs is taken a step further by analyzing not only the text and sentiment of online reviews (Bigne et al., 2020) but also the content of images as emotions, and the set of metadata associated with the content published by the user (UGC).

Figure 1. Theoretical model



Methodology

To build the database, the web scraping method has been used, which has allowed extract 7,000 Instagram posts in the same European city by location between 2015 and 2022. The chosen city stands out for being an inland cultural tourist destination, belonging to the Smart Tourism Destination network and linked to UNESCO World Heritage, therefore the results can be generalized to a large number of similar destinations. To find tourists in the database, and differentiate them from locals, two methods have been used. Visitors are considered those who have posted photos in the destination for 30 days or less (Gunter & Önder, 2021) and who have uploaded 30 photos or less in the destination, discarding users with names from other cities, phone numbers or emails, and a high rate of hashtags (Gomez et al., 2019). Finally, 1,071 tourist posts were obtained with 2,129 people found in the total of the posts.
To extract information from the photographs, the deep learning method en python has been used through neural networks with facial attribute analysis como la age, gender, emotion and race, así como para las variables involvement, dynamism and social interaction. To do this, we work with previously trained neural networks to which the necessary characteristics are added in their last layers to adapt them to specific research areas (in this case, tourism and consumer behavior), and we look for the similarity between the first network and the adapted (Koch et al., 2015).
The evidence of memorability has been obtained through the texts shared on Instagram. For this, it has been considered that an experience is memorable if the tourist defines it as such, either using "memorable" words or related words. Thus, words or phrases such as: "memorable", "remember", "memory", "unforgettable", "memory", etc., have been searched for, in the different languages found in the database (Bigne et al., 2020).

Findings

In order to demonstrate and validate the relationships between the different variables proposed in the theoretical model and following the extant literature, this study employed the boot-strapping method 1.000 re-samples with SmartPLS. According to the extant literature, bootstrapping, a nonparametric method, allows testing the processed relationships' significance level in a structural model, assuming that the data is not normally distributed (Hair et al., 2016). This study does not suffer from collinearity among the indicators of the different variables. Reliability and validity of the constructs are all close to one. R2 of MTE is 60,5% and R2 of engagement is 15%. VIF are all one or superior.

Table 1. Structural model and hypotheses testing

Relations	**Hypotheses**	**Path coefficient**	**P value**
Emotion → MTE	**H1**	**0.356**	**0.000**
Involvement → MTE	**H2**	**0.469**	**0.000**
Dynamism → MTE	**H3**	**0.582**	**0.000**
Social interaction → MTE	**H4**	**0.157**	**0.000**
MTE → Engagement	**H5**	**-0.005**	**0.843**
Popularity → Engagement	**H6**	**0.375**	**0.000**

The main results of the PLS are that hypothesis H1, H2, H3 and H4 are supported. On the other hand, H5 is not supported.

Theoretical and practical implications

The present study contributes to the literature in five ways. First, through the use of non-declarative and non-post-trip data, the information that may be a reflection of the memorability of the experience at the current moment is analyzed, providing an impartial approach. Second, the metadata extracted from Instagram is analysed, which allows to differentiate between tourists and locals. Third, variables extracted from the images are analysed, such as emotions physically expressed by tourists in a photo, which is not the same as the sentiment detected in the texts associated with these photographs, which adds novelty to this research. Fourth, research on memorable tourism experience has a geographical bias, many studies in this review focus on the experiences of non-Western tourists, particularly Chinese (Hosany et al., 2022), for this reason, this research collects data from a European tourist city. Finally, variables such us travel group, involvement, dynamism and emotions of the tourists in the destination, that have not been previously tested in the literature, are analysed to try to find the MTEs.

Limitations and future studies

This research contributes to the study to close several of these existing gaps such us the need to study the positive and negative dimensions of MTEs; to overcome the limitations of self-reported surveys; to use mixed methods and to conduct cross-cultural studies.

Some limitations of this research are based on the qualitative nature of the information and the difficulty of generalizing the results to other destinations. However, the present study responds to the call of the academy that the MTE scale should be measured by other tools (Hosany et al., 2022).

Future studies can analyze and explain the satisfaction introducing items such as the user's expectations prior to the trip (Sie et al., 2018). Of course, it is necessary to extend this research to other social networks linked to tourism, such as Flickr, Pinterest or TikTok. Finally, other lines of research should make an effort to measure the dimensions of MTEs (J. H. Kim et al., 2012) through artificial intelligence (Hosany et al., 2022).

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Feeling vulnerable with AI. How interaction modality influences consumers responses to interactions with AI digital assistants.

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Type of manuscript: Extended Abstract

Keywords: AI digital assistants, modality, digital vulnerability, comfort, self-disclosure

Theoretical Background

Nowadays, major tech companies are heavily investing in the development of AI digital assistant primarily designed to facilitate voice interactions between users and the systems (e.g., Amazon Alexa, Apple Siri,). However, many of the current voice-activated digital assistants offer additional modality options to interact with their users, including "type-in" features. Despite technological advancements and research into text-based (e.g., chatbots) and voice-based (e.g., voice assistants), literature has often investigated voice-based and text-based assistant communication separately and few studies have explored the influence that AI digital assistant modality has on consumers responses and behaviors (Melzner et al., 2020). We aim to fill this gap and we investigate how the modality by which conversational AI digital assistants interact with users influence their responses.

Research from Information and Computer Science literature suggests that consumer preferences, choices and behaviors can be affected by the modality (i.e., text, voice, haptic feedback) through which consumers interact with technology (Melumad et al., 2020).

As voice assistants use natural language and are characterized by inherently human-like attributes such as a voice, they generally elicit more social responses in the users (Pitardi & Marriott, 2021). At the same time, voice interactions are often perceived as more difficult to understand and perform (Berry et al., 2005; Jeng et al., 2013). Moreover, since voice interactions are 'openly spoken', they can increase privacy risks and prompt consumers' concerns (Melzner et al., 2020).

Another potential consequence of interactions with digital assistants is perceptions of vulnerability. We define consumer vulnerability as the 'state of being exposed' (Baker et al., 2005), which is not merely defined by personal characteristics of a person (i.e., at-risk groups), but it concerns more the state that someone may find themselves in. Recently, it has been observed that technology has the capabilities of increasing customer perceptions of vulnerability that in turn may results in behavioural reactions (Del Bucchia et al., 2020).

Psychological comfort is a positive emotion generally defined as the feeling of 'being at ease', calm and worry-free during an interaction. In technology interactions, types of devices and their characteristics can affect individuals' feelings of comfort. For instance, smartphones can act as a source of psychological comfort for their owners (Melumad & Pham, 2020) and service robots can alleviate discomfort in embarrassing encounters (Pitardi et al., 2021). Most importantly, previous studies showed that when individuals feel comfortable during an interaction, they are also more willing to disclose their personal information (Melumad & Meyer, 2020).

Based on the above, we propose that when individuals interact with digital assistants through voice (vs text) interfaces, their willingness to disclose personal information decreases, and such effect is driven by an increase (decrease) of perceptions of vulnerability, and a decrease (increase) in psychological comfort.

Methodology

The study adopts a mixed-method approach. Study 1 uses in-depth consumers interviews and explore interactions with digital assistants. Preliminary findings identify vulnerability and comfort as psychological reactions promoted by the modality of the interactions.

Next, two experimental studies tested the hypothesized relationships. Study 2 uses a two-cell (modality: text vs. voice) between-subject design (N= 203). The scenario used a restaurant booking through a digital assistant and followed previous studies. Results showed a significant main effect of modality on all the dependent variables. Specifically, individuals displayed lower willingness to disclose their personal information when interacting with the conversational agent through voice (M_{voice} = 3.78) than text (M_{text} = 3.11; F[1,203] = 3.5, $p < .05$; $\eta^2 = .05$). Similarly, individuals showed higher perceptions of vulnerability (M_{voice} = 5.61 vs M_{text} = 4.89; F[1, 203] = 15.5; p = .04; η^2= .06) and lower feelings of comfort (M_{voice} = 3.07 vs M_{text} = 3.60; F[1,203] = 7.5; p = .001; η^2= .05) following a voice than a text interaction.

Study 3 examines the mediating role of perceived vulnerability and comfort and analyses the role of social presence as potential alternative explanation (Van Doorn et al., 2017). The study adopts the same design of study 2 in a different setting (N= 253).

First, we replicated the results of Study 2. Then, we tested the mediating role of vulnerability and comfort on consumers' willingness to disclose by employing PROCESS SPSS macro (Hayes, 2017; Model 4). Results reveal that the direct effects of modality on vulnerability (β = .45; 95% CI [.02, .88]), and comfort (β = - .53; 95% CI [-.91, -.15]) are significant. The impact of vulnerability (β = -.13, SE = .08, 95% CI [-.29, -.02]), and feelings of comfort (β = .47, SE = .16, 95% CI [.29, .66]) on willingness to disclose are significant. Furthermore, modality is no longer a predictor when controlling for the mediators (β = -.24, SE = .22, 95% CI [-.69, .19]), which indicates a fully mediated model. Finally, the results from a one-way ANOVA revealed a not significant effect of modality (p = .67) ruling out social presence.

Discussions

While voice-based technology is often perceived as offering higher levels of social presence in comparison to technology facilitated text-based communication, we remain unclear on the effects of voice-based technology interactions on individuals' behavioural responses. This research provides a theoretical understanding on how such modalities can affect consumers' psychological responses and subsequent behavior. Specifically, we contribute to the current research on AI conversational assistants (Hildelbrand & Bergner, 2021) and technology modality (Melumad et al., 2020) by providing insights into the influence of interaction modality with AI assistants on consumers' willingness to disclose their personal information. Moreover, the paper adds to the AI literature by shedding light on the role of perceptions of vulnerability and comfort in responses to such technologies. Our results advance theoretical understanding into the role of vulnerability within consumers' minds when interacting with AI agents showing how such vulnerability changes as a function of the technology's modality and illustrate the relevant role of comfort in such interactions. The study also advances practitioner understanding into what modalities could be used for varying consumer needs across the consumer decision-making journey.

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Customer interactions between expert users and smart voice assistants: how experiences and love drive to long-term relationships

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Type of manuscript: Extended abstract

Keywords: smart voice assistants; long-term relationships; experience.

Introduction, theoretical background and research model

In recent years, voice-controlled smart personal assistants (hereinafter, SVAs) have strongly emerged as new artificial intelligence service platforms. SVAs generate experiences based on values inherent to interpersonal relationships such as assistance, empathy and learning (Belk, 2017; Hoffman & Novak, 2018). In this way, SVAs become humanized in the minds' of their users, who interact with the technology as though it was a person, despite knowing that it is really a machine (Xu, 2020).

Although research into SVAs has increased exponentially in recent years, there are still important gaps that should be bridged. First, most previous studies have focused on new users, adoption and initial interactions. To the best of the authors' knowledge, no research has studied expert users and why they establish long-term relationships with smart technologies. Second, smart technologies have sophisticated capabilities that previous technologies lack. So, most traditional theoretical frameworks based on the user's reflective cognitive processing cannot adequately address the innovative experiences evoked by SVAs (Belk, 2017; Hoffman & Novak, 2018). Third, previous studies have not taken into account that users can relate in an interpersonal way to smart technologies and can develop affective bonds very close to those established between humans (McLean & Osei-Frimpong, 2019).

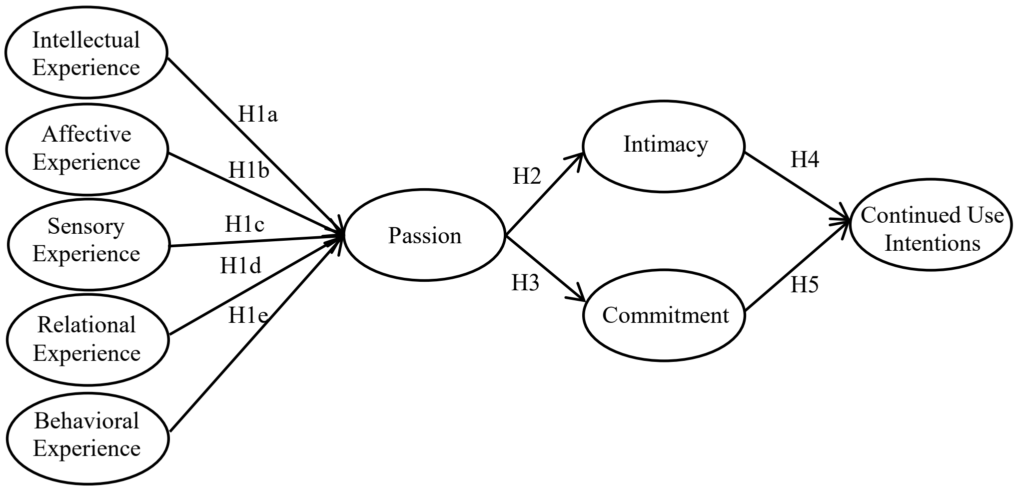
This study aims to examine why expert users develop long-term relationships with SVAs; strong emphasis is put on the analysis of the importance of generating experiences and love feelings during interactions. To do so, it draws on the stimulus-organism-response (SOR) framework (Mehrabian & Russell, 1974) and postulates that the five dimensions of experience that arise during users' interactions with their SVAs -that is, intellectual, affective, sensory, relational and behavioral- act as the stimuli that generate feelings of love for the SVAs (the organism). Specifically, this study addresses the formation of love by drawing on the triangular theory of love (TTL) (Sternberg, 1986), and examines the relationships between love's three components, passion, intimacy and commitment. Thus, the study considers whether passion acts as a key driver in the formation of the other feelings, doing these feelings encourage continuance intentions to use SVAs and the establishment of long-term relationships (the response).

Continued use has been defined as the long-term use of a technology beyond its first use (Bhattacherjee, 2001), that is, the continuous employment of a technology on a regular basis (Meister & Compeau, 2002). When users have experienced a technology they become familiar with, and less uncertain about, it; thus, intentions are more comprehensive, stable and permanent. The present study employs continued use intentions to examine expert users' long-term relationships with SVAs.

Sternberg´s (1986) triangular theory of love (TTL) established the influence of three components of interpersonal love: passion, intimacy and commitment. Customer's love exists when the individual feels an intense desire for products and brands (Ahuvia, 2005). Brand love has been defined as "the degree of passionate emotional attachment a satisfied customer has for a particular trade name" (Carroll & Ahuvia, 2006, p. 81), and reflects the individual's strong preference for a certain brand (Hatfield & Walster, 1985).

One of the most influential multidimensional customer experience frameworks was developed by Schmitt (1999), who proposed five strategic modules of experience: relate, think, feel, act and sense. These modules relate to the functional domains of the individual's mind and behavior, which involve different structures and processes. The present study examines the five key constituents that define customer-SVA experiences and drive the user to feel love toward a technology: intellectual, affective, sensory, relational and behavioral. Figure 1 depicts the proposed model.

Figure 1. Conceptual model and hypotheses.



Methodology

To test the proposed model a quantitative study was undertaken with expert SVA users. Expert users are those who use a SVA regularly (i.e., almost every day) and have been using a SVA for more than a year. The data were collected from a sample of U.S. participants in November 2018. More than 6,900 panel members (3,286 women) were contacted by email. First, they had to answer a question that guaranteed that they belonged to the target segment. Only those participants who were frequent users of SVAs could continue with the survey, thus ensuring the relevance of the responses. A total of 717 valid responses were obtained, a response rate of 10.4%. Second, these users had to explain for how long they had been employing their SVA. Those participants who claimed to be users for less than 1 year were removed. Finally, the sample was made up of 342 expert users. Of the respondents, 79.8% were men, 57% were aged between 25 and 44 and 59.7% had a university degree.

The information was obtained through a survey posing closed questions. The research constructs were operationalized using items adapted from previous research. customer experiences are based on Brakus et al. (2009), items for love constructs are obtained from

Sternberg (1997), while continued use intentions are measured by the Roca et al. (2006)' scales. The variables were measured using 7-point Likert scales, where 1 indicated complete disagreement with the statement, and 7 complete agreement.

Results

Structural equation modeling (CB-SEM) was employed to test the model, using a robust maximum-likelihood estimation procedure to avoid problems of data non-normality. First, the measurement model was estimated through a confirmatory factor analysis (CFA) to test the psychometric properties of the scales (i.e., reliability and validity). Second, the structural model was estimated to test the hypotheses (EQS 6.1 software).

Table 3. Results of the structural model.

Relationship	Hypothesis	Standardized coefficient (t-value)	Results
IX → PAS	H1a	.239**	Supported
AX → PAS	H1b	.396***	Supported
SX → PAS	H1c	*-.032*	*Not supported*
RX → PAS	H1d	*-.108*	*Not supported*
BX → PAS	H1e	.353***	Supported
PAS → INT	H2	.920***	Supported
PAS → COM	H3	.909***	Supported
INT → CUI	H4	.535***	Supported
COM → CUI	H5	.269**	Supported

Note: *** $p < 0.01$; ** $p < 0.05$;

Conclusion

This study makes three notable contributions to the literature. First, this study contributes to research into smart technologies by going beyond adoption behavior to focus on continued use intentions. It establishes the necessary premises for expert users to develop profitable and prolonged relationships over time, which can help companies to achieve maximum performance. The second contribution relates to the application of a new theoretical approach to studying smart technologies. Third, this study is an initial step in the application of an interpersonal approach to examining human-computer interactions.

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Exploring the role of Twitter communication flow in tourism demand forecasts

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Type of manuscript: Extended abstract

Keywords: tourism demand forecast; Twitter data; MIDAS; communication flow.

Research objectives

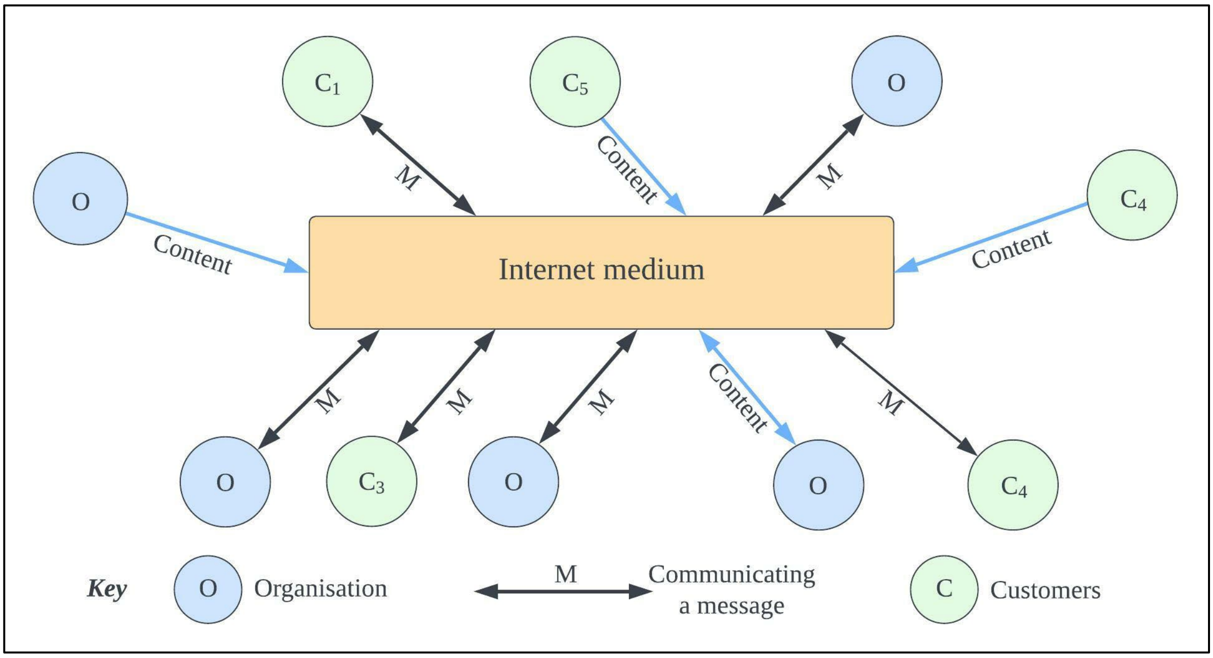
The literature has explored social media data to address real-world issues (Asur & Huberman, 2010), yet the role of social media data in tourism demand forecasting remains in its infancy (Hu, Li, Song, Li, & Law, 2022). Existing tourism research utilized online reviews retrieved from online travel agencies' webpages or data from online travel forums to reveal tourists' travel preferences (i.e. see Hue et al, 2022, and Li, Hu and Li, 2022). Limited research utilized data from platforms such as Facebook or Twitter (see Önder, Gunter, and Gindl (2019) for an exemption). Demand forecasts made at the attraction level are even more scarce (Bi, Li, Xu, & Li, 2021). This is surprising given that attractions have to manage tourist arrivals carefully due to their limited physical capacity (Peeters et al., 2018). Motivated by the need to manage the volume of visitors to attractions, this study aims to adopt mixed-frequency models to exploit social media data's high-frequency features. Underpinned by signalling theory, and with the focus on communication flow on Twitter, this study provides empirical evidence on the applicability of Twitter data to tourist arrival forecast for attractions and derives managerial implications

Theoretical background

Lacka et al (2021) has recently confirmed that tweets contain important information signals. In the tourism context, tweets can signal tourists' interest in visiting an attraction (Leung & Bai, 2013). Twitter data is noisy, which makes it challenging to extract useful information (Kraaijeveld & De Smedt, 2020). The 'noise' origins from the nature of communication flow on Twitter (Connelly et al, 2011). According to the digital marketing communication framework (see Figure 1), social media users can freely interact through the internet medium (e.g. Twitter) and hence making the signalling environment noisier. The noisier the context in which the signalling process occurs, the more the signalling value is expected to diminish (Connelly, Certo, Ireland, & Reutzel, 2011). To capture the signalling value of tweets, it is necessary to identify communication flows in the Twittersphere (Branzai et al, 2004).

Emerging studies derive evidence to confirm the importance of Twitter-generated variables such as volumes, likes, and retweets in addressing various real-world issues. First, the volume of tweets has been recognized as a good attention measure by research in finance (Behrendt & Schmidt, 2018; Shen, Urquhart, & Wang, 2019). It is worth investigating if tweets volume can serve as an efficient predictor of tourist arrivals. Second, since 'likes' is the only type of reaction Twitter users can give to a tweet. While the importance of Facebook likes has been established (Gunter, Önder, & Gindl, 2019), it is worth exploring if Twitter likes can also be utilized as an efficient predictor Third, retweets are found to play an important role in the information diffusion process in micro-blog platforms like Twitter (Hou, Huang, & Zhang, 2015), it is hence valuable to investigate if the volume of retweeting activities can help predict tourist arrivals.

Figure 1. Many-to-many communication via internet medium (Chaffey & Ellis-Chadwick, 2019) (p. 426)

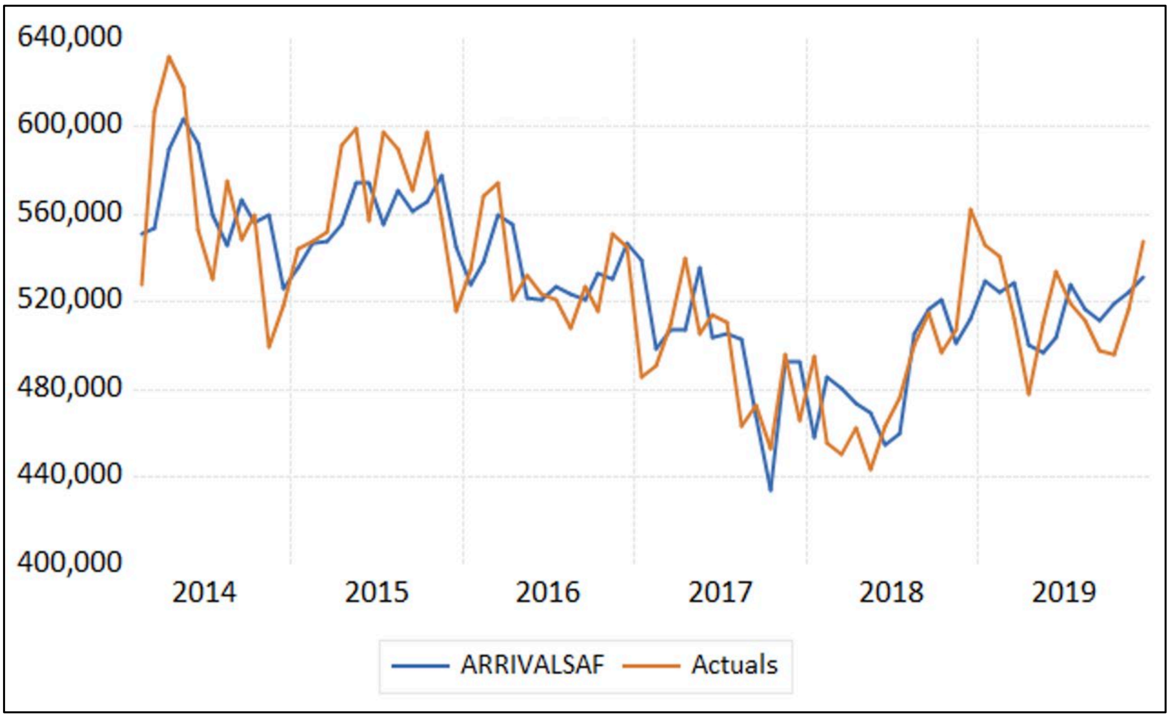


Research methodology

We use the British Museum (BM) as the case study for the following three reasons: (1) BM is one of the most famous tourist attractions in the UK, (2) BM has constant Twitter activities, (3) BM has been studied in previous research (see Volchek, Liu, Song, and Buhalis (2019)). We use BM's monthly tourist arrivals data from January 2014 to December 2019 to construct the dependent variable $Arrivals_t$. $Arrivals_t$ are then seasonally adjusted through a moving average filter to form the series $Arrivalsa_t$. Using the selected query keyword 'British Museum', tweets are collected in the same sample period resulting in a Twitter dataset containing 582,742 tweets. We clean Twitter data by removing tweets criticizing BM's stolen artefacts, UK's colonial history and BP's sponsorship. Tweets are then clustered into three subsets in accordance with the communication flow: (C_1) Twitter users talk to BM, (C_2) Twitter users talk about BM, and (C_3) BM talks to Twitter users. for each subset, variables including $Volumes_t$, $Likes_t$ and $Retweets_t$ are constructed through temporal aggregation and adjusted based on results of the Augmented Dickey-Fuller (ADF) test.

With the ability to incorporate lags of the dependent variable as additional explanatory variables, the autoregressive distributive lag (ARDL) model has been frequently used in tourism demand forecasting literature (Gunter et al., 2019; Narayan, 2004; Önder et al., 2019) and hence been selected as the benchmark in this study. To ensure a parsimonious model specification while allowing for the use of data sampled at different frequencies (Andreou, Ghysels, & Kourtellos, 2011), the restricted mixed data sampling auto-regression (R-MIDAS-AR) model is selected. Following Gunter et al. (2019), we apply a non-exponential Almon function with four shapes for the specification of the parameter θ as it has been suggested to generate the best overall in-sample model fit. To verify the forecasting performance of constructed models, four widely used evaluating criteria, including mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (SMAPE) are employed. Empirical results are presented in Table 1, Table 2 and Figure 2 below.

Figure 2. Pseudo-out-of-sample one-step-ahead static R-MIDAS-AR(1, 50) forecasts for tourist arrivals to BM from Jan 2014 to Dec 2019.



Findings and implications

As shown in Table 1, R-MIDAS-AR models yield higher adjusted R^2 and lower BIC than ARDL models. Variables generated from the C_2 subset (i.e. tweets reflecting individuals' activities in terms of talking about BM) cannot explain the fluctuation of tourist arrivals. After filtering out tweets from the C_2 subset, the models' forecasting performance improves further. More specifically, the R-MIDAS-AR (1, 50) model that incorporates likes as the exogenous predictor provides the best in-sample model fit and pseudo-out-of-sample on-step-ahead static forecasting performance among all 36 models (see Table 2 and Figure 2).

Table 1. In-sample model fit and Pseudo-out-of-sample One-step-ahead forecasts evaluation

No	Model	Exogenous predictors	P-values	**Adjusted R^2**	**BIC**	**RMSE**	**MAE**	**MAPE**	**SMAPE**
1	ARDL (1, 0)	$Volumes_t$	0.0524	0.59	23.38	34420.49	27233.68	5.23	5.18
2	ARDL (1, 0)	$Likes_t$	0.0697	0.58	23.41	35416.18	28081.33	5.37	5.34
3	ARDL (1, 0)	$C1\_Volume$	0.0743	0.60	23.38	37702.04	29277.79	5.65	5.57
4	ARDL (1, 1)	$C2\_Volume$	0.0039 (lag 1)	0.60	23.41	32042.45	25798.47	4.92	4.90
5	R-MIDAS-AR (1, 50)	$Volumes_t$	All < 0.05	0.64	23.41	29611.05	23839.19	4.56	4.53
6	R-MIDAS-AR (1, 49)	$Likes_t$	All < 0.05	0.61	23.49	29704.97	23871.56	4.51	4.51
7	R-MIDAS-AR (1, 50)	$C1\_Volume$	All < 0.05	0.66	23.34	30356.33	24338.38	4.68	4.65
8	R-MIDAS-AR (1, 51)	$C1\_Rewtee$	All < 0.05	0.62	23.48	38001.19	30717.52	5.87	5.84
9	R-MIDAS-AR (1, 50)	$C1\_Likes_t$	All < 0.05	0.61	23.49	33312.07	26279.11	4.99	4.97
10	R-MIDAS-AR (1, 50)	$C3\_Volume$	All < 0.05	0.64	23.42	32173.52	26499.62	5.10	5.07
11	R-MIDAS-AR (1, 19)	$C3\_Replies$	All < 0.05	0.64	23.41	31732.14	25154.03	4.84	4.81
12	R-MIDAS-AR (1, 27)	$C3\_Rewtee$	$PDL_{2 \text{ to } 4} < 0.1$	0.60	23.52	37088.07	29565.13	5.62	5.61

Source: the UK government's official website, Twitter Inc., and own calculations using EViews Version 11.
Note: 1. ARDL models with insignificant (i.e. below the 10% significant level) exogenous predictors do not enter the persuade-out-of-sample forecasting process. 2. R-MIDAS-AR models with insignificant exogenous predictors (i.e., all PDL lags are below the 10% significant level) do not enter the persuade-out-of-sample

forecasting process. 3. Only models with significant coefficients for the exogenous predictor are included in the table. A full table can be provided on request.

Table 2. In-sample model fit and Pseudo-out-of-sample One-step-ahead forecast evaluation for adjusted dataset (filter out C_2 data)

No	Model	Exogenous predictors	P-values	Adjusted R^2	AIC	RMSE	MAE	MAPE	SMAPE
1	R-MIDAS-AR (1, 50)	$A\_Volumes_t$	all<0.01	0.67	23.34	30084.09	24071.70	4.63	4.60
2	R-MIDAS-AR (1, 27)	$A\_Replies_t$	all>0.1	0.63	23.45	34889.86	27495.29	5.21	5.22
3	R-MIDAS-AR (1, 14)	$A\_Rewteets_t$	$PDL_{3\ to\ 4}$ < 0.05	0.62	23.47	38690.12	31867.26	6.14	6.10
4	R-MIDAS-AR (1, 50)	A_Likes_t	all< 0.05	0.65	23.40	26774.11	21327.96	4.03	4.03

Source: The UK government's official website, Twitter Inc., and own calculations using EViews Version 11.

This study adds to the tourism literature by providing empirical evidence on Twitter data's capability to forecast tourist arrivals in accordance with communication flow at the attraction level. It further confirms MIDAS models' ability to sample high-frequency Twitter-based predictors and generates improved forecasts. More importantly, the findings of this study indicate that, for demand forecasting purposes, tourist attractions should pay more attention to conversations directly made between them and Twitter users (i.e. C_1+C_3). Future research can explore: (1) if proposed demand forecasting models can achieve improved performance in other cases and research contexts (i.e. other attractions, provinces, and regions), and (2) if attractions, such as BM, can shape tourist arrivals by altering their social media communications.

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Attachment styles moderate applicant's responses to face-to-face vs asynchronous job interviews

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Type of manuscript: Extended abstract

Keywords: asynchronous video interview (AVI); attachment styles; applicant reactions.

Research Objective

As technology and human resource practices have evolved over the past years, the employment interview, one of the most popular selection methods, has experienced an important transformation (Torres & Gregory, 2018). We have seen a growing implementation of emerging technologies in the hiring process such as Asynchronous Video Interview (hereafter, AVI), an on-demand alternative to traditional face-to-face and videoconference job interviews, which allows applicants to log into an online platform and records video-responses to predefined employment interview questions on camera. AVI has been considered a low-cost alternative to hire candidates and make the interview process easier to manage, enabling organizations or recruiters to fast-screen or skip specific candidates, saving time, reducing travel costs, and improving the overall efficiency of the hiring process (e.g., Guchait *et al.*, 2014)

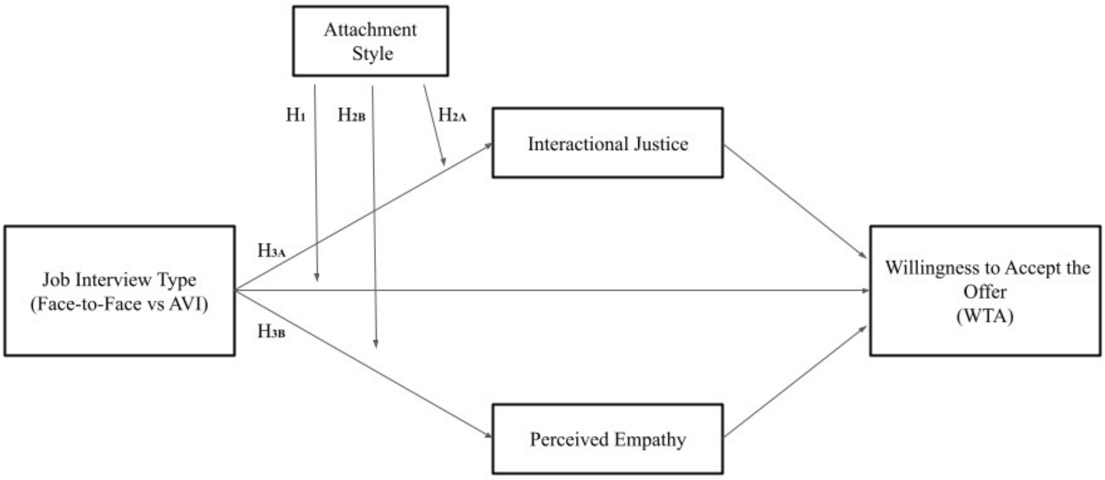
However, there is still limited research on job candidate responses to asynchronous interviewing (Torres & Gregory, 2018). In fact, although they may be composed of the same interview questions, different interview methods may trigger different reactions which may relate to key outcomes for organizations, such as applicants' willingness to accept the job offer (Zhang *et al*, 2017).

The present work answers the call by comparing job candidate responses (e.g., willingness to accept the job offer; hereafter, WTA) to Face-to-Face interview (hereafter, FTF) versus AVI. Additionally, grounding on attachment theory (e.g., Mikulincer *et al*., 2001), our research proposes that applicants' attachment styles, defined as relationship-based models of behavior in a social context, influence job candidate reactions to the type of job interview (Pozharliev et al., 2021). Building on attachment theory, we believe that impersonal interviewing techniques that lack face-to-face meetings (e.g., AVIs), may lead certain types of people, such as people with a secure attachment style, to react less positively (i.e., lower WTA) compared to face-to-face job interviews. For instance, highly automated interviews provide a restricted social bandwidth which hinders the opportunity to exchange social signals and to have direct interactions (Langer *et al*., 2020), limiting secured attached people interpersonal skills and unsatisfying their social-emotional needs.

Moreover, we hypothesize these effects will be mediated by the perceived interactional justice and the perceived empathy of the recruiter. Interactional justice is interpersonal in nature and concerns the quality of the interpersonal treatment received by customers when procedures are implemented, encouraging social exchange relationships to be formed (Vázquez-Casielles *et al*., 2010). The adoption of a FTF (vs AVI) interview, given its features, is likely to positively influence candidates' perception of interactional justice, and this perception may be visible in an increase in their subsequent WTA. Additionally, some types of people, such as those which base their relationship on honesty and tolerance as

securely attached people, are more likely to prefer a selection method in which a proper interpersonal treatment is guaranteed. Therefore, we expect that candidates will react differently to FTF (vs AVI) differently based on their attachment style.
Empathy is a wide concept that relates to customers' cognitive and emotional responses to others' perceived experiences (Hossain & Rahman, 2022). We believe that recruitment activities such as a FTF interview (vs AVI) may signal a greater interest in the candidate and favor mutual social-emotional empathy, leading to a higher perceived recruiter's empathy, which in turn will increase candidates' WTA.
Moreover, for some types of attachment styles, such as the secure one, social-emotional skills of the counterpart and social feedbacks are critical for a healthy social interaction (Mikulincer *et al*., 2001). Drawing on these insights, we believe that applicants' will perceive recruiter's empathy of FTF (vs. AVI) differently based on their attachment style.

Figure 1. Conceptual model



Research Method
We test our hypotheses through two experimental studies which use a real selection procedure. Two experimental groups are formed based on the type of job interview (FTF vs AVI) to be performed by applicants.
The procedure consisted of three stages: (1) the publication of a job post and pre-interview questionnaire to apply for the job, (2) the actual job interview (AVI or FTF), and (3) a post interview questionnaire.

Preliminary results
Our preliminary results showed a decrease of WTA for candidates who have performed the AVI (vs. FTF) job interview, as hypothesized. Moreover, we found a moderating effect of individual attachment style: *secure* and *fearful-avoidant* applicants are more willing to accept the job offer in the FTF job interview (vs AVI).

Original contribution
HR managers are challenged to improve their knowledge about job candidate responses to emerging online technologies used during the hiring process. We answer the call by examining and comparing how real applicants react to automated and (vs) face-to-face hiring

processes. Moreover, we identify a novel moderator, attachment style, which shapes these reactions. To this end, our research may provide actionable implications for segmenting applicants, tailoring specific hiring procedures toward specific segments (e.g. proposing a FTF interview to *secure* and *fearful-avoidant* candidates), and customizing marketing communication for these segments.

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Understanding how lenders' social presence in peer-to-peer platforms can boost consumers' prosocial behaviour

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Type of manuscript: Extended abstract

Keywords: prosocial behaviour, peer-to-peer platforms, lenders' social presence

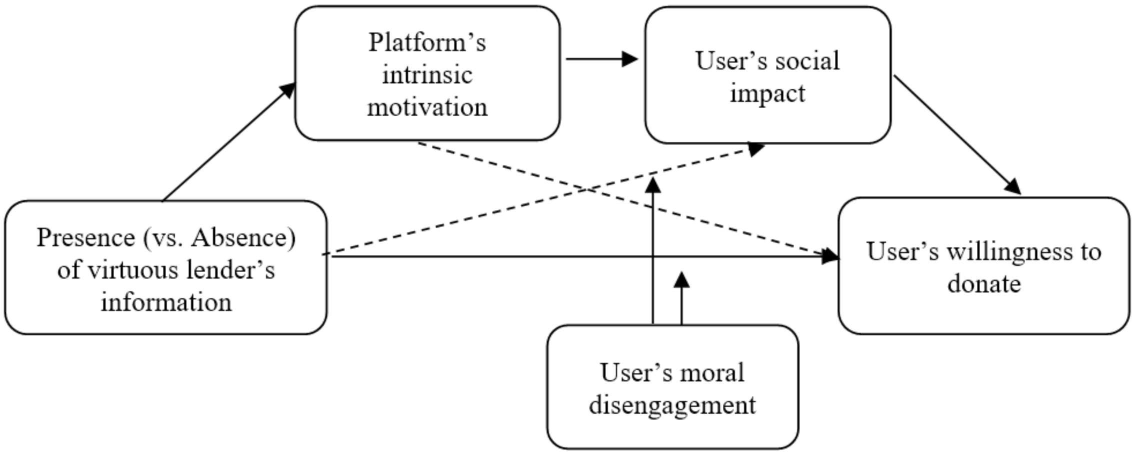
Research objectives and questions

Many peer-to-peer (P2P) service platforms connecting users to individuals interested in sharing their personal possessions (e.g., houses, dresses, tools, etc.) support prosocial causes (Piscicelli *et al*., 2018). Communicating such commitment effectively is key for encouraging users to support the platform's efforts and engage in prosocial behaviours (e.g., donations), which typically involve some cost to the self to benefit others or society as a whole (White *et al*., 2020). However, users' reactions to these communications may vary substantially depending on the extent to which they perceive P2P platforms as socially responsible organizations (Dean, 2003; Pomering & Dolnicar, 2009; Sen & Bhattacharya, 2001).

Individuals offering their services through P2P platforms—hereafter "lenders"—may play an important role in fostering users' support for prosocial causes as they can communicate prosocial values. Past studies on the role of lenders in P2P platforms noted that users tend to trust these persons, especially when they display information about their identities (Ert *et al*., 2016). Furthermore, users tend to perceive the act of using a P2P service as helpful when they interact directly with a lender, rather than the organization managing the platform (Costello & Reczek, 2020). However, the emerging literature on P2P services has so far neglected to investigate users' reactions to platforms' prosocial communications.

This research attempts to fill this gap and proposes that lenders conveying *virtuousness*, that is the pursuit of the highest aspirations in the human condition (Bright *et al*., 2006) through the information they display on a P2P platform might increase the platforms' perceived commitment to prosocial causes and foster user intention to support such causes. More specifically, this work investigates whether lender's virtuousness spills over onto the platform and increases: (a) users' perception of the platforms' intrinsic motivation to support a social cause; and (b) the extent to which users think that their help can have a social impact, which in turn enhances their willingness to support the cause. Toward this end, this work developed a conceptual model (Figure 1) that assesses: (1) the effect that the social presence (vs. absence) of virtuous lenders in P2P platforms may exert on users' prosocial intentions; (2) the mechanism that explains this effect (i.e., user's perception of the platform's intrinsic motivation and their own social impact); and (3) the moderating effect of users' moral disengagement, which refers to those cognitive mechanisms that deactivate a person's moral standards.

Figure 1. Conceptual model



Research method

The empirical part of this work comprises two online experimental studies that respectively considered a real P2P car rental platform (*SnappCar*) and a real P2P fashion rental platform (*Tulerie*). Both studies used a between-subjects design and recruited participants through Prolific Academic ($N_{\text{Study 1}} = 179$; $N_{\text{Study 2}} = 132$). In both studies, participants were informed that the platform supported a social cause. Half of them were exposed to a virtuous lender describing him/herself as highly committed to that cause; then, all participants completed seven-point scales that assessed the platform's perceived intrinsic motivation, participants' social impact, and participants' willingness to donate (by choosing one of seven possible options: from $0 to $10). Study 2 participants also completed a moral disengagement scale.

Preliminary results

Study 1 results – Participants assigned to the "virtuous lender present" condition rated the car rental platform's intrinsic motivation as significantly higher than their counterparts ($p = .001$; Table 1); they manifested a significantly stronger willingness to support it with a donation ($p = .027$), and, compared to their counterparts, they rated their social impact as marginally significantly higher ($p = .069$). A serial mediation analysis (Table 2) showed that virtuous lender's information (a dichotomous variable coded as: -1 = "virtuous lender's information absent" and 1 = "virtuous lender's information present") exerts a significantly positive effect on the platform's intrinsic motivation ($p < .001$), which, in turn, positively impacts the user's social impact ($p < .001$). Finally, the user's social impact positively influences his or her willingness to donate ($p < .001$). Thus, a virtuous lender's social presence affects users' willingness to donate directly and indirectly ($b = .49$; 95% CI: .21, .81) through the aforementioned variables.

Table 1. Study 1: Descriptive statistics and comparison between the control and treatment conditions.

	Lender absent		Lender present			
	Mean	SD	Mean	SD	*F*	*p*
Platform's intrinsic motivation	5.12	1.42	5.78	1.05	12.57	.001
User's social impact	3.85	1.86	4.33	1.59	3.34	.069
User's willingness to donate	3.51	3.10	4.57	3.26	4.99	.027

Note: $N = 179$; $df = 1, 177$.

Table 2. Study 1: Serial mediation analysis.

Dependent variable: Platform's intrinsic motivation (*Me1*)	*b*	*SE*	*t*	*p*
Constant	5.12	.13	38.74	< .001
Virtuous lender's information (*X*)	.66	.19	3.54	< .001
	$R^2 = .18$, $MSE = 2.20$, $F(3, 128) = 9.23$, $p < .001$			
Dependent variable: User's social impact (*Me2*)	*b*	*SE*	*t*	*p*
Constant	.37	.49	.76	.45
Virtuous lender's information (*X*)	.02	.23	.10	.92
Platform's intrinsic motivation (*Me1*)	.68	.09	7.47	< .001
	$R^2 = .25$, $MSE = 2.30$, $F(2, 176) = 30.11$,$p < .001$			
·pendent variable: User's willingness to donate (*Y*)	*b*	*SE*	*t*	*p*
Constant	-1.35	.81	-1.66	.10
Virtuous lender's information (*X*)	.46	.39	1.18	.24
Platform's intrinsic motivation (*Me1*)	.13	.17	.76	.45
User's social impact (*Me2*)	1.09	.12	8.74	< .001
	$R^2 = .40$, $MSE = 6.27$, $F(3, 175) = 39.39$,$p < .001$			
Indirect effects of X on Y:	*b*	*SE*	*LLCI*	*ULCI*
Via Platform's intrinsic motivation (*Me1*)	.09	.11	-.12	.33
Via User's social impact (*Me2*)	.02	.27	-.52	.53
Via *Me1* and *Me2*	.49	.15	.21	.81

Note: $N = 179$; X was coded as: -1 = Virtuous lender's information absent; 1 = Virtuous lender's information present; *Me* = Mediator.

Study 2 results – Participants assigned to the "virtuous lender's information present" condition rated the fashion rental platform's intrinsic motivation as significantly higher than their counterparts ($p = .028$; Table 3); they manifested a significantly stronger willingness to support it with a donation ($p = .001$) and rated their social impact as significantly higher than their counterparts (p = .001). A serial mediation analysis confirmed that virtuous lender's presence exerts a significantly indirect positive effect on users' willingness to donate via an increase in the platform's perceived intrinsic motivation, which, in turn, enhances users' perception of their social impact (b = .18, 95% CI: .01, .40). Moreover, a moderated mediation analysis (Table 4) identified a significantly negative interaction effects of virtuous lender's information and participants' moral disengagement on participants' perceived social impact (p = .01) and willingness to donate (p = .03). This result suggests that morally disengaged users think that their contribution might have a lower social impact compared to less disengaged users. Importantly, the analysis returned a significant index of moderated mediation (b = -.13, 95% CI: -.66, -.03) and, consistent with our prediction, the conditional direct and indirect effects of lender's presence were significantly positive at a low level (M–$1SD$) of moral disengagement, but not significant at a high level of moral disengagement (M+1SD).

Table 3. Study 2: Descriptive statistics and comparison between the control and treatment conditions.

	Lender absent		Lender present			
	Mean	SD	Mean	SD	*F*	*p*
Platform's intrinsic	5.48	1.07	5.86	0.91	4.93	.028
User's social impact	3.73	1.58	4.62	1.54	10.59	.001
User's willingness to donate	3.45	2.73	5.06	2.76	11.31	.001

Nota: N = 132; df = 1, 130.

Table 4. Study 2: Moderated mediation analysis.

Dependent variable: User's social impact	*b*	*SE*	*t*	*p*
Constant	3.85	.44	8.71	< .001
Virtuous lender's information (*X*)	2.27	.61	3.72	< .001
User's moral disengagement (*Mo*)	-.04	.13	-.30	.76
X × *Mo*	-.47	.18	-2.55	.01
	R^2 = .18, *MSE* = 2.20, *F*(3, 128) = 9.23, *p* < .001			
ependent variable: User's willingness to	*b*	*SE*	*t*	*p*
Constant	.20	.91	.21	.83
Virtuous lender's information (*X*)	3.07	1.05	2.93	< .001
User's social impact	.70	.14	4.85	< .001
User's moral disengagement (*Mo*)	.21	.21	.99	.33
X × *Mo*	- .69	.31	-2.26	.03
	R^2 = .30, *MSE* = 5.84, *F*(4, 127) = 12.06, *p* < .001			
Conditional direct effects of X on Y	*b*	*SE*	*LLCI*	*ULCI*
Low level of *Mo* (*M-1SD*)	1.96	.64	.70	3.22
High level of *Mo* (*M+1SD*)	.00	.60	-1.18	1.18
Conditional indirect effects of X on Y	*b*	*SE*	*LLCI*	*ULCI*
Low level of *Mo* (*M-1SD*)	1.07	.30	.50	1.68
High level of *Mo* (*M+1SD*)	.14	.30	-.47	.75
ndex of moderated mediation	-.13	.16	-.66	-.03

Note: *N* = 132; *X* was coded as: -1 = Virtuous lender's information absent; 1 = Virtuous lender's information present; *Me* = Mediator; *Mo* = Moderator.

Originality

Research on the effects that lenders' ethicality may have on users' prosocial behaviour is still very scarce (Farmaki *et al*., 2019). Therefore, this study aimed at advancing knowledge in this field and found that virtuous lender's information presence (vs. absence) in P2P platforms may boost users' intention to support the platforms' prosocial initiatives. Our results indicate that the presence of virtuous lenders may significantly enhance the effectiveness of prosocial communication messages as such lenders not only increase a platform's perceived commitment to social causes but also lead users to believe that their help can have a significant impact; this ultimately motivates users to support a cause with their donations. This tactic can, therefore, help P2P platforms increase the effectiveness of their prosocial communications, possibly enhancing their contribution to social causes.

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Exploring the effects of spectators' identification with esport players and the community on consumer behaviour

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Type of manuscript: Extended abstract

Keywords: esports; identification; consumer behaviour.

The video game industry has become one of the most important in the global entertainment sector. One of the fastest growing modes of playing is through the multiplayer experience of video game competitions, known as esports. They are organised into teams, leagues, tournaments and professional championships (Borowy & Jin, 2013; Taylor, 2012). It represents a multi-agent ecosystem with content creators, players, teams, audiences and communities (Scholz, 2019).

Its significant audience brings players fame that empowers them to influence spectators' behaviours. However, very few studies have examined the industry from the perspective of influencer marketing. The ability of influencers to deliver very targeted messages makes it necessary to examine them more rigorously to better understand their impact on the consumer-brand relationship (Taylor, 2020). The aim of this ongoing work is to investigate the impact of esport players as influencers from the perspective of social identity theory (Tajfel, 1974). This research proposes and empirically evaluates a conceptual model that suggests that identification with esports players and communities are antecedents of purchase intention, stickiness intention and behavioural loyalty.

Data from esports viewers were collected through an online survey (N=393). All constructs were measured using Likert scales validated in the previous literature. The model was tested using partial least squares path modelling (PLS-SEM) with SmartPLS 3.3 software (Henseler, Müller and Schuberth, 2018), following a two-phase process: (1) Evaluation of the reliability of the measurement scales and of convergent and discriminant validity: All the parameters are consistent with the recommended values; thus the reliability, convergent validity and discriminant validity of the measurement model are confirmed; (2) Evaluation of the structural model, and hypotheses testing (bootstrapping = 10,000): Five of the seven proposed hypotheses were accepted. Esport player identification had a positive influence on community identification and purchase intention. The effects of community identification on purchase intention, stickiness intention and behavioural loyalty were positive and statistically significant. On the other hand, the impacts of esport player identification on stickiness intention and behavioural loyalty were not accepted. The possible indirect effects of identification with the esport player/team through community identification were also evaluated. The results showed that mediation is partial in the relationship between community identification and purchase intention and total in the relationship with stickiness intention and behavioural loyalty.

The preliminary results of this ongoing work help to explain the influence of esport players on their audience and the preponderant effect that identification with the community has on followers' behaviours. No previous studies have analysed the relationships proposed in this work. In addition, the results confirmed that social identity theory is a framework suitable for the study of esports and its effects on followers.

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A Cross-Cultural Analysis of Emoticon Utilization in Social Media Branding Communication

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Type of manuscript: Extended abstract

Keywords: emoji; Twitter; big data; cross-cultural; brand communication.

Background

Emojis were first introduced as emoticons in the 1990s by arranging several textual characters to resemble faces. It was proposed by American computer scientist Scott E. Fahlman that ":)" and ":(" indicate humor and seriousness, respectively, in computer-mediated communication (Krohn, 2004). Later, at the start of the 2010s, emoticons were standardized as icons and dubbed "emoji characters" as part of Unicode 6.0 (Davis, 2021). Following the standardization of emoji characters, they were integrated into a vast array of mobile devices and browsers, which increased consumer interest in using them in social media messaging (Evans, 2017). Besides representing facial emotional expressions, emojis lately come in different flavors to indicate a variety of states and situations to symbolize travel, places, flags, animals, nature, or activities.

Emojis are used to express basic emotions such as happiness or sadness as well as complex feelings and attitudes such as sarcasm, boredom, and friendship (Chang, 2016; Coyle, 2019). Emojis in text messaging positively affect consumers' perceived enjoyment, usefulness, playfulness, and social connectedness, thereby promoting word-of-mouth (Huang, 2008; Hsieh, 2017). Analyzing their extracted emotional meaning is essential to comprehending the effective mechanisms involved in conveying the intended message's delivery to result in perception in the desired manner. There is a growing body of literature on cultural differences in the preference for emojis in text communication (Das, Wiener, & Kareklas, 2019; Kavanagh, 2010; Lee & Hsieh, 2019; Lo, 2008; Takahashi, Oishi, & Shimada, 2017). However, the majority of these studies use experimental design with limited external validity (Cook, Campbell, & Shadish, 2002). There is a gap in the literature for further research that focuses on how individuals use emojis, particularly in branding communication (Park, Baek, and Cha, 2014).

This study aims to quantify cross-cultural differences in the preferences and use of emojis as nonverbal cues regarding brand communication context among English-speaking and Turkish-speaking Twitter users. Using distributional measures and information-theory methodologies, we seek answers to the research questions listed in Table 1 by dividing our investigation into three sections.

Table 1. Research Questions

Section	Research Question	
1	RQ-1	*How different is the attitude toward using emojis in messages across cultures/languages?*
2	RQ-2	*How different is the set of popular emojis preferred across cultures/languages?*
	RQ-2a	*Does one culture use a more diverse set of emojis?*
	RQ-2b	*How much different is the set of popular emojis across cultures/languages?*
3	RQ-3	*How different are emojis preferred semantically by basic emotions (Happiness, Surprise, Sadness, Anger, Fear, Disgust)?*

Our findings are useful for comprehending the significant differences in consumer preferences between local and global markets. We contribute to the fields of marketing communication and social media marketing while highlighting alternative approaches to methodological analysis that capture the inherent benefits of big data and information theory:

(1) In our first contribution, we use zero-inflated regression models to compare the attitudes of English- and Turkish-speaking Twitter users towards the use of emojis. Our findings indicate that Turkish-speaking users prefer to use a single emoji in their messages, while English-speaking users prefer to use multiple emojis within a single message.
(2) To understand how popular emoticons are among English- and Turkish-speaking Twitter users, we analyze the variety of emojis preferred in messages for both languages and the similarity of emojis preferred at high, moderate, and low popularity levels. Our results show that as a function of time, the diversity of emojis decreases, while the similarity of mostly preferred emojis increases for English-speaking and Turkish-speaking users. The preferences in both communities converge to a similar and smaller subset of emojis over time.
(3) As part of our final contribution, by using co-occurrences of emotional words and emojis in messages, we calculate the probability distribution of emojis for the six basic emotions (Ekman, 2005; Matsumoto, 2009), namely, happiness, surprise, sadness, anger, fear, and disgust. With the help of probability distribution distance measures, we analyze how emojis are preferred semantically in English and Turkish regarding their emotional representation. It is observed that semantically emojis with negative sentiment are more similarly used than emojis with positive sentiment by English- and Turkish-speaking users.

Methodology
In order to answer the proposed research questions, a representative sample of Twitter posts of 42 companies that are active in FMCG, Fast Food, Technology, Automotive, Apparel, Retail, Finance, and Logistics industries with Twitter accounts both in English and Turkish languages were sampled. The initial dataset included 8,101,034 English and 852,348 Turkish Twitter posts shared between June 2016 and June 2021, which we collected via the Twitter 2.0 API.

In Section 1, the mean number of emoticons in Twitter messages was compared between English and Turkish datasets. Also, to differentiate between brands' and consumers' messages, the data was divided into conversational parts, such as brand posts and consumers' replies. As shown in Table 2, the deviation was higher than the mean number of emojis in messages, and a fair number of zero counts appeared. Therefore, using a T-test to compare the means of the skewed data could have led to unreliable results (Koplenig, 2019). To remedy this, we created a binary variable for language, with English as the base, and compared the fits of Linear, Poisson, and Negative Binomial Regression and the zero-inflated versions of these models to assess the zero and non-zero counts better.

Table 2. Summary statistics

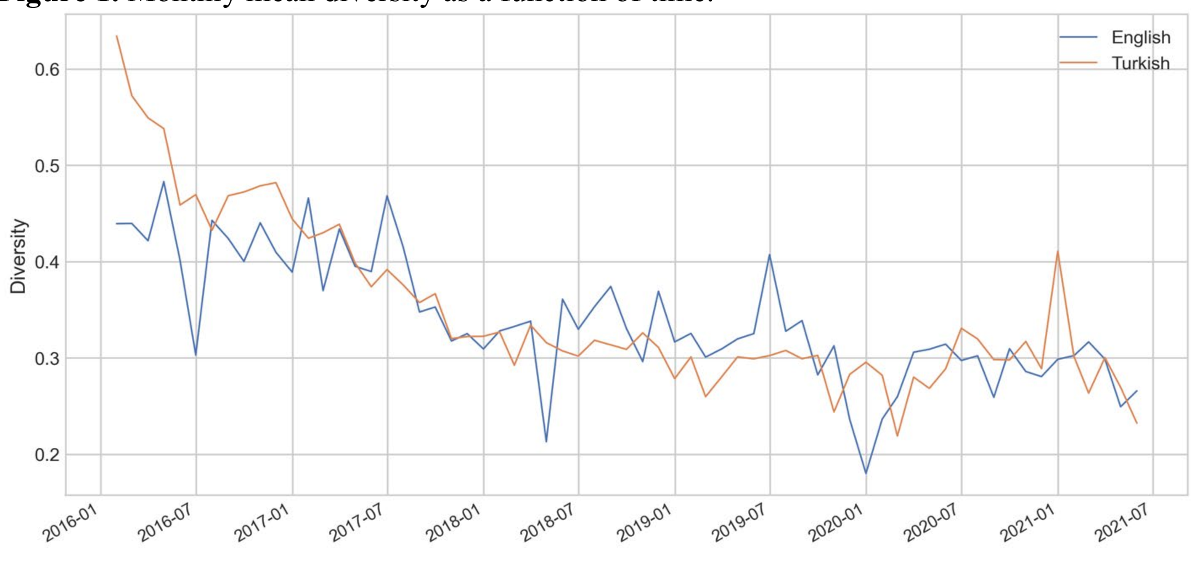
	English			**Turkish**		
	Posts	**Replies**	**Overall**	**Posts**	**Replies**	**Overall**
Mean	**0.27562**	**0.29040**	**0.28546**	**0.35917**	**0.26884**	**0.29898**
St. Dev.	0.68610	1.25476	1.09833	0.72689	1.24005	1.09668
Median	0	0	0	0	0	0
IQR (1,3)	0, 0	0, 0	0, 0	0	0, 0	0, 0
Minimum	0	0	0	0	0	0
Maximum	100	136	136	51	136	136

In Section 2, firstly, the lexical diversity of emoticons preferred in both languages was calculated by the type/token ratio (TTR), which was originally proposed for calculating word diversity in text (Koplenig, 2019). Our modified version of the equation for emojis is as follows:

$$TTR_i = \frac{V(C)}{C}$$

where V(C) is the distinct count of emojis, and C is the total count of emojis in corpus *i*.
In order to control corpus size, which affects C in this case, both datasets are divided into 1000 messages, and TTR is calculated for each of these chunks. Finally, TTR is averaged over chunk size for an estimate of mean diversity and unbiased corpus size. The application is also repeated as a function of time. Our results showed that a more diverse set of emojis was preferred in English. However, the mean monthly diversity of emojis decreased for both languages from 2016 to 2021 (Figure 1).

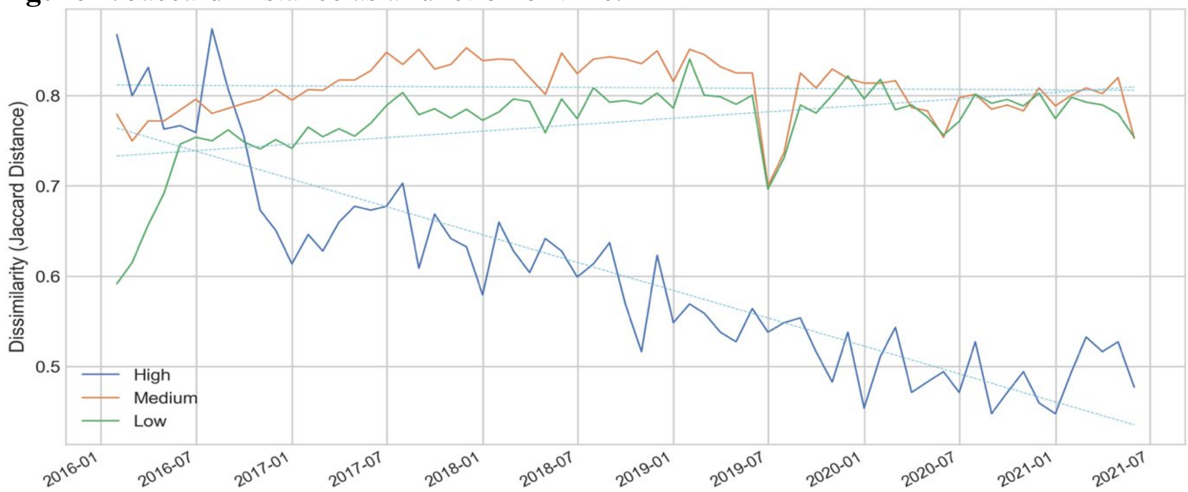
Figure 1. Monthly mean diversity as a function of time.



We followed an earlier formulated approach to analysis (Kejriwal, 2021), where emojis for both corpora were counted and ranked according to their frequencies, then their log (base 10) transformed values were plotted. The curve is then decomposed into three popularity segments (high, moderate, and low), with the high popularity segment containing 90% of all emoji appearances in the message dataset.

Next, the segmentation of emojis according to their popularity was analyzed by evaluating the differences of emojis preferred for each popularity segment between languages, where Jaccard Distance between each popularity segment was used as a measure of dissimilarity. At the aggregate level, emojis in the high popularity segment were most similar, and emojis in the medium and low popularity segments differed significantly between English and Turkish. Moreover, the 200 most popular emojis were becoming more similar since 2016 (Figure 2).

Figure 2. Jaccard Distance as a function of time.



In Section 3, the top 90 scored words for each basic emotion were selected as emotional seed words from the Turkish Emotion Lexicon for Turkish (Tocoğlu, 2019), and the NRC Emotion Lexicon (Mohammad & Turney, 2010; Mohammad & Turney, 2013) for English languages. The relevance of an emoji according to a set of emotional words was calculated using a co-occurrence matrix of emojis and emotional words. Finally, a discrete probability distribution for each emoji was attained to show their relevance to the six basic emotions. The probability distributions of emoticons for English and Turkish were compared against each other using Jensen-Shannon Divergence, a symmetric distance index for discrete probability distributions. Following the manual coding of emojis according to their sentiment use (Kralj Novak, 2015), it was observed that negative emojis were emotionally more similarly used than positive emojis, and the variance of distance was the highest regarding neutral emojis (Figure 3). Table 3 also provides a sample of the semantically most similar and dissimilar emojis.

Figure 3. Distribution of emotional distance by the sentiment of emojis.

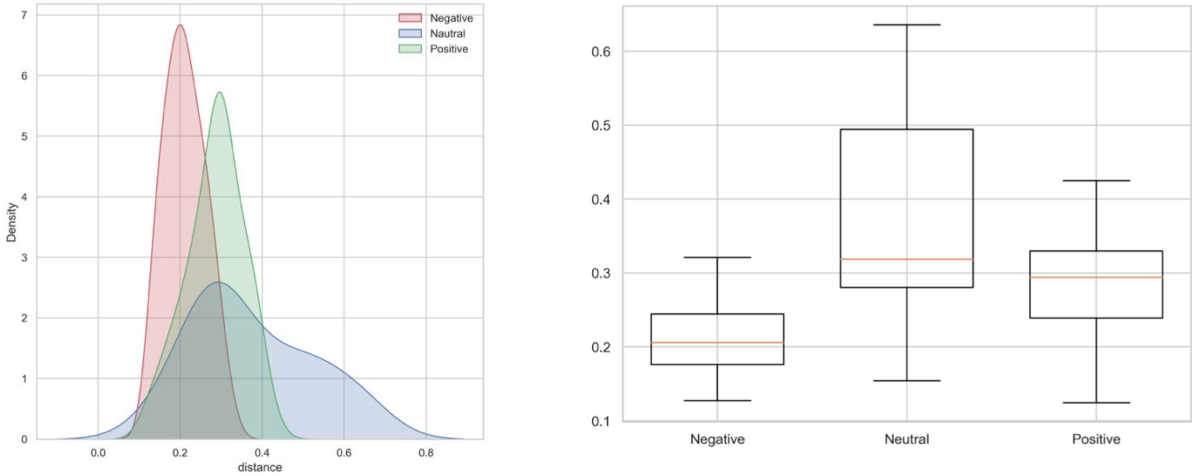


Table 3: Emotional similarity of emojis

Most Dissimilar emoji	distance	Most Similar emoji	distance
□♀	0.6358	□	0.1906
□	0.6221	□□	0.1832
□	0.5156	□	0.1823
□	0.5095	□	0.1778
□	0.4794	□	0.1776
□	0.4249	□	0.1775
‼	0.4060	□	0.1768
□	0.4051	□	0.1756
♥	0.3925	□	0.1747
□	0.3859	□	0.1746
□	0.3821	□	0.1739
□	0.3804	□	0.1720
□	0.3764	□	0.1612
□	0.3758	□	0.1606
□	0.3746	□□♀	0.1548
□	0.3743	□	0.1543
□	0.3608	□	0.1488
□	0.3538	□	0.1462
□	0.3527	□	0.1432
□	0.3465	□	0.1411
□	0.3423	□	0.1399
□	0.3398	□	0.1299
□	0.3395	□	0.1286
□	0.3297	□	0.1275
□	0.3293	□	0.1244

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Lexicon-based sentiment analysis of fake news on social media

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Keywords: Lexicon; sentiment analysis; fake news; Twitter; emotions.

Introduction

Social media is considered one of the primary sources of information. Besides all benefits that social media bring to human life, the popularity of social media simultaneously caused a rapid spread of fake news. Fake news poses a serious threat to societies since it enhances the polarity among different ideas, such as political parties. The fake news issue was further exacerbated during the COVID-19 Pandemic, and fake news studies attracted the attention of plenty of researchers (e.g., Apuke & Omar, 2021; Elías & Catalan-Matamoros, 2020). For example, Fake news claiming that 5G cell towers affect the human immune system has led to the burning of some cell towers in Europe (Mourad et al., 2020). Researchers claimed that fake stories spread more rapidly than true ones on social media (Vosoughi et al., 2018). The rapid spread of fake news makes companies and organizations vulnerable. Fake news about a company can directly affect the company's stock price and cause financial losses. A literature review reveals that scholars from multidisciplinary areas are interested in this topic; for instance, psychology scholars aim to answer research questions such as why people believe and share fake news (Talwar et al., 2019) and what are the characteristics of people who share or are involved in the spread of fake news (Ben-Gal et al., 2019; Brashier & Schacter, 2020). Computer science scholars aim to find ways to detect fake news, using machine learning techniques to create detection models (Faustini & Covões, 2020; Ozbay & Alatas, 2020). Emotion and sentiment analysis of fake news have not been studied in the literature; thus, this research will contribute to the field significantly.

Fake news publishers apply multiple methods to make their news impressive and attractive to the readers. The aim of this research is to study the sentiments of fake news. The sentiment of fake news can be used as a feature for automatic fake news detection or as a warning alarm for readers who have been exposed to fake news on social media. In this research, multiple sentiment lexicons such as VADER, Textblob, and Sentiwordnet are utilized to recognize the news's positive, negative, and neutral emotions. The analyses are implemented on a Twitter dataset of fake and true news (Patwa et al., 2020). The results indicate that fake news in social media mainly includes negative emotions and fake news publishers use words with negative emotions more than positive emotions in their sentences. Possible reasons for this observation and some future research suggestions are suggested in this study.

Methodology

Sentiment analysis techniques are applied to find the polarity of fake and true news and compare them. The dataset is collected from Twitter with hashtags related to COVID-19. It is a balanced data with 5600 real news and 5100 fake news (Patwa et al., 2020). The preprocessing steps include eliminating any characters apart from alphabets, lowercasing the letters, deleting stop words and lemmatization applied to the dataset before any other analysis. Lexicon-based sentiment analysis outputs a polarity for every input text data. VADER, Textblob, and Sentiwordnet lexicons are utilized to extract the sentiments of the tweets. VADER (Valence Aware Dictionary and sentiment Reasoner) is an open-source lexicon and rule-based sentiment analysis tool, specifically attuned to social media (Hutto, 2014). Textblob is a python library for processing textual data. Textblob provides an API for natural language processes such as speech tagging, translating, and sentiment analysis (Loria, 2018). Sentiwordnet is an opinion lexicon adapted from WordNet database. (Esuli & Sebastiani, 2006).

Findings

Table 1 shows the percentage of the positive, negative, and neutral tweets in two classes of fake and real news for all three lexicons. The sentiment classification of the three lexicons for fake and true news is quite different. Twenty percent of the data were manually labeled (labels: positive, negative, and neutral). The lexicon results were then compared with a manually labeled part of the dataset to find the best performing lexicon.

Table 1. Comparison of three lexicons

Lexicon	Fake			Real		
	Positive	Negative	Neutral	Positive	Negative	Neutral
VADER	31.15 %	39.31 %	29.53 %	46.45 %	35.20 %	18.35 %
Textblob	32.23 %	21.35 %	46.42 %	57.05%	18.91%	24.04%
Sentiwordnet	41.10%	26.81%	32.08%	53.42%	32.90%	13.68%

Accuracy and precision were calculated for all three lexicons. Table 2 reports the metrics. As Table 2 illustrates, since VADER lexicon performs better than other lexicons (with an accuracy of 0.64), the forehead analysis is based on the output of VADER.

Table 2. Performance metrics of lexicons

Lexicon name	VADER	Textblob	Sentiwordnet
Accuracy	0.64	0.41	0.40
Macro Precision	0.64	0.46	0.41
Macro Recall	0.64	0.44	0.41
Macro F1-score	0.63	0.41	0.40
Weighted Precision	0.65	0.49	0.43
Weighted Recall	0.64	0.41	0.40
Weighted F1-score	0.63	0.41	0.41

39.31 percent of the fake news is classified as negative, and 31.15 percent is classified as positive; thus, fake news on social media mainly includes negative emotions. Fake news publishers use words with negative emotions more than positive emotions. They might do this to attract many audiences and subsequently increase the number of shares. Psychology research suggests that bad news, bad emotions, and bad feedback have a more significant impact than good ones, and negativity bias is "one of the most basic and far-reaching psychological principles"(Baumeister et al., 2001). Negativity bias theory implies that humans give more importance to negative experiences than positive (Lewicka et al., 1992). The effects of this theory can be seen in reactions of social media users such as sharing and retweeting. Fake news publishers make use of this theory to attract the attention of more

people. The other important observation is that the number of positive tweets is more than negative ones in the class of real news since real news is mostly published by reliable sources which aim to improve public information and develop society's awareness.Future work
We believe that fake news publishers use extreme emotions in their speech or text to influence and attract readers. The next step of the research is to extract the basic and specific emotions such as anger, fear, anticipation, trust, surprise, sadness, joy, and disgust. Preliminary results imply that the most dominant emotions in fake news are fear, trust, anger, and sadness. The classification performance of these emotional features can be examined for fake news detection models. The analysis of this study can be done on other social media platforms such as Facebook to see if the findings are generalizable to other platforms or not.

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Development and Validation of a Technology Paternalism Scale

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Type of manuscript: Extended abstract

Keywords: smart technology; technology paternalism; technology acceptance; technology resistance.

With the rise of digitalization, more and more products we handle become smart and context-aware. These products collect, process, and produce information (Rijsdijk & Hultink, 2009). A prominent example are autonomous cars: robotic taxis already exist (West, 2022). Besides increasing efficiency, comfort and overall safety, surrendering control and decision competence to a technology can lead to increased technology resistance or dampened technology acceptance (Heiskanen et al., 2007; Nordhoff, Winter, Kyriakidis, van Arem, & Happee, 2018; Schweitzer & van den Hende, 2016). One reason for this effect is technology paternalism (TP), which is defined as a situation when an action X by a technology T, which is controlled by a patron A, directly affects a user and the user (1) perceives X as limiting, punishing or in any other way cutting down on freedom, (2) cannot overrule or in any other way disregard X without sacrificing functionality. Furthermore, (3) the X is claimed to be mainly in the interest of the user and (4) is performed by the technology autonomously (Spiekermann & Pallas, 2006). The existing literature on TP is to a large extent anecdotal, conceptual, or based on qualitative studies. To better understand the phenomenon of TP it is necessary to investigate it empirically. This is why there is a strong need for a measurement scale. By using a multi-study approach, we provide this scale to quantify TP on individual level.

With increasing anthropomorphism, human-like technology changes human-computer interaction profoundly. For instance, awarding a technology a humanlike mind leads to the perception of this technology as a moral instance (Epley & Waytz, 2010). Consequently, as most smart products are highly anthropomorphic (for instance, Amazon's Alexa), smart devices impact consumer engagement and use intention (Schweitzer, Belk, Jordan, & Ortner, 2019). One reason is that artificial intelligence (AI) only processes binary data (like, 1 and 0, yes or no), it leaves no negotiation scope. As a result, users of smart technologies face risks that they may not be able to overrule the smart technology anymore without sacrificing functionality.

In study 1 we explored factors, topics, and hypotheses, which are unknown in the recent body of literature on TP, by conducting several qualitative interviews. We used the rule-based and theoretically grounded qualitative content analysis procedure based on Mayring and Fenzl (2019) to reduce the complexity of the transcripts. The interviews revealed different antecedents to TP; e.g., the interaction with smart devices leads to a tension area between device autonomy and user perceptions. Additionally, in situations, when a technology acts fully autonomous and these actions cannot be interrupted by the user, users feel overruled by the technology or even feel like being captive. Furthermore, it is important that the actions made by an autonomous technology are reasonable for users.

To answer further questions and to prove the identified factors empirically, and whether (2) some of these antecedents are part of a common higher-order factor, and (3) whether and how these factors are related to perceived TP, we conduct further (more quantitative) research attempts in study 2.

In study 2, we use a mix of original and adapted scale items to provide a comprehensive assessment of a construct (Churchill, 1979). However, following proven tracks of technology adoption research, we conducted supplementary qualitative research in the next step. The generation of an item battery started with a re-analysis of the interview manuscripts of study, which lead to 163 statements about perceived TP at first. After subtracting duplicates and redundancies, the final item set consisted of 74 items. This list was shown to proven experts of the subject area and consumers for evaluation. Only items which had a first quartile score of “4” or higher for both questions and both groups where selected for the final set for the pre-test (in total 36 items). To elicit the developed scale and to identify underlying factors of TP, we use exploratory factor analysis, validation of higher-order factor structure (confirmatory factor analysis), and convergent and discriminant validity tests (following Hair, Black, Babin, and Anderson (2013)).
To test for nomological validity, we plan to check in study 3 if the scale makes accurate predictions of other concepts in a theoretically based model (Hair et al., 2013). This study will apply a SEM approach to investigate the empirical characteristics of the categories identified. We assume that the quantitative data reflects the discovered constructs of TP. With conducting subsequent analyses, we are about to provide deeper insights into the effects of TP on technology acceptance and resistance.

This research is about to contribute to the body of knowledge on technology acceptance in several ways. First, it takes into account the fact that smart devices developed towards social entities, which move consumers on both, motivational and psychological levels (Milchram, van de Kaa, Doorn, & Künneke, 2018; Shang, Zhang, & Chen, 2012; van Doorn et al., 2017). By not considering moral values like perceived paternalism, recent acceptance models, which typically focus on the benefits of technologies and how these benefits influence the acceptance of technologies (Davis, 1989; Venkatesh, Morris, & Davis, 2003), ignore the issue. From a managerial point of view, this manuscript will provide an overview of factors of product features which increase perceived TP. Understanding these factors is crucial for product developers as TP decreases technology adoption. Furthermore, this work will underline the importance to take perceived TP into account when designing new smart products. Finding the sweet spot between supportive information delivery and paternalizing the user is key for future smart product development.

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Does age matter in webrooming?

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Type of manuscript: Extended abstract

Keywords: webrooming; perceived risk; need for touch; perceived usefulness of sales personnel.

Research problem

New technologies and social networks enable consumers to better understand the purchasing process, find the information they need and evaluate all the opportunities offered by the market. The multichannel marketing method, during which the consumer uses different sales channels, is becoming more and more popular in society (Piatkovskytė and Ulbinaitė, 2018). Different sales channels can be interconnected and create common benefits for both the consumer and the seller. One such example of cross-channel behavior is webrooming, in which a consumer finds a product of interest and information about it online but goes to a physical store to purchase it (Shankar and Jain, 2020; Aw, 2019). During the purchasing process, the consumer is faced with a variety of internal and external factors that determine an individual's decisions, so it is particularly important to understand the perceived risks of online shopping and the perceived benefits of physical stores in webrooming behavior.

Up until now, the level of research on this topic is low, and there is very little research on the perceived risks and benefits of user-friendly webrooming behavior (Marmol and Fernandez, 2019; Aw, 2019). The main factors that the authors single out in their research are the desire to reduce risk and the need to communicate (Aw, 2019; Ortlinghaus, Zielke and Dobbelstein, 2019; Arora and Sahney, 2018; Santos and Goncalves, 2019; Kaduškevičiūtė and Urbonavičius, 2019). For consumers, contact with the seller is important in the purchasing process, allowing them to have more confidence in the product offered and reducing the risk of frustration when shopping online (Riquelme and Roman, 2014). Also, the need to touch and feel the product is often mentioned as an important motive for webrooming behavior. Consumers do not have the opportunity to check the quality, appearance and suitability of a product when shopping online, so there is a need to go to a physical store to inspect that product (Flavian, Gurrea and Orus, 2016; Shankar and Jain, 2020; Rathee and Rajain, 2019).

Webrooming behavior is common in the daily lives of many people and is widespread around the world among users of all ages. Representatives of different age groups have different needs, consumption habits, and their purchasing behavior often depends on the environment and the period during which they grew up (Bansal, 2015). Age is one of the most important socio-demographic characteristics that influences consumer behavior, but it is also important to understand that each consumer may have a different understanding of perceived risks and different needs during the purchasing process, which is important to assess in order to provide a smooth and reliable consumer experience while purchasing in a multichannel environment (Slaba, 2019; Kang, 2018).

Literature and methodology

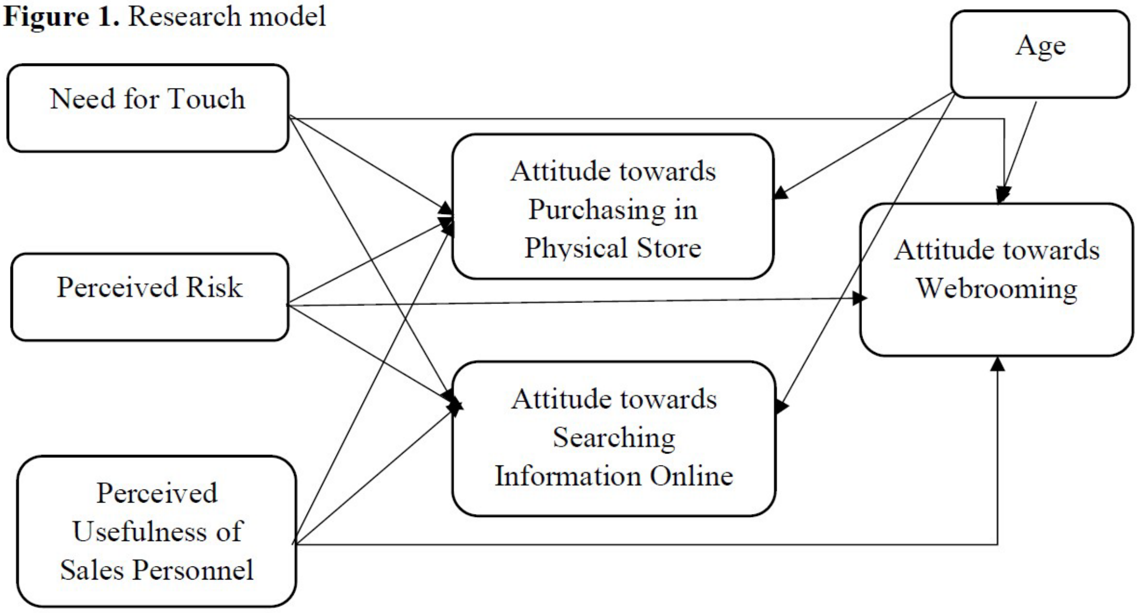
According to the National Retail Federation (2018), 73 % of consumers go to the brick-and-mortar to purchase the products that they have chosen, 27% of consumers go to physical stores to search for goods, socialize, or spend time. 46 % consumers choose online channels to search (National Retail Federation, 2018), suggesting that online channel is more popular for product search, and physical stores are chosen to make purchases (Flavian, Gurrea, and Orus, 2020; Zaharia and Schroder, 2008). In a study by Flavian, Gurrea, and Orus (2020), consumers said they save time and make better decisions when searching for a product online and buying a product in a physical store than when searching for product information in physical stores and buying online. Consumers in webrooming behavior engage in online searches to find out the details of a product, critically evaluate it, and go to physical stores to make a purchase decision, where consumers often go to know exactly what they want to buy (Fernandez, Perez and Casielles, 2018). Consumers face risks during the purchasing process that prevent them from making sure that the product is suitable and making a final decision. Searching for information in one channel and purchasing a product in another channel increases the likelihood of avoiding the risks that the consumer might face when performing actions in only one channel (Zhuang, Leszczyc and Lin, 2018). According to Forsythe and Bo (2003), those who simply search for information online perceive less risk than those who buy online, so consumers engage in webrooming behavior to avoid risk. The most commonly identified risks consumers are facing by the consumer are financial (Lim, 2003), product compliance (Shankar and Jain, 2020), convenience (Forsythe and Shi, 2003), privacy (Bach et al., 2020), and delivery (Reid, Ross and Vignali, 2016). Perceptions of risk vary depending on the brand category and brand credibility (Tan, 1999). When a consumer faces a lack of information about a product online, there is a need to communicate live, to hear the opinion of a specialist, to help the consumer make a decision. The need to communicate usually stems from the desire to learn more from vendors (Arora, Parida and Sahney, 2020) and the opportunity to socialize (Kang, 2018). If a consumer, after analyzing a product online, still does not trust the product and has questions, it is likely that dispelling doubts will go to the physical store (Aw, 2019). Such consumer behavior encourages webrooming. However, the impact of the need to communicate often depends on the consumer's personal characteristics, product category, and the availability of salespeople in the physical store (Aw, 2020; Arora, Parida and Sahney, 2020).

While online channels often present bigger variety of categories and products, the examination of physical attributes of those products is not possible, hence consumers have to use various indirect sources to judge the performance of a product in terms of quality, and that remains one of the main disadvantages of online shopping (San-Martin, Gonzalez-Benito and Martos-Partal, 2017). According to Peck and Childers (2003) theory, the time spent physically examining a product is way more valuable and necessary for some customers than reading descriptions about the attributes of a product online. Touching a product increases confidence in evaluating it (Peck and Wiggins, 2006). Haptic information can be classified as instrumental – referring to the examination prior the purchase that results in the outcomes related to the customer (comfort and certainty of the judgments) as well as the targeted product (quality or worth), and autotelic – as having a purpose in itself (it is connected to the hedonic shopping motivations pursuing fun, desire and enjoyment) (Peck and Childers, 2003).

Summarizing different aspects mentioned before proposed research model was developed (Figure 1). First of all, consumers can evaluate a product in a variety of ways and form an opinion about it when browsing the Internet (Bhatnagar and Ghose, 2004; Holmes, Byrne and Rowley, 2014). However, the information they collect alone is not enough to reduce the perception of risk of purchasing online. Therefore, perceived risk has a positive impact on attitude towards searching for product information online (H1), purchasing it in physical channel (H2) as well as positive attitude towards webrooming itself (H3). Moreover, when purchasing high involvement products, consumers tend to consult professionals who can tell more about the product of interest (Arora, Parida and Sahney, 2020; Aw, 2020; Kim, Saenz, & Park, 2019). Thus, perceived usefulness of sales personnel has a positive impact on attitude towards purchasing in physical store (H4) and webrooming(H6), while it has a negative impact on attitude towards searching information online (H5). Online channel often lacks sufficient amount of information about the products. When consumers are unable to evaluate the characteristics, appearance, quality and suitability of the product of interest online, consumers go to the physical store. This suggests, that need for touch has a positive impact on attitude towards purchasing in physical store (H7) and webrooming (H9), while it has a negative impact on attitude towards searching information online (H8). Moreover, positive attitude towards searching for information online (H10) and purchasing in brick-and-mortar (H11) are suggested to have a positive impact towards webrooming attitude. Finally, older consumers, especially the baby boomers, like to shop in physical stores because they feel safer and more secure when shopping in this way. Lack of knowledge of technology often leads to distrust of websites and creates additional risks that they choose to take to physical stores. Therefore, older consumers are believed to have more positive attitude towards purchasing in brickand-mortar (H12), while younger consumers would have a greater attitude towards product search online (H13). Finally, it is hypothesized that there is a significant difference between age groups when choosing to webroom (H14).

In order, to prove hypothesis proposed, the quantitative study was carried out. Total amount of 438 respondents participated in the study. For hypothesis testing exploratory factor analysis (EFA) was performed, as well as subsequent testing on the basis of correlation analysis. EFA was chosen because nature of webrooming behaviour is still not fully investigated and relationships with different factors are still being explored.

Figure 1. Research model



Conclusions

The study proved that there is a significant and positive relationship between perceived risk of purchasing online and attitude towards purchasing in physical channel as well as webrooming. This goes in line with Flavian, Gurrea and Orus (2016) study results. Moreover, the finding of need for touch being an important predictor in the case of webrooming also supplements the findings of Manzano et al. (2016). Finally, perceived usefulness of sales personnel was found out to be significant when choosing to webroom. This finding goes in line with previous study by Shankar and Jain (2021). In addition, previous studies did not take into consideration age of consumers. This study found out, that younger consumers are looking more favorably to product information search online, while the older respondents showed more favorable attitude towards purchasing in the physical store. All in all, there is a significant difference between age groups when choosing webrooming behavior.

This study gives clear signals for business. First of all, it is not enough to concentrate on one channel. In digital era consumers use a variety of different channels to search for information and to purchase products. Therefore, retailers must ensure sufficient amount of information in all of them this way making customer journey as effortless as possible. Secondly, retailers should invest more in training their sales personnel.

Consumers are willing to hear from them not only technical information but as well to help them in finishing their decision-making process.

However, this study has some limitations. First of all, for this study only respondents who have experience with webrooming were chosen. It would be important to investigate if there are differences in attitudes for consumers who did not have this particular experience. Secondly, majority of respondents were rather young (18-25 y.o.) If there would be bigger part of respondents of older age, study results might differ.

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Determinants of intention to use autonomous buses: a qualitative study

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Keywords: autonomous buses; intention to use; qualitative study.

Artificial intelligence applied to autonomous driving is expected to provide opportunities that can contribute to improved mobility and more efficient and sustainable transportation systems. Despite these advantages, previous studies have noted drawbacks that have slowed down its adoption such as those related to users' concerns about security, safety, legal issues, and potential hacks. This study aims to better understand the users' perceptions and intention to use autonomous buses for urban transit on the part of individuals who have both tried, and not tried, the technology. The research was undertaken in the framework of the project "Automost" carried out in Málaga by the Avanza company in collaboration with Malaga City Council, the Empresa Malagueña de Transportes (EMT) (Malaga Transport Company), and the Chair of Transport Management at the University of Malaga. It is the first autonomous bus to circulate in a European city without being separated from other vehicles. We applied inductive qualitative content analysis to explain consumers' perceptions and intention to use autonomous buses. The data were collected during June 2021 through two focus groups discussions with 6 randomly selected people from each group under study. The key questions were designed based on the literature review about prior knowledge, safety, emotions, social influence, perceived control, perceived benefits, attitude, trust, and satisfaction. The results show that previous experience is a fundamental factor. The reduction in accidents and increased international recognition of the city are the main perceived benefits by participants. However, the loss of the driver's job was one of the main disadvantages, although they recognised that this negative aspect does not compare to the benefits. While attitudes were positive, intention to use was conditioned by need. Future research should use a larger sample size, and could evaluate the model in different cities and cultural contexts to allow greater generalization of the results.

New horizons in customer resistance: Exploring consumer difficulties in adopting Autonomous Vehicles (AV) from a marketing perspective

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Type of manuscript: Work-in-Progress

Keywords: Tech 4.0; AV (autonomous vehicle) technologies; resistance, psychological reactions; hybrid review.

Advances in artificial intelligence (AI) and technology are transforming society and consumer behaviour. However, many consumers continue to be resistant to adopting innovative new products and services. In particular, the adoption of fully autonomous vehicles that require no human intervention and have proven technological benefits, as well as the potential to transform the travelscape, has been slower than forecasted. In this paper, we address gaps in research focusing on resistance to AV adoption. We use the results of a hybrid literature review and draw upon technological resistance and theories to develop a conceptual framework for exploring psychological resistance to AVs. Based upon a sample of 671 Australian and USA consumers, we empirically test our framework by investigating consumers' resistance to AVs with differing levels of intelligence. We extend the AI and AV adoption literature by examining the relationship between AV stressors, perceived benefits, adoption difficulty and resistance.

Introduction

Technology 4.0 such as artificial intelligence (AI), advanced robotics and Big Data was until recently in the domain of science fiction, but is now rapidly transforming the ways in which consumers can enjoy travel while undertaking other activities such as eat, sleep, work, play, live stream, sightseeing, foreplay, lovemaking and so on (Belk, 2022; Puntoni *et al.* 2021). Despite technology 4.0 having the ability to enhance performance, research in the field of marketing and psychology suggests that consumers continue to have major reservations and are resistant to adopting some new technologies owing to the risks and uncertainties involved (Kim *et al.* 2021). As such, it is essential to incorporate behavioural insights when commercialising technological developments, or risk undermining the consumer experience with AI, which from a psychological perspective, may alienate consumers (Puntoni *et al.,* 2021). There is a need to develop psychological frameworks that enable a better understanding of how consumers embrace or reject technology 4.0 (Belk *et al.* 2022). This is particularly relevant for disruptive new technologies such as fully autonomous vehicles (AVs) where greater knowledge of the influence that consumer characteristics and psychological mechanisms may increase adoption and lower apprehension (Charness *et al.,* 2018; Hegner *et al.,* 2019).

While most extant research has concluded that AVs are technically superior to traditional vehicles, many consumers continue to be concerned about their safety (Levin and Wong, 2018) as well as societal, ethical and other considerations (Bonnefon *et al.,* 2016). Much AV research has focused on the benefits and usefulness of AVs (rather than the drawbacks that have a negative influence on AV adoption), lacking strong behavioural frameworks and theoretical foundations (Huang and Qian, 2021). The first objective of this paper, therefore, is to address the gaps in research focusing on resistance to AV adoption by developing a conceptual framework for exploring psychological resistance to AVs. We provide a discussion of narratives and systematic reviews on consumer resistance to AV technologies, theories, and analytical approaches used in AV studies, in order to further understanding of unfavourable psychological reactions to AVs. Our second objective is to empirically test our framework.

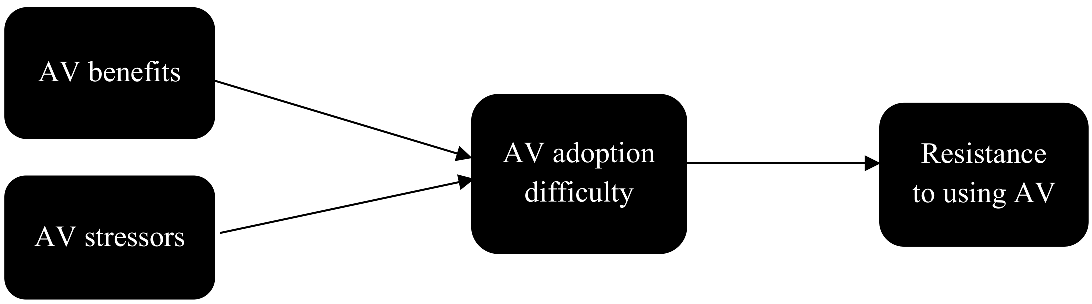
We contribute to the literature by answering calls for further research within both general Tech 4.0 and more specific AV contexts - for example, research on uncharted AI experiences (Puntoni *et al.,* 2021) that explore AI-related fairness, privacy, ethics and loss of autonomy concerns associated with AI across different geographic settings (Pitardi and Marriot, 2021; Mariani *et al.,* 2021; McLeay *et al.*, 2022). With exceptions (e.g., Huang and Qian, 2021), most AV research has focused on consumer perceptions of less intelligent AVs that require human intervention rather than highly intelligent fully autonomous AVs. Therefore we address the need for research with strong psychology and marketing underpinning that compares and contrasts consumers' perceptions of AVs that have different levels of intelligence (Huang and Qiaun, 2021; McLeay *et al.,* 2022)

Following Joshi (1991) who developed a theory-based understanding of user resistance to change, suggesting that users evaluate their net gain prior to adopting new technology, this work-in-progress sets out to investigate how AV stressors (i.e., conditions that lead to stress/distress) can influence consumer resistance to AV technologies. We conduct a hybrid review of the core elements of the relevant studies to explain the complex nature of technostress and the unfavourable psychological reactions to AVs.

Initial results of hybrid review and conceptual framework development

Following Mehran and Olya (2019), this study uses a hybrid review (i.e., an annotated bibliography), combining narrative and systematic quantitative review, supplemented by qualitative thematic reviews and semantic network analysis. The steps involve drawing up a list of sources that we plan to use, each with a summary of the source and an explanation of how we intend to use the source in our study, as follows: 1. Listing the bibliographic information; 2. Summarising the argument of the source; 3. Explaining why the source is significant; 4. Listing the # of times the source has been cited by others (cf., Google Scholar or Web of Science). The conceptual framework developed from the hybrid literature review is presented in Figure 1.

Figure 1: Conceptual framework and proposed research model



Mediation role of AV adoption difficulty:
AV benefits→ adoption difficulty→ Resistance to using AVs
AV stressors → adoption difficulty→ Resistance to using AVs

Control variables:
Types of AV (AV3 vs AV5); context (Australia vs US); Sex (1: male, 2: female); Age; Education level; Income Level; Martial Status

AV benefits, AV stressors and resistance to using AVs are described in the sections that follow. As this is a working paper, AV adoption difficulty will be further developed in the final manuscript.

AV Benefits
Powered by AI, AVs are one of the most potentially disruptive forces in the travelscape (McLeay *et al*., 2022). Fully autonomous vehicles require no human intervention to drive - as AI decision making can take over all of the mechanical operations of driving without the continuous monitoring or control of a human (Huang and Qiaun, 2021). Scientific evidence highlights numerous benefits of AVs in comparison to traditional cars including: safety; comfort, increasing transportation efficiency; reducing accidents; less pollution; and improving mobility for the elderly and disabled (Brell, Philipsen & Ziefle 2019; Cohen and Hopkins, 2019, Huang and Qian, 2021, McLeay *et al*., 2022). Major car manufacturers including BMW, Ford, Nissan, Toyota have developed aggressive plans for commercialising fully autonomous AVs with the highest level of automation and no need for human intervention (Huang and Qiaun, 2021), as well as brands that will be new to the automobile industry, such as Google and Chinese tech giants — AutoX, Baidu, Deeproute.ai, Didi, Momenta, Pony.ai and WeRide. However, uptake of AVs lags significantly behind expectation, which suggests that consumers may be resistant to the technology (Acheampong and Cugurollo, 2019; Rubio *et al*., 2020; McLeay *et al*., 2022). The benefits of using AVs are linked to the adoption of AVs and will decrease difficulties associated with adoption. Thus, we propose:
H1. AV specific benefits decreases adoption difficulty

AV stressors and technostress
In today's environment, consumers are faced with a vast amount of information from the ubiquitous technology that has been integrated into their daily routine (Sanz-Blas *et al.* 2019). This has resulted in informational anxiety, which refers to the amount of information that exceeds what individuals can understand and grasp (Peljito et al. 2012) and has led to negative feeling of losing information, heightened physiological activation, tension, and discomfort (Negahbhan and Talawar 2018), information overload (Sthapit et al. 2020), technology overuse (Gui and Büchi, 2021) and stress (Sanz-Blas *et al.* 2019; Fischer, Reuter & Riedl 2021). Stress is a feeling that endangers the tranquillity and well-being of an individual (Sanz-Blas *et al.* 2019). Stressors that are specific to digital technology include privacy, security, unreliability and usefulness (Fischer *et al.* 2021). Stressors will increase through fears surrounding AI-based technologies (Koopman and Wagner, 2017), such as risks of hacking and technology security risks linked to health risks due to loss of control in the AV (Meyer-Waarden and Cloarec, 2022). A facet of stress is technostress, which refers to the negative effects that the use of AI can have on an individual's attitudes, thoughts or behaviour (Weil and Rosen 1997). There has been little research focussing on AV stressors,

however. Based on technostress theory, we hypothesise:
H2. AV Stressors increase adoption difficulty

Consumer Resistance to innovation and using AVs
Radical innovation can be defined as the commercialization of an entirely novel idea that has the potential to disrupt industries and consumer markets (Garcia and Calatone, 2002). AVs are considered to be radical innovations (Casidy et al. 2020), given that they can lead to the emergence of completely new markets (Ritala and Hurmelinna-Luakken 2013). Radical innovations can provide significant benefits to consumers while posing significant risks and uncertainty (Colombo et al. 2017), and can lead to strong resistance from consumers (Konig and Neumayr 2017). For instance, AVs have been involved in fatal accidents (Tesla Deaths, 2020) caused by the failure to perform simple tasks such as avoiding obstacles (Cuzzolin et al. 2020). By means of an illustration, the autopilot system of Tesla Model S failed to apply the brakes, when the brightly lit sky obliterated the presence of a tractor trailer (Tesla 2016). These incidents have raised questions about the technology (Casidy *et al.,* 2020) and have contributed to a decline in the willingness to pay for (i.e., consume) AVs (Deloitte, 2017). Furthermore, research shows that the majority of consumers have concerns over the safety and liability issues surrounding AVs and expressed reservations about the evolving technology (Favre 2019).
Consumer resistance can be conceptualised as the unwillingness among consumers to try new innovations in the market (Tansuhaj *et al.,* 1991) and is considered to be one of the major reasons for market failure (Talke and Heidenreich 2014). Adopting innovations requires consumers to accept significant changes, which invariably creates uncertainty and risk (Garcia 2007) and can evoke strong negative reactions (Heidenreich and Talke 2020). Despite its importance, consumer resistance to technology has received little attention (Kaur *et al.* 2020; Leong *et al.* 2020); instead, a large stream of literature has focused on the willingness to adopt (rather than resist) technology (Casidy *et al.,* 2020). However, there have been calls for research to understand why consumers are not willing to adopt new offerings (Nel and Boshoff 2019) and how psychological barriers (Joachim, Spieth & Heidenreich 2018) occur when the innovation is in conflict with a consumer's social norms, values or usage patterns (Talke and Heidenreich 2014).

Further hypothesis that will be developed and discussed in the final paper
H3. AV adoption difficulty increases resistance to using AVs
H4. AV adoption difficult mediates the impacts of AV benefits (H4a) and AV stressors (H4b) on resistance to using AV

Methodology for empirical research
We use a quantitative approach to test the proposed conceptual model. Items were extracted from validated scales (for operationalisation, see Table I in Appendix). Using online surveys, we collected 671 samples from two countries: Australia (N=361) and the USA (N=310). Using the between subject design, respondents were randomly assigned to two different types of AV: partially automated similar to a Tesla (N=357) and fully automated with no human driver (N=314), and provided with a description of the relevant AV. The demographics of the respondents are shown in Table 2 in the Appendix. The sources of items, descriptive statistics, and results of reliability and validity tests are shown in Table 1 (please see Appendix). Reliability and validity of the scale items were checked using Chronba's alpha test and exploratory factor analysis. The results indicated an acceptable level of reliability as the alpha values for the scales were greater than 6 (Pallant 2001). Scale composition of the items were checked using exploratory factor analysis and all items were loaded sufficiently

(factor loading>.05) under the respective scales. The results of the harman single factor test showed that common method variance is not a threat as the largest percentage of variance for the emerging factors was 20.27% which is less than the commonly accepted level of 40%. None of the items cross-loaded, which confirms validity of the study measures. Items are normally distributed because values for skewness and kurtosis fall within the acceptable range of ±3. The proposed hypotheses tested using regression analysis (Hayes, 2017).

Results of empirical study

AV benefits significantly reduces adoption difficulty (b= -.108, P< .01) and resistance to use AV (b= -.663, P< .001). Following Model 4 of Hayes's process, adoption difficulty mediates the effect of AV benefits on resistance to use AV ($b_{\text{indirect effect}}$ = -.041, Lower level CI: -.083; Upper level CI: -.008). AV stressors significantly increase adoption difficulty (b= .350, P< .01) and resistance to use AV (b= .852, P< .001). The impact of AV stressors on resistance to use AV is mediated by adoption difficulty ($b_{\text{indirect effect}}$ = .065, Lower level CI: .025; Upper level CI: .108). Adoption difficulty significantly increases resistance to use AVs (b= .385, P< .001).

AVs adoption difficulty is not significantly influenced by the context of the study (Australia vs the US), types of AVs (AV3: partially automated vs AV5: fully automated), marital status, income level, gender, education level, employment status, and gender. However, senior individuals have more difficulty to adopt AV (b=.101, p<.001). Resistance to use AVs is not affected by the context of the study (Australia vs the US), types of AVs (AV3: partially automated vs AV5: fully automated), marital status, income level, gender, and employment status. Like adoption difficulty, senior people are more resistant to use AVs b=.113, p<.01). According to the results, educated people are less resistant to use AVs (b=-.091, p<.05).

Discussion and Conclusions

Our study provides theoretical and managerial contributions. First, we contribute to the AI-powered technology adoption literature by drawing upon the technology resistance theory (Joshi 1991). In line with this integrative theoretical approach, we answer the call to develop psychological frameworks that enable a better understanding of how consumers embrace or reject technology 4.0 (Belk *et al.* 2022) and examine a framework that investigates consumers' perceptions of AVs with different levels of intelligence (Huang and Qiaun, 2021; McLeay *et al.,* 2021). Specifically, we demonstrate that AV stressors and benefits have a significant direct impact on the adoption of AVs and consumer's resistance to using AVs. Thus, we extend the AV adoption literature by examining the relationship of AV stressors and benefits on the adoption of AVs and resistance. Our results indicate that AVs benefits reduce the adoption difficulty of AVs while the stressors increase the adoption difficulty of AVs. This is in line with the work of Huang and Qiaun (2021) who suggest that perceived benefits of AVs would increase the adoption of AVs due to the positive evaluation of AVs even though the technology is still in its nascent stage. Second, we theoretically extend the TRT and Status Quo Bias theory by introducing adoption difficulty as a mediator to shape the influence on AV benefits and stressors on the resistance to use AVs. Through empirical evidence, we suggest that adoption difficulty mediates the relationship between AV stressors and benefits on resistance to use AVs. This would be in line with the findings of Sanchez-Prieto *et al.* (2019) and Cham *et al.* (2021) which suggest that the adoption difficulty of technology would impact the adoptive and non-adoptive intentions to use that technology. This suggests that although there are positive advances in the AI-technologies which could contribute towards the adoption of AVs increasing physical safety (Lee et al. 2019), there is a resistance to use AVs as they are not a commonplace technology in the automobile industry (McLeay et al. 2022). Finally, we enrich the AV adoption literature by examining the antecedents to adoption difficulty and the resistance to use AVs in the Australian and US marketplace. The markets in Australia and the US are expected to grow substantially from 2022 to 2030, owing to the large-scale testing in the transportation sector (Research and Markets 2022; Khoury 2017).

Our findings provide important managerial recommendations, and suggest that consumers are concerned about AI which has an impact on their attitudes, thoughts, or behaviour (i.e., conditions that lead to stress/distress). However, the benefits of an AV could result in lowering the risk barriers of adopting and using an AV. Thus, managers should strive to communicate the benefits of using an AV when introducing them in the marketplace. For instance, they could clarify the capabilities of using an AV and focus on the novelty of the AV technology; or additional entertainment capabilities of using an AV (Erskine *et al.* 2020). Furthermore, marketers could highlight the hedonic benefits of an AV (Erskine *et al.* 2020), which could reduce the adoption difficulty and increase the usage of AVs. Another important implication is educating consumers regarding the capabilities and benefits of AVs. Marketers should continually inform consumers of the facts about AVs, such as safety features and road worthiness especially for consumers who have high risk barriers and are hesitant to use AVs. Trialability of AVs would be an important factor to consider as both indirect and direct experiences are important for diffusion (Rogers 2003). The provision of more hands-on experiences with an AV is likely to reduce the technostress, improve adoption and decrease the resistance to use AVs. Furthermore, this would increase the consumer's knowledge about AVs (Huang and Qian 2021) which would increase the usage of AVs. Finally, given the newness of the technology, only a handful of innovative consumers are likely to adopt AVs. Thus, focusing on these consumers would be crucial as they may become trailblazers (or ambassadors) of the technology, and can shape the information being dispersed and therefore possibly influence much of the remaining population (Erskine *et al.* 2020). Limitations and areas for future research are presented in the Appendix.

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Consumer responses to private versus public transportation services by autonomous vehicles

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Type of manuscript: Extended abstract

Keywords: autonomous vehicles; service failure; private vs. public transportation

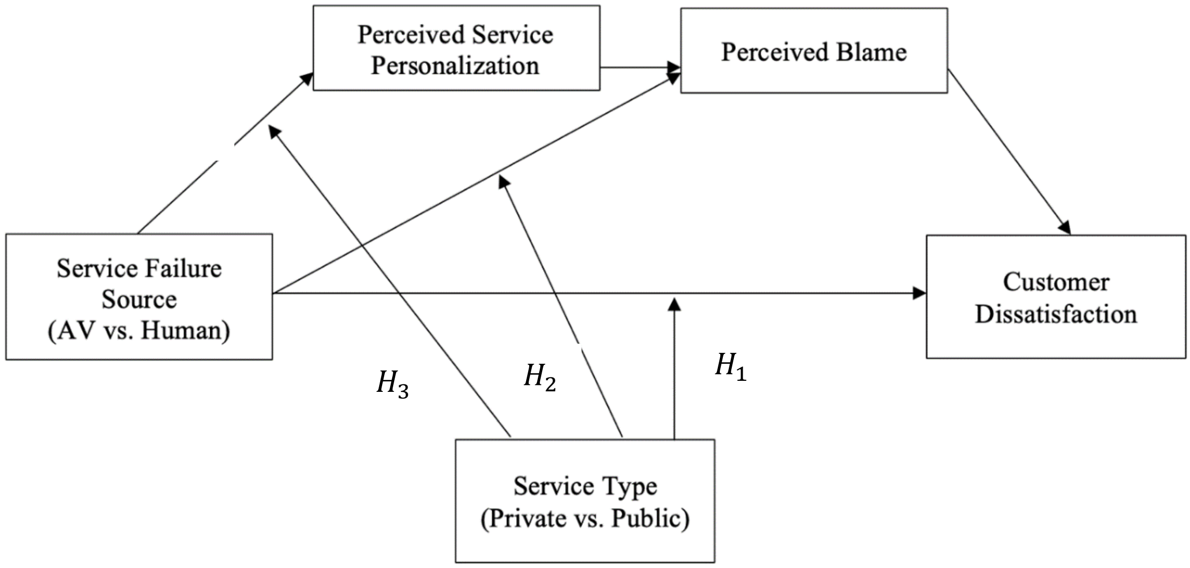
Research idea and conceptual framework

Autonomous vehicles (levels 3 – 5), defined as those that carry out all driving functions in an automated way and the driver or passenger interaction with the system is limited to specifying the destination (Shladover, 2018), is expected to revolutionize both the private and the public mobility systems in the coming decades (Gill, 2020). Therefore, the question of how consumers respond to the introduction of autonomous vehicles in the transportation service sector and the underpinnings of such responses is of critical importance (Huang & Qian 2021). Notably, marketing researchers have grown more interested in this topic, but produced mixed results. Along with evidence of consumers' low aversion towards autonomous vehicles, driven by hedonic motivations (Erskine et al., 2020) and self-efficacy (Chen & Yan, 2019), there is evidence of consumers' preference for driving performed by humans rather than autonomous systems due to perceived loss of control (Baccarella et al., 2020), safety concerns (Gill, 2020) or autonomous vehicles taking away the joy of driving (Casidy et al., 2021).

While barriers to consumers' adoption of autonomous driving certainly exist, the relative weight of these barriers remains unclear. For example, Joachim et al. (2018) found that "the effect sizes of each barrier ... vary with the context present" (p. 105). Previous literature on service interaction between humans and autonomous technology suggests that one such context variable could be the service outcome (Gill, 2020; Srinivasan & Sarial-Abi, 2021). In particular, some studies indicate that people respond more negatively to a technology failure than to an employee failure (Fan & Mattila, 2016). Other studies suggest that consumers respond more negatively toward a human service provider than toward an autonomous service technology in case of a service failure (Leo & Huh, 2020).

We offer a possible reconciliation of such conflicting findings by arguing that whether consumers react more negatively to driving service performed by humans versus autonomous system depends on whether the transportation service is private (i.e., taxi) or public (i.e., bus or train). Building on the idea that private (vs. public) transportation services trigger a higher feeling of personalization and on attribution theory (e.g., Kelley and Michela 1980), we propose that in case of service failure consumers will show higher dissatisfaction to the human agent (vs. autonomous vehicle) when the service is private (H1). In particular, we hypothesize that the higher dissatisfaction with the human agent (vs. autonomous vehicle) can be explained by perceived service personalization (H3) which in turn affects perceived blame (H2) (Srinivasan et al., 2002) (see Figure 1).

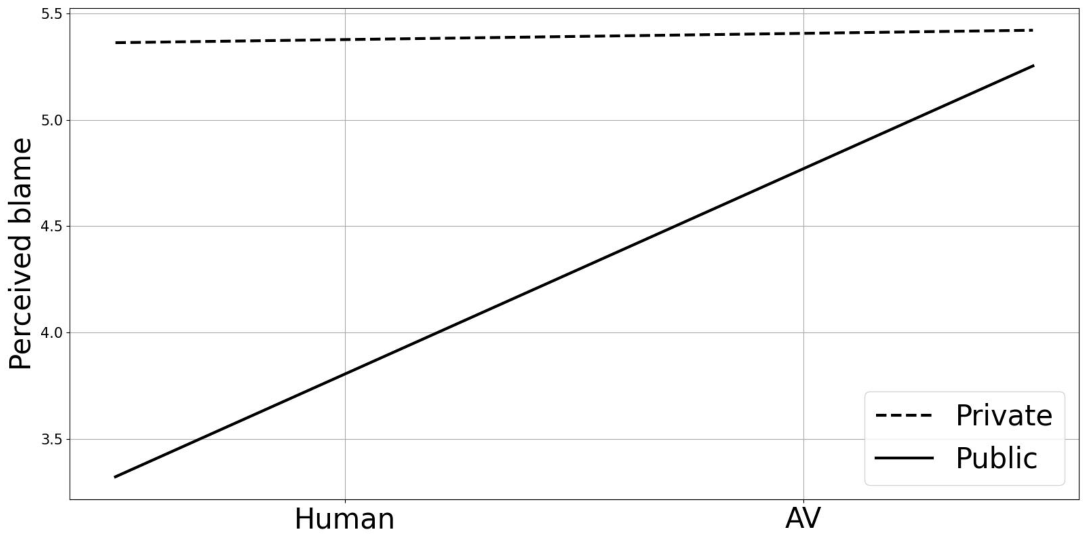
Figure 1: Conceptual Model



Methodology and preliminary results

We test our hypotheses through three experimental studies. Participants have being recruited online through Prolific. We expose respondents to a hypothetical service scenario asking them to imagine being in that situation. Our preliminary results show that consumer responses to autonomous vehicle (vs. human) differ in the case of service failure in the expected direction. Specifically, we found that consumers attribute more blame and are more dissatisfied with private (vs. public) transportation service provided by a human agent, while we found non such differences in relation to autonomous vehicles which were perceived as equally blameworthy in both cases (see Figure 2).

Figure 2. Interaction effect of type of driver and type of service domain on perceived blame.



Originality of the Paper

To the best of authors knowledge, this is the first paper to investigate differences in consumer acceptance of autonomous vehicles between public and private transportation services. From a managerial perspective our research provides useful insights for transportation industry decision makers debating on how to effectively implement autonomous vehicles in the public and the privite services sectors. Specifically, our results could contribute to the ongoing debate about the acceptance of self-driving car technology in the public transporting sector (Chen & Yan, 2019).

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Consumer willingness to disclose personal information to conversational agents (CAs): The double-edged sword of CAs' perceived intelligence

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Type of manuscript: Extended abstract

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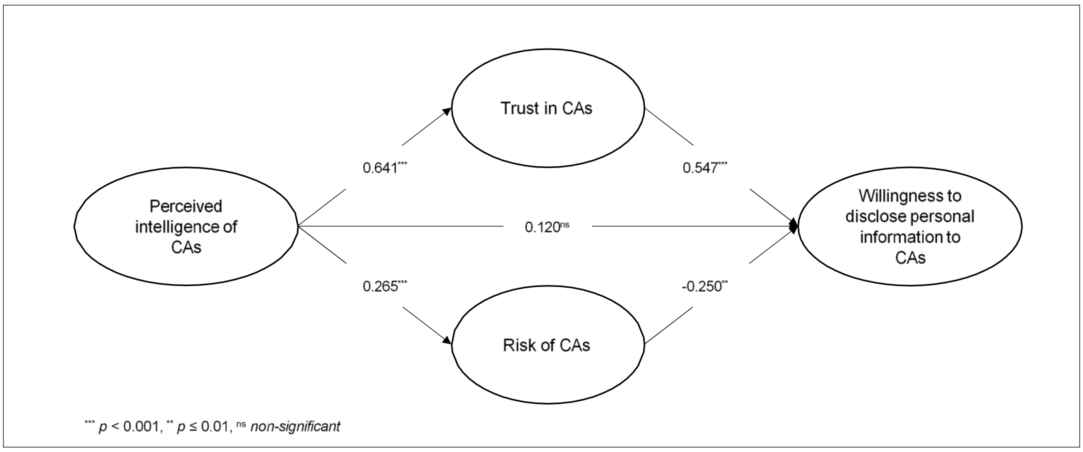
Conversational agents (CAs) are technological entities that act proactively and/or reactively to assist humans. They can enter social conversations with their users as CAs can process and generate natural language. CAs can be found in physical and digital realities: Ex- amples are social robots (e.g., Pepper), digital voice assistants (e.g., Alexa), and chatbots (Moussawi et al., 2021; De Keyser et al., 2019). Even though CAs have become one of the most promising technologies in the service industry, research on consumers' willingness to interact with CAs is still in its infancy. For instance, knowledge is missing on the determinants of consumers' willingness to disclose information to CAs. Developing an understanding in this regard is of key relevance as CAs learn from inputs (e.g., from a user's disclosure of infor- mation) and can unfold only in this way their full potential (e.g., offer tailored services to con- sumers) (Huang & Rust, 2018). Therefore, this study develops and empirically tests a model of consumer willingness to disclose personal information to CAs. In doing so, this research refers to social exchange theory and underlies the assumption that a consumer's self-disclosure to CAs (i.e., communication of personal information to CAs) is directed by the characteristics of those involved in the interaction and the nature of their relationship.
Specifically, this research hypothesizes that while consumer trust in CAs enhances the willing- ness to disclose personal information to CAs, consumer perceived risk of CAs inhibits the willingness to disclose personal information to CAs. Most importantly, this research suggests that the perceived intelligence of CAs (i.e., the extent to which CAs can mimic humans and thus have the ability to learn, adapt, evaluate, solve problems, communicate, perceive, and act (Huang & Rust, 2018) positively influences both the trust in and the perceived risk of CAs. While previous research has revealed the positive effects of the perceived intelligence of CAs (Moussawi et al., 2021; Blut et al., 2021), knowledge is missing on its adverse effects. The theory of human intelligence states that increasing intelligence can be associated with socially exploitative behaviors (i.e., evil genius-hypothesis) (O'Boyle et al., 2013). Hence, this research tests for the first time the assumption that an increasing perceived intelligence of CAs fosters consumers' perceived risk of using CAs.

This study conducted a survey to assess our hypotheses with Mturk panelists (n = 282, 49.1% females, M_{age} = 38.07). At the beginning of the survey, participants were asked to read a de- scription of CAs that included several examples of CAs. Afterward, participants were asked to fill in a questionnaire that started by explaining the questioning procedure (e.g., confidential processing of anonymous data). Then, participants were asked to rate multi-item

concepts measuring the key concepts of this research model. Scales from the literature were used to capture them: willingness to disclose information to CAs (Ioannou et al., 2021), trust in CAs (Park 2020), perceived risk of CAs (Park, 2020), and perceived intelligence of CAs (Bartneck et al., 2009). Finally, respondents were asked to reveal socio-demographic information and their familiarity with different CAs.
The data was analyzed using covariance-based structural equation modeling and the software MPlus 7.4. The results of the confirmatory factor analysis showed an acceptable fit: χ^2/df = 1.71, RMSEA = 0.050, CFI = 0.957, TLI = 0.949, SRMR = 0.062. All factor loadings were statistically significant and higher than the recommended level of 0.60 (Kline, 2015). Moreover, each factor exhibited strong reliability and validity as represented by indicators of composite reliability and average variance extracted (Bagozzi & Yi, 1988; Fornell & Larcker, 1981). Discriminant validity was also met because the individual factor's AVE was greater than the squared correlation of this factor with the other factors in the model (Fornell & Larcker, 1981).
A structural model was run to test the hypotheses. The results indicated that this model provided an acceptable fit to the data: χ^2/df = 1.70, RMSEA = 0.050, CFI = 0.958, TLI = 0.949, SRMR = 0.062. The results showed that consumer trust in CAs positively ($\beta = 0.547$, $p = 0.000$) and perceived risk of CAs negatively ($\beta = -0.250$, $p = 0.010$) influenced the willingness to disclose personal information to CAs. As expected, the perceived intelligence of CAs enhanced both trust in CAs ($\beta = 0.641$, $p = 0.000$) and perceived risk of using CAs ($\beta = 0.265$, $p = 0.001$) but did not directly affect the willingness to disclose personal information to CAs ($\beta = 0.120$, $p = 0.308$) (Figure 1).

Figure 1. Results of the model of consumer willingness to disclose personal information to CAs



The findings of this study provide preliminary evidence for a model of consumer willingness to disclose personal information to CAs. The findings show that consumer relationships with CAs and their beliefs about using CAs direct their willingness to disclose personal information to CAs. Specifically, trust in CAs enhances, whereas the perceived risk of using CAs mitigates consumers' willingness. Most interestingly, the perceived intelligence of CAs was found to enhance both trust in CAs and the perceived risk of using CAs. Therefore, an increasing perceived intelligence of CAs reflects a double-edged sword for consumers' willingness to disclose personal information to CAs.

This research enriches the understanding of consumer interaction with CAs as it (1) looks for the first time at the disclosure of personal information to CA and (2) relates the perceived intelligence of CAs to consumers' willingness to disclose personal information to CAs. Most importantly, this research is the first to provide evidence for the adverse effects of the perceived intelligence of CAs. Even though this finding has important implications for the design of CAs, it also points to the need for additional research. For instance, a nuanced understanding of the concept of the perceived intelligence of CAs (e.g., by considering individual dimensions of intelligence such as mechanical, analytical, intuitive, and empathetic intelligence, as suggested by Huang and Rust (2018)) could help to gain in-depth insights on when the perceived intelligence of CAs inhibits consumer willingness to disclose personal information to CAs.

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Scared off by the joneses: Exploring the complex social nature of adoption of smart home technology for ageing consumers

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Type of manuscript: Extended abstract

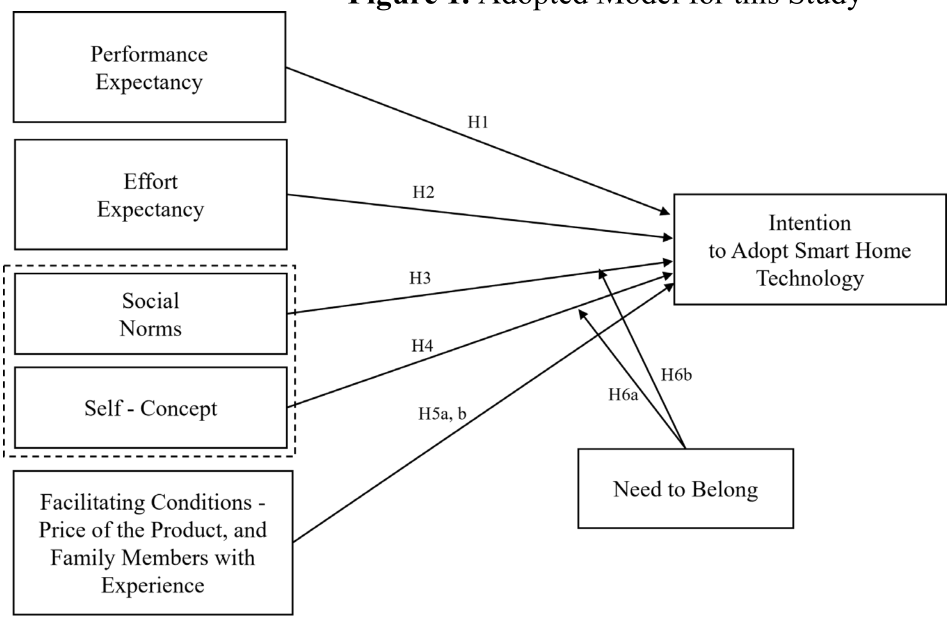
Keywords: technology acceptance; aged consumers; social factors.

Introduction
The old stereotype that ageing consumers are sick, poor, inactive and unlikely to want to spend their money is slowly giving way to a more realistic image which shows ageing consumers to be active, technology enabled and willing to spend money (Cole et al., 2008; Cuddy et al., 2005; Nielson & Curry, 1997; Tréguer, 2002). Ageing consumers are particularly displaying greater desire for independence (Beswick et al., 2010). Emerging technologies such as smart home technology (i.e google home) could provide better ways to enable independence and encourage social interaction amongst aged consumers (Reis et al., 2018). However, despite the many benefits of technology (Peek et al., 2016; Ziefle & Calero Valdez, 2017), researchers have noted that the adoption and use of smart home technology is multi-faceted, complex, and subject to various influences (Rybaczewska & Sparks, 2021). This is particularly true for ageing consumers, where researchers highlight various barriers to adopting technology, many of which are social factors (Peek et al., 2016). Therefore, this study aims to better understand the adoption process of smart home technology for ageing consumers, and the role that social influences such as self-concept and the need to belong play within this process.

Background and Conceptual Model
Peek et al. (2016) suggest that the adoption of technology by aged consumers is much more of a social process compared to a technology process. While the technology may be useful, adoption is often hindered by a range of perceived barriers, many of which are social. These barriers include fear of being unable to control the technology (Yusif et al., 2016), fear of it being just too complicated and fear of dependency on the technology, including the fear that it would make them look old or that the technology would actually work well and family would visit less (Ziefle & Calero Valdez, 2017). To better understand this process for smart home technology, the unified theory of acceptance and use (Venkatesh et al., 2003) was adopted as the underpinning theory for this study. The theory has been used in numerous other ageing consumer studies (Dai et al., 2020; Gao et al., 2015).

The model suggests that performance expectancy, effort expectancy, social influence and facilitating conditions will lead to intention to accept (Venkatesh et al., 2003; Williams et al., 2015). Performance expectancy refers to "the degree to which an individual believes that using the system will help him or her to attain gains" (Venkatesh et al., 2003). These 'gains' could be the ability for the consumer to live independently, stay connected with family or simply get things done that they otherwise couldn't (Ziefle & Calero Valdez, 2017). Effort expectancy refers to "the degree of ease associated with the use of the system" (Venkatesh et al., 2003). Social influence refers to "how strongly others believe they should use the technology" (Venkatesh et al., 2003). Facilitating conditions refers to other factors which affect their ability to accept. Consistent with this theory, we expect that ageing consumers will be more likely to accept smart home technology if the expected performance is high, expected effort is low; social influence is high; and facilitating conditions are high. We further extend the model by including an additional social measure 'ideal self', inline with the self enhancement theory. Within an ageing context, self-concept has a particularly important role, as consumers are transitioning through life stages, where their self-concept may be challenged, potentially leading them to consume products which allow them to maintain their ideal selves (Anderson, 2015; Peters et al., 2011). Likewise, we posit that the 'need to belong' will moderate the relationship between social predictors and intention to adopt. Need to belong refers to a '*pervasive drive to form and maintain at least a minimum quantity of lasting, positive and significant interpersonal relationships*' (Baumeister & Leary, 1995; Edson Escalas & Bettman, 2017). Researchers note that some consumers have a high need for social inclusion and belonging, and such consumers are likely to worry about how they are valued by others. Therefore, it is likely that when a consumer has a high need for belonging, they will be more likely to adjust buying behavior inline with social norms and how they want to be perceived (i.e ideal self). Below is the model adopted for this study:

Figure 1. Adopted Model for this Study



Methodology

Data were collected using panel survey data, with a screening question ensuring that respondents were over the age of 60 years. 253 responses were collected, with all respondents residing in Australia. The google home was used as the stimulus, with four key features of the product presented to respondents (Renaud & Van Biljon, 2008). Established quantitative scales were used and adapted from Venkatesh et al.(2003). Data were analysed using SPSS with linear regression. (Hair et al., 2016, 2012).

Results

The results showed that performance expectancy, effort expectancy, social norms, self-concept and family ownership all had significant influence on intention to adopt. However, while family ownership was significant, the relationship was negative, suggesting that when family members owned smart home technology, ageing consumers are less likely to have an intention to purchase. Likewise, affordability which is often quoted as a barrier for ageing consumers, was shown to be insignificant in predicting adoption intention. Performance expectancy was also shown to be the strongest predictor, which suggests that effort barriers may not be as significant in hindering adoption as previously thought. Finally, the moderating effect of need to belong on social norms and self-concept on intention to adopt was shown to be insignificant, thus suggesting that while consumers may adopt technology in line with their ideal self, it is not primarily to fit in.

Implications

The current study significantly contributes to our understanding of technology adoption amongst ageing consumers. To test theory, the study applies the unified theory of acceptance and use model in an aged consumer smart home technology context. The study also provides new insights for brands seeking to develop technology for ageing consumers, specifically highlighting the need to develop products specifically for the ageing market.

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More than Just a Chat: A Classification of the Anthropomorphised AI – User Relationships

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Type of manuscript: Extended abstract

Keywords: anthropomorphism; artificial intelligence; self-congruence.

Introduction

Artificially intelligent (AI) agents are a product of the contemporary digital age (Koike and Loughnan, 2021) which have been imbued with humanlike traits, a phenomenon otherwise known as anthropomorphism. Importantly, consumers form relationships with anthropomorphised AI like Siri, Alexa, Replika, etc. User-AI relationships have been examined in terms of the functional or emotional value that AI agents deliver to individuals, but they remain understudied (Koike and Loughnan, 2021).

Consumers often evaluate inanimate entities such as products or brands against their own self, which can make them note similarities between their self-concept and external entities, also known as self-congruence (MacInnis and Folkes, 2017). In the case of anthropomorphic AI, such self-congruence could be established based on AI humanlike cues like “humanlike properties, characteristics, or mental states” attributed to these AI agents (Epley, Waytz, and Cacioppo, 2007, p. 865). However, there is yet no empirical understanding of the link between anthropomorphic AI and self-congruence and its effect on the formation of consumer-AI relationships. Our empirical study was thus guided by the following research question: What relationships do consumers build with anthropomorphised AI agents depending on their self-concept?

Anthropomorphised AI agents project a variety of anthropomorphic traits that can be physical (e.g., voice, names), personality (e.g., interactive characters), or emotional traits that carry social meanings that are relevant for one’s identity (Belk, 1988). These cues help consumers situate these objects in the same cognitive space as their own self-image (Quester, Karunaratna, and Goh, 2000) and relate them to their self-concept (Sirgy, 1982), which evokes self-congruence and build affective bonds (Blut et al., 2021).

In some cases, consumers can view them as part of their self (Hoffman & Novak, 2018; Belk, 1988; Troye and Supphellen, 2012) and invest self-related resources into these agents. To explain this phenomenon in the context of AI agents and self-concept, we propose a new concept i.e., *self–AI integration*, which occurs when consumers perceive anthropomorphised AI agents to be so meaningful or relevant that they become a part of consumer self-concept. In the case of AI, such integration can be fueled both by anthropomorphic cues and by self-congruence with anthropomorphised AI.

Consumer-AI relationships can therefore differ depending on how consumers experience self-congruence and self-AI integration. Prior literature introduced the possibility of users forming relationships with virtual agents but does not address a possible variety of user-AI relationships (Koike and Loughnan, 2021; Hoffman and Novak, 2018).

Methodology

Using purposive sampling, we interviewed 15 consumers of different types of AI agents (e.g., emotional AI - Replika, functional AI - Alexa, Siri), who had extensive experience with AI agents (Churchill, 1979). The interviews were audio-recorded, transcribed, and analysed using thematic analysis (Braun and Clarke, 2006). The analysis of the interviews revealed insights on the dynamics of the user-AI interaction, which bridge the gaps in literature on how users form relationships with AI agents from an identity perspective. These findings helped develop a classification of user-AI relationships.

Results and Discussion

Results indicate that functional roles were assigned by users of functional AI agents that perceived their agents as personal secretaries. Social roles (e.g., companion) and personal roles (e.g., mirror) were allocated to AI agents that satisfied the users' need for social connection and mirrored their traits using personalisation techniques. The findings also suggest that humanness can be inferred from the agent's humanlike responses and traits (e.g., physical and personality traits). Another group cited the agents' lack of sentience and mechanistic traits as factors that inhibited the user's anthropomorphic thinking.

Results also suggest that self-congruence occurs due to the agents' similar personality and emotional traits that mirrored the users' own traits, specifically with emotional AI agents. Conversely, incongruence can be linked to the fragmented flow of interaction, which highlights the fundamental differences between users and AI. In a similar vein, self-AI integration can happen by utilizing the AI agents' resources over time to complete daily tasks, reduce loneliness, overcome emotional traumas, or improve self-expression and self-love.

In a social context, some users were hesitant to disclose their personal user-AI relationship due to potential negative stigma. While some identified with users of similar AI agents for the same usage purposes, others mentioned it is not enough for agents to make them relate to others.

Based on these findings, we categorise user-AI relationships based on a) (dis)similarity with the agents' anthropomorphised traits, i.e., self-congruence, and b) how closely associated the AI agents become with one's identity, i.e., self-AI integration. We propose four different types of such relationships. The *functional relationship* is characterized with low levels of self-congruence as users perceive AI agents as programmed lines of code. However, it entails high self-AI integration by utilizing the AI agents' functional value to achieve self-related motives. The *aspiring relationship* entails a general sense of self-congruence with AI agents' generic traits and satisfying the need for relatedness. However, there is low self-AI integration due to existing mechanistic exchanges, despite the longing for it. Despite the high levels of self-congruence in the *committed relationship* due to the agents' mirroring of the user traits, the agents' lack of sentience hinders stronger self-AI integration. Finally, the *replacement relationship* has the strongest form of self-congruence and self-AI integration where users prefer AI agents over humans and utilise their resources to overcome hardships.

This study responds to previous calls for a better understanding of the user-AI relationship dynamics from a self-perspective by empirically investigating the processes of self-congruence and self-AI integration (MacInnis and Folkes, 2017). We complement the anthropomorphism and AI literature by proposing a classificatory typology of user-AI relationships (Koike and Loughnan, 2021; Hoffman and Novak, 2018). From a practitioner perspective, managers can exploit the findings to identify how to better target users that seek different types of relationships with their AI agents. Additionally, researchers can build on the findings by investigating the applicability of these relationships in different contexts, like culture or personal motives.

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The impact of voice assistants on flow: a comparison between virtual reality stores and websites.

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Type of manuscript: Extended abstract
Keywords: *virtual reality; voice Assistants; Media Richness Theory; Flow Theory.*

Extended abstract

Virtual reality (VR) as a multi-sensory experience, is acknowledged as a helpful tool among retailers for promoting products and services (Hilken *et al.*, 2022). Virtual reality is a computer-generated 3D environment – called a 'virtual environment' in which the user, who can navigate and interact with it, perceive this environment in a manner that appears to be real via one or more of the users' five senses (Wedel *et al.*, 2020).

Media Richness Theory (Daft & Lengel, 1986) has been adopted to describe the higher informative value of immersive content. In this sense, VR delivers a direct and richer sensory experience that is expected to be more useful for consumer decision-making than websites. Voice assistants enrich the customer experience in both VR formats and website stores. When individuals highly concentrate on their voice interaction with a VA, they experience a flow state, and their experience becomes satisfying (Poushneh, 2021).

The purpose of our study is to compare the flow states on two types of store experiences in retailing (immersive VR versus website). We also assess the effect of using Virtual Assistants in the purchase process. The specific goals of this research are: (i) to analyze the impact of flow state on consumer responses (intention to visit a physical store and intention to recommend the store); (ii) to analyze the moderating role of the use of Voice Assistants in the effect of the flow state experience on consumer responses to the store.

Drawing from the Media Richness Theory (Daft & Lengel, 1986) and Flow Theory (Csikszentmihalyi, 1988), we argue,

H1. Consumer flow state is greater in a VR store than in a website store.

H2a/b. The positive influence of flow state on future intentions to (a) visit the physical store, (b) to recommend the physical store, is greater in the VR store experience than in the website store experience.

H3a/b. The use of Voice Assistants in an VR and website shopping experience has a positive influence on the relationship between flow state on future intentions to (a) visit the physical store, (b) to recommend the physical store.

The empirical study, taking place in May 2022, has been contextualized in an episode of sale of two products for the home: a sofa and a SmartTV. We designed a 2 (immersive VR setting vs. website store) x 2 (Avatar: Yes vs. No) between-subjects experimental design. A virtual space has been designed, recreating a living room. Two versions of the virtual space were recreated with 3D modeling to be viewed with virtual reality glasses (we use the HTC Vive Pro Eye 2 device), one with the presence of an avatar, and the other without avatar. The other two versions of the virtual space were designed as a 2D environment to be viewed through a Web browser, again one supported by an avatar and the other without avatar.

For each product model, the participants could access to seven information cues: intrinsic cues (i.e., price, technical information, delivery time, environmentally friendly, brand name) and extrinsic cues (i.e., reviews and star rating). These information cues were presented randomly for each participant and for each scenario. As can be seen, fictitious brands have been used to mitigate the effect of prior knowledge on the brand and very similar purchase criteria have been defined for each cue, trying to isolate the effect of the type (and not the content) of information cue (intrinsic vs. extrinsic) on visual attention and the intention to visit the physical store. 152 subjects, 38 for each scenario, participated in the fieldwork. These subjects have been randomly assigned to each of the four scenarios. Once the task was finished (having selected a sofa model and a SmartTV model for purchase), they self-reported in an online questionnaire with 7 point likert scales the intention to visit the physical store in the future, flow state and intention to recommend the store.

Preliminary results showed a main effect for platform used (VR/website) on flow ($F = 7.87$; $p < .01$); the VR store provoked significantly more flow ($M = 5.35$) than the Web store ($M = 4.82$); thereforen, H1 was supported. We performed two multigroup analyzes (VR vs. Web; Avatar yes vs. Avatar no) with Smart PLS 3.0, in a causal model taking flow as the independent variable and intention to visit and recommend as dependent variables. The results of both multigroup analyzes lead us to reject H2ab and H3ab: the positive influence of flow on the intention to visit and recommend is the same regardless of the platform used and the presence or absence of an avatar. At this moment we are analyzing data from neurophysiological measures, in this case visual attention as measured by eye-tracking to explain shed light on the omnichannel paths from online setting to physical stores.
Results from this research contribute to existing literature and provide implications for the retailing industry. Retailers control, combine and use product information cues to capture consumer attention and assist purchase. Understanding which factors generate flow state and how these are related to actual purchase and future intentions to visit and recommend the physical shop will help retailers to creating an optimal shopping environment. These factors may also have the indirect benefit to the consumer in making the shopping process more efficient and pleasurable. This research also extends flow theory (Csikszentmihalyi, 1988). To the authors' best knowledge, this study is one of the first attempts to investigate the role of Voice Assistants to product information cues in the purchase process in VR retail environments. Combining VR with Voice Assistant agents has been identified as an opportunity to better understand consumer behavior in a retail environment.
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Customer Perspectives on the Process of Co-Creation with Chatbot

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Keywords: co-creation; co-creation process; chatbots; customer-to-chatbot interaction.

Chatbot use is becoming increasingly prevalent in service industries, as chatbots are being deployed as a first point of contact for many customer service enquiries (Sheehan et al., 2020). The academic literature has interpreted interactions between customers and AI applications, such as chatbots, using a co-creation lens (e.g. Lalicic & Weismayer, 2021; Ramaswamy & Ozcan, 2018). In this context, the interaction between multiple active actors, that is, the chatbot and the customer, is viewed as resulting in the generation of value beyond which each actor can achieve independently (Neghina et al., 2015). At the core of co-creation is communication and joint collaboration (Lusch et al., 2007), as well as a process of resource integration, which specifies that actors need to apply and integrate a range of resources for value co-creation to be activated (Kleinaltenkamp et al., 2012). Value co-creation is a suitable lens to explore customer-chatbot interaction, because it moves beyond producer-to-consumer relationships, and instead emphasizes actor-to-actor networks that create value for each other (Vargo & Lusch, 2004). However, whereas service encounters traditionally took place between human actors, new human-to-non-human interactions, add an uncharted dimension to the study of actor-to-actor networks in value co-creation (Belanche et al., 2020; Kaartemo & Helkkula, 2018). The utilisation of AI in service promises value co-creation that changes as the AI adapts to other actors (such as customers), and these actors then adapt to the AI.
Although academic literature increasingly relies on the co-creation lens to explore customer-chatbot relationships, there is a lack of understanding regarding the way that customers, specifically, perceive the co-creation process when interacting with chatbots. The aim of this study is therefore to understand and map out the process of co-creation that customers perceive when interacting with AI chatbots.

The exploratory nature of this research question necessitated that the research focused on the individual, and his/her subjective lived experiences in relation to chatbot interactions. Consequently, semi-structured interviews were selected as a data collection method as these enabled the researcher to investigate individual respondents' point of view and the meaning and understanding that the interviewees attach to their experiences (Creswell & Poth, 2018). A total of 27 interviews were conducted with respondents who had interacted with a chatbot in the 12 months prior to the study. The data collection process was concluded when additional interview data showed that theoretical saturation was reached (Glaser & Strauss, 2017).

The results show that value creation is activated when customers integrate simpler resources such as their time and skills, as well as more complex mental inputs, which include gathering, amalgamating, evaluating, and comparing information in relation to the service that the customer intends to enter into. These inputs are akin to customers engaging in "cognitive labour" (Risch Rodie & Schultz Kleine, 2000, p. 112), a process that sees customers making a mental effort to comprehend the service situation, understand what they are supposed to do as an actor and how to structure the information they should provide to the company through the chatbot. Although under-researched in the context of co-creation, this study shows that such behaviours may also have an important role in the value co-creation process, as they can determine the outcomes to be achieved from co-creation.

Several studies propose that the process of co-creation between humans and AI technologies may be more complex as such technologies are empowered with agency (e.g. Kleinaltenkamp et al., 2012). However, this study shows that rather than agency, it is interdependence that renders the process of co-creation more complex as the customer and the chatbot are both reliant on each other at crucial points of the process (e.g. guiding each other and learning from each other). If something goes wrong at any of these stages, it is likely that the interaction deteriorates and may also possibly result in the destruction, rather than the creation, of value (Echeverri & Skålén, 2011; Plé & Chumpitaz Cáceres, 2010). In line with extant literature (e.g. Belanche et al., 2019; Følstad & Skjuve, 2019) this study also shows that it is functional and utilitarian benefits that customers predominantly obtain from interactions with chatbots; although the attainment of anonymity is also an important finding and may carry implications for specific customer service situations which involve embarrassing products or situations (c.f. Pitardi et al., 2022).

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Personalized Technology Services for In-store Shopping: Impact on Customer Engagement and Shopping Satisfaction

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Keywords: personalized technology services (PTS), customer engagement, satisfaction

Introduction

In-store personalized technology is gaining popularity among researchers, practitioners, and consumers as it transforms shopping behavior and facilitates a seamless omnichannel shopping experience (Cakir et al., 2021; Verhoef, 2021). For example, the global market value of smart mirrors, a key in-store personalized technology, is expected to grow 12.25% from 2019 to 2025 with $4,100 million by 2025 (Allied Market Research, 2018). Riegger et al. (2021, p. 142) define technology-enabled personalization as "the integration of physical and digital personalization dimensions at the point of sale to provide individual customers with relevant, context-specific information, according to historic and real-time data in combination." In-store personalized technology refers to technology-enabled personalization operated with an in- store digital device (e.g., smart mirrors, assistant robots) for a seamless shopping experience. Due to its recency, research on personalized technology service (PTS) is limited to conceptualizations (e.g., Riegger et al., 2021). This study intends to contribute to current knowledge about the phenomenon. First, we provide an empirical illustration of drivers and barriers relevant to in-store PTS based on Riegger et al.'s conceptual model. Second, we explore how consumer perceptions of the identified PTS factors affect shopping satisfaction via customer engagement with PTS.

Theoretical Background and Hypotheses

Riegger et al. (2021) developed a conceptual framework of personalized technology that summarizes key factors including drivers (hedonic, utilitarian, control, interaction, and integration) and barriers (exploitation, privacy, interaction misfit, and lack of confidence). Hedonic value relates to emotional responses to the experience while utilitarian value means functional benefits such as efficiency (Babin et al., 1994); control represents one's authority in maneuvering technology (Chen et al., 2001); interaction captures such benefits as synchronicity (Liu, 2003); integration refers to the degree of expected value derived from personalization technology (Riegger et al.,2021). As for barriers, exploitation concerns an individual's fear of being disadvantaged by personalized technology (Riegger et al., 2021); privacy refers to the potential loss of personal information (Featherman & Pavlou, 2003); lack of confidence represents an individual's difficulty with using new technology; and interaction misfit refers to one's aversion toward technology due to reducing human interaction (Riegger et al., 2021). Following Riegger et al.'s framework, we first posit consumers' experience with PTS while shopping in a store to be multi-dimensional, embracing drivers and barriers.

Given the multi-faceted experiences with PTS, of further interest is how such multi-dimensions influence consumer shopping behaviors (i.e., customer engagement and shopping satisfaction). Customer engagement refers to a customer's participation and connection with the PTS-related activity (Vivek et al., 2012); satisfaction represents how much a consumer is satisfied and pleased with their shopping experience accompanied by PTS (Churchill & Surprenant, 1982). Research on technology-mediated shopping demonstrated that various technology attributes including drivers and risks impact shopping satisfaction through customer engagement with shopping devices (McLean & Wilson, 2019; Tandon et al., 2019).

Accordingly, we hypothesize that:

H1. Consumers' perceptions of drivers of in-store personalized technology increase shopping satisfaction.

H2. Consumers' perceptions of barriers to in-store personalized technology decrease shopping satisfaction.

H3. Customer engagement mediates the relationships between perceptions of in-store personalized technology (a: drivers, b: barriers) and shopping satisfaction.

Method and Results

A web-based survey was administered to US consumers recruited from Amazon MTurk. Those who used smart mirrors or assistant robots, key personalized technologies in operation for in- store shopping, were qualified ($N = 311$). Items from existing scales were modified to measure all research variables on 7-point scales (Arghashi & Yoksel, 2022; Balaji & Roy, 2017; Chen, 2001; Featherman & Pavlou, 2003; Im et al., 2008; Liu, 2003; Meuter et al., 2003). Participants indicated their most recent experience with a smart mirror or assistant robot and completed the questionnaire based on it.

The data set was split into two: estimation and validation samples. The estimation sample ($n = 120$) was used to estimate the dimensionality of in-store PTS using exploratory factor analysis (EFA) and the validation sample ($n = 191$) was applied to validate the identified dimensionality of PTS experience using confirmatory factor analysis (CFA). The two analyses should be performed with different data sets to ensure the dimensionality obtained from EFA is supported across multiple samples (Cabrera-Nguyen, 2010).

EFA with maximum likelihood (ML) extraction with the direct oblimin rotation in SPSS 26.0 ($M_{age} = 36.5$, 49.2% women) revealed two barriers (privacy and exploitation) and one driver (controllability), verifying the multi-dimensionality of PTS (cumulative variance of 61.75%). For each dimension, internal reliability was confirmed (alphas > .78). Next, CFA confirmed the measurement model in AMOS 26.0 ($M_{age} = 35.6$, 54.5% women). Convergent and discriminant validity of each factor was also confirmed. Therefore, the results confirmed consumer experiences with in-store PTS to be multi-faceted consisting of privacy, exploitation, and controllability, supporting our proposition.

SEM showed that controllability was significantly associated with customer satisfaction ($\beta = 0.59$, $p < 0.01$). However, privacy and exploitation were not. Further, the mediation test (5000 bootstrapping samples) showed that engagement fully mediated the controllability–satisfaction association (indirect effects 95% CI: 0.48; 1.21). Thus, H1 and H3a were supported, but H2 and H3b were not.

Discussion

Practically, our findings can guide retailers to design and implement in-store technologies for a seamless in-store shopping experience. Theoretically, this study empirically validates in-store personalized technology service experiences as a multi-faceted concept encompassing positive and negative aspects. Controllability, privacy, and exploitation are three main aspects of PTS, thereby resulting in a much simpler model than Riegger et al.'s conceptualization. This finding together with the result that only controllability predicts satisfaction via PTS engagement warrants further in-depth investigations with a heterogeneous population of shoppers. Future studies should compare our results with different PTS using a random sample of consumers representative of the study population.

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Investigating consumers' hesitant adoption of medical artificial intelligence

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Keywords: artificial intelligence; healthcare; affective trust; adoption intention; digital autonomy; digital health literacy.

Unlocking the potential of artificial intelligence (AI) for healthcare is one of the major challenges medical companies and policy makers are currently facing (World Health Organization, 2021). Medical AI has the potential to revolutionize healthcare by improving diagnoses and reducing costs related to medical treatments (Agarwal et al., 2020; Longoni et al., 2019; Yokoi et al., 2021). Medical AI are algorithms that analyze patients' data to provide advice in the context of healthcare such as diagnoses and treatment recommendations (based on Castelo et al., 2019; Longoni et al., 2019). Increasingly, AI begins to outperform human experts in medical tasks (Brinker et al., 2019; Haenssle et al., 2018; Chen et al., 2020). However, consumers tend to be reluctant to use medical AI (Dietvorst et al., 2015; Longoni et al., 2019; Promberger & Baron, 2006) and prefer to interact with a human doctor over a medical AI (Castelo et al., 2019). This preference may arise from trust beliefs, as Promberger and Baron (2006) found that patients tend to trust physicians more than a computer program. Even though the adoption of AI is essential for the exploitation of its full potential (Agarwal et al., 2020), research on the causes of the low adoption of medical AI and potential ways to address it remains scarce (Longoni et al., 2019; Cadario et al., 2021). The present study addresses this lack of research via three online consumer experiments identifying affective trust as an underlying mechanism explaining consumers' low adoption intention of medical AI. Further, this study explores digital autonomy and digital health literacy as potential levers to increase consumers' affective trust in medical AI and, consequently, adoption intentions.

Figure 1 gives an overview of the studies. We employed scenarios in medical contexts involving either a human doctor or medical AI. We identified the context of chronic diseases, such as diabetes, as a promising use case for medical AI, since chronically ill patients usually need regular medical appointments which are time- and cost-intensive (U.S. National Health Council, 2014). The use of medical AI could render these interactions more time- and cost-efficient. While Study 1 and 2 were set up in the context of a diabetes risk analysis, Study 3 featured the diagnosis of a (chronic) headache via a health app. Study 1 tests whether affective trust mediates the relationship between the healthcare provider (AI vs. human) and consumers' adoption intention (H_1 and H_2). Studies 2 and 3 additionally consider digital autonomy (H_3, Study 2) and digital health literacy (H_4, Study 3) as potential moderators. Table 1 summarizes the Studies' design, procedures, samples, and results.

Study 1 followed a 2 (healthcare provider: AI vs. human) x 1 between-subjects design. The results of Study 1 demonstrate that the healthcare provider (AI vs. human) influences consumers' adoption intention. Consumers' adoption intention is higher for the human healthcare provider compared to the medical AI. More importantly, mediation analysis

(Model 4, Preacher & Hayes, 2004) reveals that affective trust fully mediates the relationship between healthcare provider and consumers' adoption intention. Compared to the human healthcare provider, consumers appear to adopt medical AI less due to a lack of affective trust. The results of Study 1 support H_1 and H_2.

Study 2 again used a 2 (healthcare provider: AI vs. human) x 1 between-subjects design. Study 2 validated the findings of Study 1. This time, we additionally controlled for consumers' disposition to trust (McKnight et al., 2002). Further, the results of Study 2 show that consumers' digital autonomy significantly moderates the relationship between the healthcare provider and affective trust. Thus, low digital autonomy strengthens the relationship between the healthcare providers and affective trust, whereas high digital autonomy weakens it, providing evidence for H_3.

Study 3 used a 2 (healthcare provider: AI vs. human) x 2 (digital health literacy: low vs. high) between-subjects design. First, we introduced the option of a headache diagnosis facilitated by a health app to all participants. Participants in the high digital health literacy condition then saw a short step-by-step guide that introduced the functionality of the health app. Participants in the low digital health literacy condition did not see the step-by-step guide. Again, the indirect effect of the healthcare provider on adoption intention via affective trust was significant. Moreover, consumers' digital health literacy significantly moderates the relationship between the healthcare provider and affective trust. Thus, digital health literacy weakens the relationship between the healthcare provider (AI vs. human) and affective trust, providing support for H_4. Study 3 confirms digital health literacy as a situational factor attenuating the effect of the healthcare provider (AI vs. human) on affective trust. Thus, increasing digital health literacy appears to be an effective measure to influence consumers' affective trust in medical AI and consequently their adoption intention. The direct effect of the healthcare provider on adoption intention remains significant even when including affective trust, suggesting a complementary mediation (Zhao et al., 2010). There seems to be an omitted variable additionally mediating the relationship of the healthcare provider on adoption intention.

The contribution of the present study is threefold. First, despite consumers' persistent hesitation to adopt medical AI, the underlying mechanisms of consumers' low adoption of medical AI are rarely explored (Longoni et al., 2019; Promberger & Baron, 2006). Applying insights from interpersonal trust research to AI-human interactions, our research adds to prior literature by proposing affective trust as an underlying mechanism explaining consumers' low adoption intention for medical AI. Second, we contribute to a better understanding of influencing factors that may strengthen consumers' affective trust in medical AI and, consequently, their adoption intention. Specifically, we shed light on the impact of consumers' digital autonomy and digital health literacy as two moderators. Finally, based on our findings, we provide healthcare stakeholders seeking to foster acceptance of medical AI with practical guidance on how to increase consumers' affective trust in and adoption of medical AI.

Figure. Overview of studies

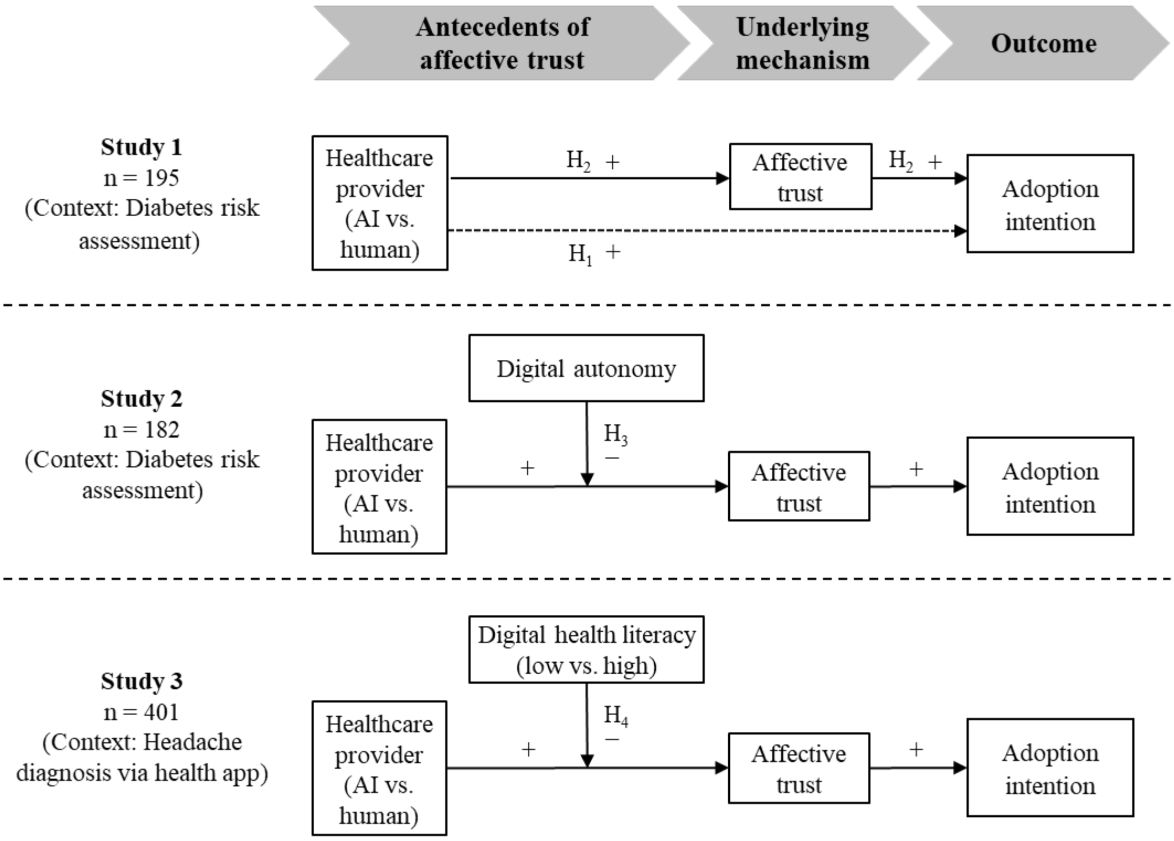

Table 1. Overview of results

Study	Design and Procedure	Sample	Results
Study 1	– 2 (healthcare provider: AI vs. human) x 1 between subjects design – Online experiment using a commercial consumer panel – Context: Diabetes risk assessment – Constructs measured on 7-point scales – DV: Adoption intention – Mediator: Affective trust	N = 195 50.8% female M_{age} = 49 years	Consumers' adoption intention is higher for the human healthcare provider compared to medical AI (b = .39; $p < .05$). Affective trust fully mediates the relationship between the healthcare provider and consumers' adoption intention (b = .67; 95% CI: [.383, .977]).
Study 2	– 2 (healthcare provider: AI vs. human) x 1 between subjects design – Online experiment using a commercial consumer panel – Context: Diabetes risk assessment – Constructs measured on 7-point scales – DV: Adoption intention – Mediator: Affective trust – Moderator: Digital autonomy	N = 182 49.8% female M_{age} = 48 years	Affective trust fully mediates the relationship between the healthcare provider and consumers' adoption intention (b = .52; 95% CI: [.308, .763]). Digital autonomy moderates the relationship between the healthcare provider and affective trust (index of moderated mediation: *ß* = -.15 [-.287; -.028]). Consumers high (low) in digital autonomy have higher (lower) affective trust in medical AI. The effect of the healthcare provider on affective trust is significant for values of consumers' digital autonomy up to the Johnson-Neyman point of 6.31.
Study 3	– 2 (healthcare provider: AI vs. human) x 2 (digital health literacy: low vs. high) between subjects design – Online experiment using a commercial consumer panel – Context: Headache diagnosis through app – Constructs measured on 7-point scales – DV: Adoption intention – Mediator: Affective Trust – Moderator: Digital health literacy	N = 401 50.6% female M_{age} = 55 years	Affective trust mediates the relationship between the healthcare provider and consumers' adoption intention. In addition, consumers' digital health literacy weakens the relationship between the healthcare provider and affective trust (*ß* = -.69, [-1.308; -.064]). Consumers high (low) in digital health literacy have higher (lower) affective trust in medical AI. The direct effect of the healthcare provider on adoption intention remaining significant (*b* = -.53, p <. 001) indicates a complementary mediation.

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Generation Zers' Engagement with Cryptocurrencies: A Behavioral Reasoning Theory Perspective

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Type of manuscript: Extended Abstract

Keywords: Cryptocurrency; Behavioral Reasoning Theory; Technology Readiness.

Generation Z is called the first generation to be a "digital native," having been born between 1997 and 2012 (Dimock, 2019), which were introduced to technology at a time of remarkable technological improvements and changes (Stylos et al. 2021). This generation has been defined as young, innovative, knowledgeable, confident, and sociable, imaginative, savvy (Chillakuri, 2020). Among all generations, the Generation Z generation is hence the one that relies most heavily on the Internet and technology (Business Wire, 2020). Cheung et al. (2020) have stated that Generation Z adopts easily smart technologies. In a similar fashion, Ng et al. (2019) have highlighted that these generations are more keening on discovering novel technologies and feel safe while using new devices. Based on this interest and curiosity, it can easily say that Generation Z's preferences in their lives are likely to be different from the other generations. To support this claim, Priporas et al. (2017) have also declared that generation Z seem to be demonstrating some differences from other generations based on their needs, wants, and choices.

Having different preferences and desires and embracing technology more than other generations have also affected generation Z's investment choices. Redman (2021) has stated that Generation Z prefers to invest their money in cryptocurrencies and non-fungible tokens (NFTs) instead of putting their money on traditional investments based on reports performed by Gambler's Pick. Locke (2021) has similarly also manifested that Gen Z invests its money in cryptocurrency rather than in classic investment ways. More specifically, the data prepared by Mittal showed that the number of Gen Z buyers is 3.5x that of the Gen X buyers and 14.3x that of boomer buyers (Gogol, 2022). Gogol (2022) also highlighted that the data illustrates that there is a straightforward correlation between age and the tendency to purchase cryptocurrency. More simply, this means the younger you are, the more likely you are to buy cryptocurrency. Thornton (2021) stated the reason might be the "once-in-a-lifetime" financial recession that Generation Z had. Hence, Thornton also emphasized that since Generation Z sees cryptocurrency as an opportunity to make money swiftly, they are more interested in investing in some cryptocurrencies like bitcoin, dogecoin, and Ethereum, and spending more time on social media to learn about new ways. Another notable finding stated by several surveys is that the biggest contributor group to cryptocurrency adoption is Generation Z (Mustafa, 2021).

Despite the recent importance and relevance of Generation Z's engagement with cryptocurrency, there is a lack of theoretically informed academic research on both Generation Z toward new-age technologies and blockchain technology. In the existing literature, even though there is some research on Generation Z interacting with new technology such as cutting-edge technology (e.g., Ameen et al., 2020), smart retailing (e.g., Priporas et al., 2017), augmented reality smart glasses (e.g., Rauschnabel, 2018), there needs more research in order to understand Generation Z' interaction with novel technology. Hence, aim of this study is to explore the influence of cryptocurrency engagement of Generation Zers with blockchain technology, and to reveal the factors affecting their engagement behavior with cryptocurrencies.

To achieve this aim, we adopted a mixed method approach. First, a qualitative method has been employed to determine context-specific reasons that show whether the Generation Zers engage with cryptocurrency usage. The qualitative study has been based on conducting semi-structured interviews to build better understanding of GenZers' behavioral patterns and develop a research model for further generalization of findings at a next step. and the questionnaire form with a sample of Generation Zers using cryptocurrency Turkey. Overall, we conducted 29 interviews. In study 2, a quantitative method has conducted with the participants recruited from blockchain clubs of universities in Turkey. Based on the qualitative study findings, which are underpinned by Behavioral Reasoning Theory (Westaby, 2005) and Technology Readiness Index (Parasuraman, 2000), we propose a comprehensive conceptual model to understand Generation Z users' engagement with cryptocurrency. In this research model, the effects of optimism and innovativeness are examined, under "reasons for" through attitude on the engagement with cryptocurrency. Additionally, the effect of discomfort and insecurity under "reasons against" on the engagement with cryptocurrency through attitude has been investigated. In addition to these constructs, and based on the qualitative research findings, additional constructs that shape "reasons for" and "reasons against" have been included to understand the engagement with cryptocurrency. Grievance redressal, transaction processing, and convenience are also other "reasons for" that Generation Z users engage with cryptocurrency. At the same time, lack of governance and anxiety are other "reasons against" Generation Z users do not engage with cryptocurrency. The quantitative study findings confirm the proposed hypothetical model, which provides significant both theoretical and managerial implications for scholars and managers. Our findings also provide new research avenues for the future.

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Exploring Experts' Perceptions of Key Factors Favoring Successful Implementation of Chatbots in Customer Service Encounters: The Case of the Canadian Financial Industry

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Type of manuscript: Extended abstract

Keywords: chatbot; customer service; user experience; privacy; fintech; empathy.

Introduction and Theoretical Background

Chatbot-based customer service has prompted a Fintech revolution that is rapidly changing the landscape of the financial industry (Ng et al., 2020). The prolific scientific research in AI has generated lots of interest in this sector (Jang et al. 2021), and by 2024, the global chatbot market is expected to reach $1.3 billion with an annual growth rate of 24% (Zeng, 2020).

In recent years, financial institutions are increasingly adopting chatbots to enhance the user experience, with a strong belief that investing in the technical knowledge and skills required to offer chatbots are effective ways to improve the customer's experience (Thomaz et al., 2020; Riikkinen et al., 2018). Despite the market's enthusiastic predictions in the future of chatbots, the successful implementation of a chatbot for the benefit of consumers is still facing many challenges (Marous, 2020), as conversational intelligence remains a key major issue (Bengio, 2017), along with regulation (Paul et al., 2020), ethical considerations (Przegalinska et al., 2019; Ruane et al., 2019); lack of humanness from the chatbot interaction (Rapp et al., 2021) and semantic limitations (Grudin & Jacques, 2019; Rapp et al., 2021). Because chatbots are human-like virtual agents and not just another new type of technology-enabled self-service, consumers tend to consider the *bot* as a person (Purington et al., 2017) with human characteristics (Lankton et al., 2015). Furthermore, as the financial industry engages in interactions that require a great deal of sensitive information sharing (e.g., credit card, account number, investment habits), users become increasingly vulnerable and concerned with their privacy when using Fintech (Ng et al., 2020; Patil et al., 2019).

Several studies have examined the benefit/risk calculation of consumers when contemplating using chatbots, but very few have conducted the investigation from an experts' perspective, and less so in the North American context. By adopting the theoretical perspective of technology humanness and the personification of machines by humans (Purington et al., 2017), we investigated how experts perceive the implementation of chatbot services in the Canadian financial industry, including the kind of challenges and opportunities they face while doing so.

Methodology

Individual semi-structured interviews were conducted with 7 experts acknowledged for taking responsibility in the design and development of digital services, and in the implementation of chatbots in the financial management sector. Recruited via LinkedIn, they ranged from 25 to 40 years old (4 men and 3 women) and were professionally titled as UX designers, consultants or CEOs of Fintech. Typical questions asked to the participants included A) *What were the main challenges faced with chatbot implementation in the organization?, B) How to improve the chatbot UX regarding empathy and privacy?, and C) What were considered the main benefits and risks of chatbots from the user's perspective?* Interviews were virtually conducted and recorded via *Zoom* and professionally transcribed. The NVIVO software was used for data categorization and coding, while the data analysis followed the procedure advocated by Gioia et al. (2013) to ensure qualitative rigor.

Results

The study findings highlight the main issues, challenges and opportunities of chatbot implementation. Three challenges emerged regarding chatbots' implementation: (1) chatbot's capabilities/immaturity, (2) systems legacy incompatibilities, and (3) regulatory frameworks which are either too rigid or inappropriate because of ethical concerns raised by chatbots. The research also uncovers three main opportunities leading to successful chatbot implementation: (1) the use of chatbot empathy or humor when interacting with users, (2) the humanization of chatbot technology, and (3) the perceived benefits from using a chatbot by older consumers such as 24/7 available support and guidance. Another key barrier which crops up the interviews was the privacy concerns/security, as experts mention that both should be top of the list in the financial industry in order to favor a better adoption of chatbots by users. Finally, according to experts, the chatbot is considered more user-friendly and is preferred to the website channel for clear straightforward transactions. Finally, the key challenges and opportunities with chatbot implementation arise for a variety of more complex tasks, such as the purchase of life insurance, or the opening of a savings account for instance.

Discussion, implications, limitations and future research

This study makes a significant contribution to the understanding of the specific issues and opportunities as perceived by North American financial services chatbot experts, complementing the studies of Jang et al., (2021) and Mogaji & Nguyen (2021). We also found that experts perceive empathy and a more human-like chatbot, as a key factor favoring a successful chatbot implementation. Chatbots' lack of capacity to better understand consumer's requests and the need to fix old IT legacy systems are the main obstacles identified, preventing the full integration of this new customer service channel.

This study provides several implications for managers. Focusing on increasing chatbot's humanness (style of interaction using humor or empathy) is important for improving the user experience with chatbots. In line with Ashfaq et al., (2020); Jang et al., (2021), experts also stress that chatbots that provide intelligent and reliable solutions are needed to accompany customers in a complex (vs straightforward) decision. The opportunities uncovered in the research are in lines with the technology humanness framework, in that consumers are more comfortable interacting with machines that display human-like conversations (Purington et al, 2017).

This study sheds light on the North American marketing financial services considering that prior research using experts was mainly conducted in Asia, where IA is far more adopted than in its Western counterpart (Chung et al., 2020). It gives a better understanding of chatbots implementation in a region where consumers are less familiar with chatbots (Marshall, 2021). Some limitations are present in this research providing opportunities for future research. First, this study uses a limited number of interviews which restricts the ability to generalize the findings. Second, chatbot humanization and the use of humor and empathy in chatbot interaction deserve more investigation. Finally, a follow-up study with customers is called for to compare their perceptions with those of the experts.

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Assessing the role of technology readiness in telemedicine adoption in an international context

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Type of manuscript: Extended abstract

Keywords: ehealth; telemedicine; technology readiness.

Purpose

The purpose of this paper is to assess the degree of technology readiness and its impact on telemedicine adoption. Based on the Technology Readiness Index 2.0 (TRI 2.0 hereafter, Parasuraman & Colby, 2014), we will validate the scale in an international context, elaborate different user profiles and connect the different segments with the telemedicine adoption process.

Digital health technologies are in the spotlight. Telemedicine is known to be one of the main disruptors of the traditional health care industry and the world has proven to rely heavily on eHealth solutions in order to deliver decentralized health care under the shadow of the ongoing health crisis. Besides, it is still necessary to care for patients with other needs and diseases. Whereas many of them might precise personal and on-site attention by health care professionals, there is a strong opportunity for telemedicine solutions to offer care, attention, consultations, and training for those who can spare physical contact (Blandford *et al*., 2020).

In line with the aforementioned, the interactions between humans and technology are becoming increasingly seamless in a wide variety of industries. Knowing the important role of technology-based innovation in the context under study, technology readiness is a crucial framework that needs to be considered in order to avoid gaps parallel developments between supply and demand (Flavián *et al*., 2022), meaning health care providers and patients for the context under study. As technology-triggered transformation is prone to accelerate in the future, it is important to know patients' trade-offs and to assess their skills and capabilities to guarantee maximum value from technology-based health care services.

From an academical standpoint, health care is a "fertile field for research" that needs help since it is a sector that "costs too much, wastes too much, errs too much and discriminates too much" Berry and Benapudi (2007). Telemedicine could mark a turning point by bringing health care closer to people's homes in ways never seen before by lowering costs associated with health care delivery and saving time for both patients and providers. However, telemedicine is by no means a cheap "knock-off" of in-person care but should rather be seen as a model that makes care more equitable and accessible (Pearl & Wayling, 2022). Therefore, it is important to ensure that the new information systems are well accepted by their potential users.

The Technology Readiness Index 2.0 (TRI hereafter) has been used in a wide variety of contexts as new technologies are increasingly impacting people's everyday lives. This 16-item scale originally developed by Parasuraman & Colby (2014) offers a solid fundament to measure people's propensity to embrace and use new technologies.

Methodology

The TRI offers a well-suiting base for this research as data has been collected via an online-survey from 1200 randomly selected participants in the United States of America, Germany and Spain, 400 in each country. 1.197 valid surveys are currently being analyzed using IBM SPSS and AMOS (versions 26). The three countries under study not only run on different health care systems, but also find themselves on different points of the telemedicine adoption curve that entail different levels of technology penetration and acceptance.

To the moment, exploratory and confirmatory factor analysis (SPSS 26) confirmed suitable goodness-of-fit indexes. The next steps of research will focus on the following: In the first place, the importance of country-of-origin effect on the matter will be empirically analyzed and validated. Based on the aforementioned, respondents will be divided into different segments (skeptics, explorers, avoiders, pioneers and hesitators). This analysis will help to draw conclusions by assessing people's beliefs and challenges that directly translate to telemedicine adoption.

Foreseen implications

People are the key element for the functioning of any society. There is a general trend towards patient-centered healthcare and technologies related to eHealth are a fundamental piece in the empowerment of patients. The foreseen implications of this paper are of great interest for both public and private providers of telemedicine services and other stakeholders. Among them, policy decision-makers may pick up the results of this paper in order to tier patients into segments with varying technology readiness levels. This will give them important inside information in understanding the role technology beliefs play and how to address and meet peoples' unique requirements to promote telemedicine adoption in the foreseeable future.

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Pay with your Face - Consumer Decision-making Journey of Trialling Facial Recognition Payment Technologies

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Keywords: facial recognition payment; trial; consumer decision-making journey.

The way in which consumers pay for goods continues to change. Payment technologies (e.g., PayWave, PayPass) have led to advancements in biometric technologies, such as facial recognition payment systems (FRPS) methods. FRPS are a payment method where consumers use a facial recognition application to verify their identity and authorize payment. In China alone, there were 61 million users of FRPS in 2018, estimated to exceed 760 million by 2022 (Liu et al., 2021). FRP product, 'PopID', was launched in 2020 and is now accepted at over 100 restaurants and retail brands across North America (Goldberg, 2021; Baimbridge, 2021). However, the application and adoption of FRPS is still limited across most other countries, including Australia, where the current study took place. Although Australian consumers have readily embraced payment methods like of PayWave, FRPS have only achieved very low level of trial and adoption (Letts, 2016).

A systematic literature review has identified researchers are beginning to explore factors that affect consumers' intention to adopt FRPS. Such nascent work tends to employ the technology acceptance model (TAM) (Zhong et al., 2021), the unified technology acceptance and use theory (UTAUT) (Ciftci et al., 2021) or the privacy calculus model (Liu et al., 2021). To explain FRPS adoption, researchers have underpinned their work with the diffusion of innovation (Rogers, 1962), or social impact theory (Argo et al., 2005). These studies have shown that although FRPS can provide significant convenience value to consumers (Ciftci et al., 2021), its use has stirred up controversy relating to security and privacy risks (Moriuchi, 2021). These initial examinations of FRPS adoption are limited in that they exclusively focus on consumers' 'adoption intention', which skips several important steps of the consumer decision-making journey for new technologies such as knowledge and information searching (Rogers 2003). In response, this current study extends Rogers' (2003) innovation-decision process model and explores the stages of and the drivers in each stage of the consumer decision-making journey before their adoption.

One-to-one Zoom interviews were taken place with 20 Australian (18-65 years old) in July 2022. For data analysis, a four-phase grounded theory approach was used (Barratt-Pugh et al., 2019), where Nvivo 12 auto coding was used during the first stage to generate key quotations from 20 interviews. A total of 1789 key quotations were generated, which were then manually categorized into 29 sub-themes during the second phase based on a grounded theory approach.
The results revealed several stages before consumers' intention to trial FRPS, including (1)

acquiring knowledge, (2) generating interest and desire, (3) performing information search and (4) trusting and liking the FRPS. Each stage was influenced by several ‘consumer’ (e.g., perceived ease of use), ‘retailer’ (e.g., consumer-store relationship), and ‘consumer-store’ relationship-related factors. Consumers’ knowledge about FRPS is influenced by factors such as ‘word-of-mouth’, their education about technology, and retailer-oriented factors (e.g., marketing communication). Consumer-related factors, such as perceived usefulness and security concerns influence consumers' interest and information search. Trust and affect toward FRP result from these two stages and are influenced by consumer-store relationship factors (e.g., existing trust toward the retailers). Key implications are reflected below.

The interviews revealed that consumers who have established a preferred payment method were less willing to trial FRPS. This finding indicates migrating consumers from a ‘preferred payment method’ like PayWave, to a FRPS will be the initial challenge for retailers. Findings also identified social barriers to adoption. While FRPS are convenient and easy to use, the presence of other consumers in-situ is likely to elevate FRPS users’ anxiety and thus, mitigate trial and adoption.

Retailer-oriented factors represent retailers’ in-store support and external communications, FRPS technology providers’ capabilities, and data governance policies (e.g., storage and use of collected data). The former underlines the role of in-store frontline employees to respond to consumers’ questions relating to the storage and security of facial image data, and assistance at the checkout. Retailer communication across social media, brand communities, and influencers might be useful to facilitate FRPS trials. Findings also point to the importance of communicating the expertise and proficiency of FRPS technology suppliers. For example, highlighting how consumers’ data (facial image) will be stored, or accuracy (i.e., the ability for the technology to deal with masks, sunglasses, or aging).

Consumer-store relationship represents the consumer’s previous interactions with the store, including their shopping frequency (behavioural loyalty), as well as their trust towards the retailer. Interviewees acknowledged and understood that frequent store patronage, particularly combined with a loyalty program, meant that retailers already had access to a large volume of purchase information. Findings indicated consumers who understood the nature of this information sharing process, and had established trust in the retailer (i.e., personal data has not been leaked), were more inclined toward sharing a new type of data (i.e., their face) and trialling new FRPS technology. Retailers with a loyal frequent-purchaser segment would be better positioned to launch a FRPS. In contrast, retailers where frequency of store visit or purchase is low or no loyalty program is in place would likely be disadvantaged.
Overall, this study provides new insights regarding consumers’ views on trialling FRP technologies. Our presentation will focus on how marketers can use such knowledge to generate better segmentation, targeting and communication strategies.

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Collectives in Social Media: Predicting their brand engagement using deep learning methods

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Type of manuscript: Extended abstract

Keywords: deep learning; collectives; consumer engagement.

Introduction

Visual content is essential in digital marketing because they attract consumers to the brand and increase attention to their experiential activities (Liu, Dzyabura and Mizik, 2020). However, brands typically follow a mass communication strategy (Matz *et al.*, 2019) instead of personalizing their brand messages according to individual collective membership status (Hawkins, 2018). The purpose of this study is three folds. First, we offer a novel conceptual framework that uses construal theory to assess the different types of collectives and their content engagement preferences. Secondly, we demonstrate how deep learning architectures can be used to extract key features from unstructured contents (textual and images) to understand how appealing specific content types to an individual collective group is. Our approach uses the Deep Clustering methodology and Transformers which achieved high levels of accuracy (86%) to explain and predict which posts will get high engagement and highlight the critical content characteristics that important for each collective group. The research provides guidelines to practice by suggesting that brand managers should shift from mass communications to personalized branding messages and adjust the style of imagery and texts that affects collective preferences and hence increase engagement.

Theoretical background

A collective is a concept that refers to a group of consumers "who share a commitment to a product class, brand, activity, or consumption ideology" (Thomas, Price and Schau, 2013). While previous studies have examined the different visual (e.g., Li and Xie, 2020) and textual characteristics (e.g., Tan, Lee and Pang, 2014) of a content to increase consumer engagement in social media, researchers have not explored yet how appealing these contents to different collective groups (e.g., brand community, consumption tribes and community of practice), which is the purpose of this study. Existing psychology literature discussed that the importance of cognitive implications of linguistic categories (e.g., emotional state, cognitive state and actionable behavior state) to describe person preferences and their behaviors (Semin and Fiedler 1988). Also, consumer engagement studies found that frequent personalized interactions through posts can trigger positive brand-associated thoughts, and increase engagement behaviors (Matz *et al.*, 2019). Building on these studies, our paper is among the first to empirically investigating the different types of collectives and their content engagement preferences in social media using construal theory.

Methodology

We collaborated with a global soccer brand and collected data from Instagram social media platforms for five months (May- September 2020). In total, we accessed 35,000 posts and their corresponding comments (n=1,743,050) from Instagram. Following construal theory

(Thomas, Price and Schau, 2013) and linguistic categories suggested by (Semin and Fiedler 1988; McColl-Kennedy; *et al.*, 2019; Zaki and McColl-Kennedy, 2020), we applied deep-learning approaches to create a set of actionable predictor variables to explain collective engagement behaviors. We used name entity recognition techniques to explain the collective actionable behaviors, classify posts into sentiment valences to explain their emotional state, and generate topics using the Transformer deep learning model to explain their cognitive behaviors. Finally, we used Convolutional Neural Network (CNN) for predicting engagement.

Results

Contextualized in sport and focusing on brand community collectives, our findings show that textual posts with image contents correlate positively (rho: 31%) with high engagement rates. In contrast, textual posts that include video content tend to correlate (rho: -31%) with engagement negatively for brand community collectives. Interesting, images of people generally score well, but how well is determined by several factors, including their eyes' position in the frame or their gaze straight ahead or off to one side. People who have their eyes shut or a sad or neutral expression tend not to score highly, whereas a smiling face looking straight ahead positively correlates with engagement. Concerning textual topics, information and emotional content have a higher positive correlation with engagement metrics than topics related to commercial content. These findings can assist brand managers in understanding how the content or style of videos and texts affects brand community collectives and hence inform appropriate actions for managers to take.

Conclusions

Our study contributes to the existing psychology and marketing literature by providing a theoretically derived conceptual framework and a deep learning approach to explain and predict which posts will be most appealing to a particular individual collective. This is to help marketers to personalize the content on social media platforms which potentially increases their engagement.

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Unpacking Emotion on Social Media Marketing in Global and Emerging Local Market Contexts with Evidence from Big Data

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Keywords: consumer emotion; social media marketing; Twitter; brand post popularity; big data; global; local; emerging market.

Background

Global brands' localization efforts are often reflected in their social media marketing practices with varying acculturation degrees on the tone, emotion, and symbols used. The similarities and differences between parent brands and their local versions' uses of emotional content present an emerging field of research that can uncover the applicable lessons for better business.

As consumers shift their traditional communication habits to social media, instead of newspapers or TV, they also access and exchange information about products and services through social media (Delia, 2015). Consequently, these environments have become an influential marketing tool for brands to promote their products (Lee, 2016). From the consumer perspective, research has shown that emotions play an important role in the consumption experience (Laverie, 1993) and impact word-of-mouth communications and brand loyalty (Crosby, 2007). Consumers develop an attitude toward the brand and form relationships by interacting with it on social media (Hudson, 2015). Ultimately, a brand may become irreplaceable to consumers (Ekinci, 2005) due to an established strong relationship. Successful online marketing efforts are known to influence consumer engagement both in spreading positive word-of-mouth and recommending the brand of concern (Edelman, 2010).

Despite the growing research on social media posts' global attractiveness to consumers, studies on the effect of cultural differences on consumer behavior regarding branding communication is still inadequate. Cultural characteristics of individualism/ collectivism, uncertainty avoidance, power distance and long term orientation (Hofstede, 2011) are shown to be useful in understanding the impact of social media campaigns across cultures (Lin, 2017). Depending on the cultural perspective, consumers might interpret the brand messages differently. Thus, culture appears as an important factor to consider by managers to tailor their social media campaigns targeted to consumers belonging to specific cultural groups. As Twitter is among the most popular four social media platforms in North America, Europe and Turkey (GlobalStats, 2022a, 2022b, 2022c), by monitoring emotions of consumers, companies can create more culture oriented, thus more effective social media campaigns.

The aim of this research is twofold to be considered under two tasks for the research questions on Table-1. Under Task-1, we explore ways to automatically extract basic emotions (Matsumoto, 2009) of happiness, surprise, sadness, anger, fear and disgust from multinational brands' Twitter messages and consumers' replies. Using statistical and state-of-the-art deep learning methodologies, we develop two different emotion models for English and Turkish separately. Under Task-2, besides determining the most prominent structural and textual features, we also evaluate the effect of emotional content of messages that increase the popularity of brand posts. Consequently the main theoretical and practical contributions of this study are as follows:

(1) Emotion classification requires extensive amount of annotated data. While such datasets are available in English, they are not very common in most of the languages like Turkish. We propose an automatic way to articulate textual data annotated by basic emotions and sentiment, by getting use of emotional signals of emoji characters in text.

(2) In order to achieve (1), we propose a scoring function and algorithm to rank emojis according to the dominant emotion they represent. As of our knowledge, our study is the first one to evaluate the emotional representation of emojis in branding communication and Turkish language.

(3) There are already examples in previous literature focusing on the important factors for effective and popular brand posts. However, these studies mostly neglect the cultural differences of consumers and report their results in global level. We aim to understand the effect of culture on these factors by building and comparing statistical models developed separately for English and Turkish datasets. Our study is the first one concentrating on the cultural influence regarding brand post popularity.

(4) As well as evaluating the cross cultural differences on vividness, practicality, personalization and interactivity features of brand Twitter posts, we integrate the emotional content of a message as an additional factor of brand post popularity. This is the first study on analyzing how emotions transmitted by brands in their social media posts influence the success of brands' social media messages comparatively across cultures.

Table-1. Research questions

Task	Research Question
Task-1	*(RQ-1) How can emotions be extracted from brands' and consumers' social media messages in different languages?*
Task-2	*(RQ-2) How does the emotional content of an international brand's Twitter marketing campaign message affect the dispersion and positive word of mouth in social media in global and emerging local market contexts?*

Research Design

Detailed flow of our research segmented into two sub-tasks is shown on Figure-1. Following data collection, the first task's main objective is extracting basic emotions from textual content produced by brands and consumers on Twitter. The second task is about understanding if there is an effect of these emotions on the popularity of brands' Twitter posts.

Social media data for English and Turkish languages is collected by using Twitter 2.0 API with academic credentials. Data is stored in Elasticsearch index for high performance of querying. Selected sample of companies having both English and Turkish Twitter accounts and their industries are listed on Table-2. For English 8,101,034 and for Turkish 852,348 messages containing all of the brand posts and consumer replies are downloaded for the period from June 2016 to June 2021.

Figure-1. Research design – Task Flow

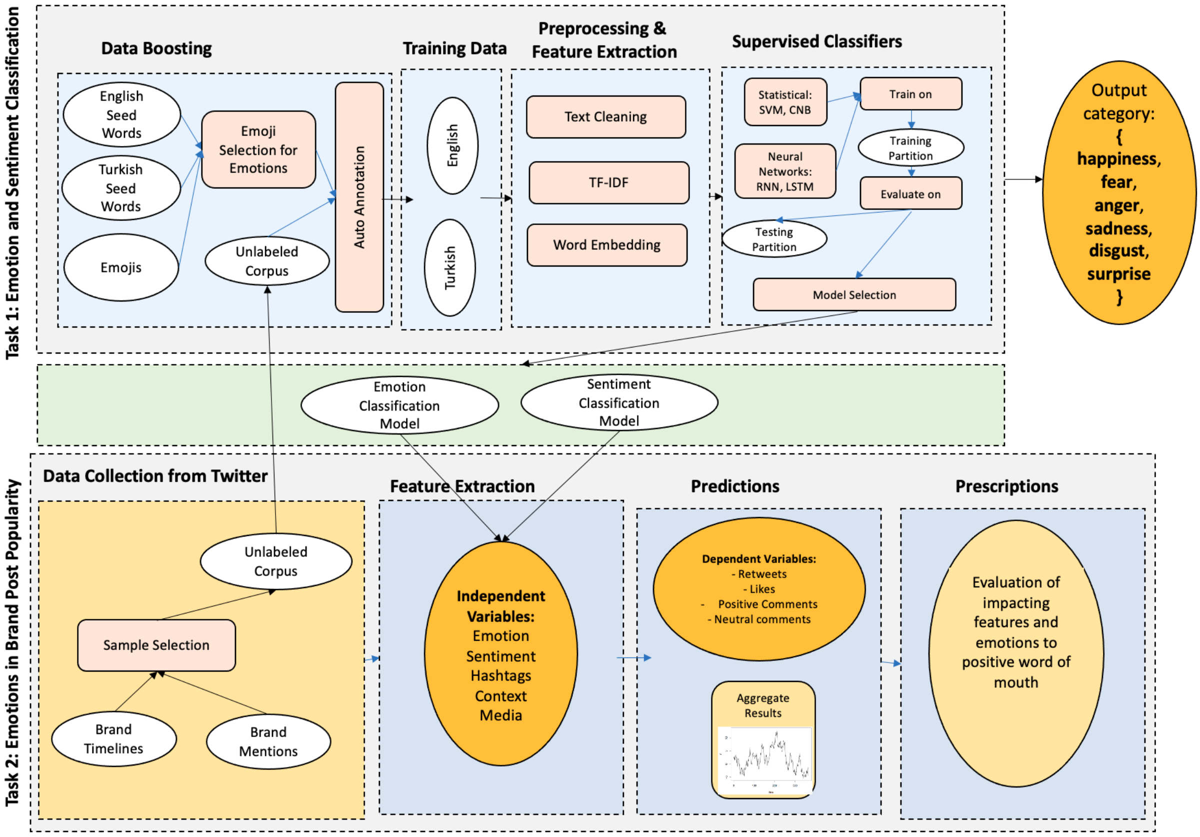

Table 2. Company Sample

Company	Industry	Company	Industry	Company	Industry
Gillette	FMCG	**McDonald's**	Fast Food	**Microsoft**	Technology
Coca Cola	FMCG	**Orkid/ Alldays**	FMCG	**HP**	Technology
L'Oreal	FMCG	**Pepsi**	FMCG	**Huawei**	Technology
Algida/Walls	FMCG	**Toyota**	Automotive	**Allianz**	Insurance
Burger King	Fast Food	**BMW**	Automotive	**Axa**	Insurance
KFC	Fast Food	**H&M**	Apparel	**HSBC**	Banking
Vodafone	Technology	**Watsons**	Retail	**Netflix**	Technology
Samsung	Technology	**Flormar**	FMCG	**UPS**	Logistics
Hyundai	Automotive	**Oriflame**	FMCG	**DHL**	Logistics
Levi's	Apparel	**Carrefour**	Retail		
Marks&Spen.	Apparel	**Yves Rocher**	FMCG		
Siemens	Technology	**Sony**	Technology		

Textual data sources annotated by humans according to their emotional content are required to build supervised classifiers. Generating these resources are both expensive and time consuming, and they are not plenty and context specific for any language. Moreover, research has shown that emojis such as smileys, angry faces or crying faces are explored as strong indicators of emotions and feelings of the users (Go, Bhayani, & Huang, 2009; Liu, Li, & Guo, 2012; Read, 2005). For Task-1, inspired by (Riloff, 1996) and (Tang, Qin, Liu, & Li, 2013), we first build a co-frequency matrix of emotional seed words and emojis, than rank emojis according to their importance by each emotion category. Following the selection of a set of the most important emojis for each basic emotion, we annotate Twitter messages automatically based on the emojis observed in them. For English and Turkish two separate long short-term memory networks are trained and we achieved 87% and 86% classification accuracy, slightly better than models proposed previous work (TOCOĞLU, 2019; Tocoglu, 2019).

Regarding Task-2, controlling the variables related with vividness, practicality, interest, personalization and interactivity measures proposed by previous work (De Vries, 2012; Schultz, 2017), we evaluate separate Poisson regression and structural equation models for English and Turkish in order to infer about emotions' effect on brand post popularity. Number of likes, number of positive and neutral comments, number of retweets and their alternative combinations are used as dependent variables for these models. Our preliminary results show that emotions are significant determinants of popularity of brands' Twitter messages for both English and Turkish speaking consumers.

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Customer relationships formation and development in AI-based organisational frontlines

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Keywords: organisational frontline; artificial intelligence; anthropomorphism.

As increasing computer power, decreasing computing costs, accessibility of big data, and the emergence of deep machine learning algorithms and models become more ubiquitous, artificial intelligence (AI) will permeate every aspect of contemporary marketing practice (Huang & Rust, 2021). This will have a significant and potentially transformational impact on the discipline (Davenport, Guha, Grewal, & Bressgott, 2020). However, research is yet to provide sufficient insights into how AI will impact customer-firm interactions (Mende, Scott, van Doorn, Grewal, & Shanks, 2019). Paramount among these is the need to examine the formation and development of relationships between humans and AI-based organisational frontlines employees (FLEs) during service encounters.

Traditional structures of organisational frontlines (OF) are becoming more digitised and virtual in nature, especially within the service sector (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017). Customers are increasingly interacting with machines (e.g., autonomous AI-powered agents) capable of displaying intelligence and other human-like behaviours. To date, research on AI-empowered technologies has focused on human-human interactions enabled by these technologies as a communication medium (Mouakket, 2019; Xu, Ryan, Prybutok, & Wen, 2012). However, the enhanced capabilities of AI-based FLEs have created conditions whereby it is possible for these agents to adopt the role of service actors in their own right. Thus, human-machine interactions take the form of social interactions which, from a social psychology perspective, may evoke emotions. Emotions contribute to social relationships through inspiring reciprocal and prosocial behaviours (Cheng & Chen, 2017; H. Kim & Qu, 2020). Hence, understanding how such human-machine interactions can trigger emotions that affect the formation and development of relationships between AI-based FLEs and customers requires further investigation. This is particularly pertinent when machines are anthropomorphised and display human-like behaviours such as mannerisms and verbal acknowledgements. This may transform the way humans perceive and interact with AI agents potentially resulting in a 'connection' with the machine (Pitardi & Marriott, 2021). To this end, this paper addressed the following research question:

RQ: How do anthropomorphised AI-based organisational frontlines affect human-machine relationships formation and development during service encounters?

In conducting and synthesising the results of two studies, we identify and explicate the factors that affect customer relationships with modern anthropo-centric OF. In doing so, we progress the work initiated by Lemon and Verhoef (2016) and Wünderlich, Wangenheim, and Bitner (2012). Study 1 consists of 31 semi-structured interviews with users of Siri, Alexa, and Google Assistant. Analyses encompassed thematic content (Braun & Clarke, 2006) using NVivo. Study 2 comprised the text mining of 12,941 comments taken from 81 YouTube videos about the same intelligent assistants. YouTube was selected as it was identified as a forum where individuals expressed their opinion on their experiences of intelligent assistants freely without the intervention of an interviewer. These opinions were subsequently compared and contrasted with the results of Study 1. In analysing big data, we applied Leximancer (i.e., an automated content analysis software). Leximancer mitigated many of the limitations of the qualitative analysis through the removal of human error during manual coding (D. Kim & Kim, 2017; Young, Wilkinson, & Smith, 2015) and providing "a researcher-independent, transparent, reliable, and reproducible means of summarising and analysing a body of text similar to the way statistical methods are used to analyse quantitative data" (Young et al., 2015, p. 112).

Data and methodological triangulation were ensured through the analyses of participant interview data and subsequently the analyses of documents (YouTube videos comments) to compare and expand findings of our interview-based data. Siri, Alexa, and Google Assistant were selected as they are considered advanced AI conversational agents, and because they are also already used by a number of businesses such as Patron Tequila, Ocado, PayPal, and Johnnie Walker as frontline employees that interact with customers (Williams, 2017). Thus, we argue that user experience of these intelligent assistants is relevant to a more generalised prediction of the formation and development of relationships between customers and AI-based OF as such technology becomes increasingly prevalent.

Our findings suggest that customers anthropomorphise AI-based FLEs evoking positive emotion in users that affect relational factors. More specifically, anthropomorphised AI agents generate different types of value for users. For instance, singing a song creates hedonic and social value, talking with customers creates social value which may evoke emotions and lead to the development of rapport. This is consistent with Qiu, Li, Shu, and Bai (2020) who identify how rapport may form in human-robot relationships. However, our results challenge their findings insofar as they suggest it is a different kind of rapport than that generated in human-human interactions while our findings show that, due to anthropomorphism, rapport is similar to human-human interactions. For example, some users reported similarities to interacting with a friend. Anthropomorphism and rapport also positively influenced trust, enhancing user perceptions of reliability and the benevolence of AI-based FLEs. The AI enhanced anthropomorphism increased perceived reliability because of the improved capabilities of the machine, which in turn, created the sense of interacting with a human. For instance, machines display mannerisms which users construe as the ability to display benevolence, thus building users' emotional affinity towards their machine. Previous research that investigated various dimensions of trust in human-machine relationships omitted benevolence (Chérif & Lemoine, 2019; K. J. Kim, Park, & Shyam Sundar, 2013; Madsen & Gregor, 2000; van Pinxteren, Wetzels, Rüger, Pluymaekers, & Wetzels, 2019), suggesting that benevolence in the human-machine relationship is specifically attributable to anthropomorphism; hence potentially attributing brand benevolence to AI agents.

In human-human service encounters, customers become committed to service providers as a result of the utilitarian, hedonic and social benefits they receive (B. Kim & Kim, 2020). In human-nonintelligent machine interactions, customers are committed to the service provider only due to receiving utilitarian and hedonic service outcomes (Bilgihan & Bujisic, 2015; Rajaobelina, Brun, Sandrine Prom, & Arcand, 2018). Previous research argues that in human-nonintelligent machines there is no significant relationship between social value and commitment (Pura & van Riel, 2005). Nonetheless, this research argues that in human-intelligent machine relationships, AI agents are perceived as behaving like humans. Human-like features resulting from advanced AI create utilitarian, hedonic, *and* social value for users influencing calculative and affective commitment towards the AI agent. This contradicts Poushneh and Vasquez-Parraga (2019) who argue there is no relationship between perceived social value and affective commitment regarding smart products (e.g., smart phones). Relational factors are also influenced by mannerisms insofar as they affect user perceptions of interacting with AI agents in that they mirror those of humans.

In conclusion, AI-derived anthropomorphism results in a distinct form of human-machine interaction that comprises characteristics that are similar to those found in other relationships (e.g., two-way interactions). These interactions enable social interaction between AI-based FLEs and users creating social and hedonic value. Social interaction with the AI agent and the resultant sense of social presence derived from its anthropomorphic features may prompt emotional affinity and rapport toward the AI agent. Hence, perceived rapport along with a sense of social presence cause users to develop benevolence and affective commitment toward an AI agent. This research contributes to the developing human-machine relationship literature by identifying how affective commitment may emerge from human-to-intelligent assistant relationships. In addition, managers can benefit from the social value (building social and emotional relationships with intelligent assistants) that customers derive through interacting with AI-based FLEs to optimize their relationship with customers similar to those of face-to-face interactions.

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Value-Attitude-Behaviour Model: Explore Consumer Emotions and Purchase Intentions in Live Streaming

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Keywords: consumer emotions; consumer purchase intentions; live streaming; Value-Attitude- Behaviour Model; generation-Z

The technological revolution of Technology 4.0 has changed the nature of business and led to the emergence of social commerce. Live e-commerce is increasingly becoming a new trend, and the combination of live streaming and shopping has been gradually integrated into people's lives and accepted by more and more people. The new business model of live e-commerce has opened up new possibilities for e-commerce platforms to break the traffic logjam and gain new high volumes of transactions." The rise of 'Generation Z' consumers is inextricably linked to the megatrend of consumer upgrading in China. This study examines how Gen Z (Born in 1994-2004) consumer sentiment influences purchase intentions in the context of live e-commerce in China. More specifically, the emotions and purchase intentions of Generation Z consumers need to be explored. Using a value-attitude-behaviour model, this study conducted a qualitative analysis of data collected from semi-structured interviews with Chinese consumers who had shopped live online. 20 Chinese consumers of Generation Z were interviewed online. The findings suggest that differences in consumers' perceptions of value when watching live-streaming lead to divergent emotional attitudes, and that consumer emotions （happy, Interested, anxiety, trust, curious and gratitude) could guide consumer purchase intentions and behaviour. The study also found that when consumers have mixed emotions, consumers are more inclined to make decisions with a hedonistic attitude, which leads to consumers being more likely to make impulse purchases. This study fills a gap in the lack of previous research exploring the emotions and purchase intentions of Gen Z consumers in live commerce.

Introduction

Live shopping merits investigation as a newer online shopping variant. Online shopping and e-commerce have been heated topics focused on by scholars over the past years. However, there have been few studies about live streaming retail which is a phenomenon that recently emerged (Peng, 2017). Because of the major differences between live streaming and the ordinary online shopping channel, it is worth investigating consumer behaviors during live streaming processes. Meanwhile, live streaming has been increasingly popular in the Chinese context (Song, n.d.2021). In 2021, a total of 1.2 trillion yuan in sales was achieved in the channel of live streaming retail. As of the end of 2021, China had 635 million online live streaming users, accounting for 70.6% of its total netizens. 66.2% of users place orders after watching live streaming e-commerce videos (Cai, 2022)

As an emerging business model, live shopping has not been fully explored (Sun et al., 2019).

Previous studies have examined different factors that may influence customers' purchase intention in live shopping from different perspectives, such as the IT burden perspective (Sun et al., 2019), the marketing strategy perspective (Min et al., 2019), and the endorsement and product matching perspective of streamers (Park & Lin, 2020). Although customer sentiment is a focal factor influencing consumer behaviour. However, in live shopping, the role of consumers' emotional attitudes on purchase intention remains ambiguous. Furthermore, there is limited research investigating the role of customer emotion in purchase intention from the perspective of the 'Generation Z' customer segment. In addressing the gaps above, this study is going to explore the roles of generation Z consumer emotions and four research questions were proposed.

Primary Research Questions:
Why customer emotion plays a key role in customer purchase intention
Secondary Research Question 1:
Why do consumers choose to buy goods on live streaming platforms?
Secondary Research Question 2：
What impact do emotions have on consumer behavior?
Secondary Research Question 3：
What emotions arise during the live streaming experience?

Literature review

Live-streaming commerce

Live streaming, an interactive form of internet-based multimedia entertainment, has quickly gained popularity across the globe (Xu et al., 2020). Customers are more likely to select live shopping with contactless service and prompt engagement than high-risk retail purchasing as a result of COVID-19's impact in recent years. When compared to conventional teleshopping, which is a direct technique of buying based on a television, live shopping is different (Alcaiz et al., 2006). Through the engaging TV host's explanations, in-depth demonstrations, and the use of live models, teleshopping may optimise the display of items (Wagner et al., 2017; Yen, 2019). Teleshopping, on the other hand, is seen as a one-way communication that lacks prompt and obvious client participation. Compared to teleshopping, live shopping offers real-time consumer interaction, a greater choice of application situations, and support for both mobile devices and PCs (Johnson and Woodcock, 2019).

Customer Emotion

Emotions influence consumers' attitudes and decision-making processes, which in turn influence their buying and post-buying behaviour (Gifford, 2002). In terms of the experience of emotions and their impact on human activity, emotions can be classified into two main categories: positive and negative emotions. Individuals in positive emotions search deeper for information about purchase decisions and tend to process product information comprehensively to make decisions. It can be seen that positive emotions lubricate positive attitudes towards product selection and enhance the ability of individuals to process information for decision making, whereas individuals in negative emotions search for information for decision making at a shallow depth and tend to use non-linear decision-making strategies, i.e. attribute-based processing in which only some attributes of the product are considered when selecting the product (Ladhari et al., 2020).

Value-attitude-behaviour model

Homer and Kahle (1988) developed the value-attitude-behavior model to explain how individual behaviors are influenced by values and attitudes. It suggests that people’s behaviors are influenced by their attitudes both directly and indirectly. However, the focus of this model is the mediating role of attitudes between values and behaviors. A hierarchy of cognition is established which describes the theoretical flow of cognitions in consciousness (Dhir, 2021). This model has been widely applied in various non-consumption and consumption-related studies. For instance, retail career choice and e-shopping behaviour.

Methodology

Semi-interviews are recruited as the main data collection. Through the interviews, the researcher viewed a variety of live streaming shows on different e-commerce platforms. Interviews were conducted with 20 participants who are heavy users to live streaming e-commerce. During the interview progress, data was collected by asking participants about the factors inspiring their emotions during live streaming and conflicting or positive emotions that motivate them to develop purchasing intentions. After that, the interview data were coded based on the themes identified to address the research questions.

Findings and discussions

Customer Motivation

The results of this study showed that customers using live streaming platforms were mainly driven by hedonistic motivation, with 73% of consumers wanting to watch live streams as a means to pass the time and relax. On the other hand, 27% of utilitarian consumers felt that the discounted prices offered on live streaming platforms were the main attraction for them. In addition, the visibility of the live streaming platform and the professionalism of the anchors made consumers feel that the product was more reliable. As a result of consumer motivation, interesting content and interactions may give rise to increased customer attention, purchase intent, or engagement. Therefore, it is important to understand the main types of motivation influencing consumers on live platforms. As motivation represents the needs of the consumer, understanding their motivations will allow vendors to provide consumers with the appropriate value they desire during the live streaming process.

Table 1. Abstract of the consumer motivation section interviews

Representative Statements	Code	Categories Frequency%
There are times when it is for relaxation and not necessarily to buy something; Many times, after a long day of work, it is nice to come home and watch a live stream to relax and feel good.	Relaxation	Hedonic motivation (73%)
...The reason for watching live broadcasts daily can be understood as being bored, so by watching live broadcasts to relieve boredom; It's for fun and entertainment, not for a specific purpose	Relieve Boredom	
I wanted to hear the anchor introduce the different crystals, I wanted to know more and see more, it was more interesting than reading a book; It's quite interesting to see what people are talking about these days. Sometimes I come across a product I'm interested in and just order it;	Interesting Content	
I usually prefer to watch live streams about beauty and snacks because I can often find fun and interesting items that suit me through the anchor's introduction.	looking for suitable product	Utilitarian motivation (27%)
I watch it when I want to buy something, but I watch the more professional ones, I don't like too much entertainment. A professional live stream makes me feel more reliable.	Reliable	
In my life it's probably a shopping platform that falls into the category of being able to get good deals at low price; But when there are holiday offers (for example, Double Eleven, etc.) will choose a specific anchor, such as, Li Jiaqi's live broadcast room to watch.	Sales Price	

Customer Emotion in Live-Streaming finding

The findings of the present study shown that positive (Fun, Interested, Trusting, Valued), negative (Anxiety, Stressed) and mixed emotions (Stimulation and Anxiety, Enjoyable and Anxiety, Excitement and Anxiety, Fun and Interested). could make customer be produce purchase intention. In other words, not only positive emotions can generate purchase intent, but negative and mixed emotions can also generate purchase intent. Also, the live streaming is more like an entertainment tool for the consumers to distract themselves from their busy life. It seems different from other promotional channels such as online shopping websites or going to the store personally regarding the consumer emotion aspect. This finding is also similar to Kim et al. (2017) in terms of the interactive role of social media promotional platforms in the current consumers. That is, consumer emotions may have a role in influencing people's decision-making process, based on this, I believe that enterprises should abandon the traditional single commodity exchange marketing model, make full use of people's perceptions, in marketing activities into the emotions, to emotions for commodity promotion, to promote the value of consumer use of goods not only in its own value, but the organic combination of emotional psychology and spirit to create a unique commodity advantage charm, so as to better marketing activities, to achieve the overall marketing can obtain greater economic benefits.

Conclusion

This study found that hedonistic motivation is the main type of motivation, and also that interesting content and interactions may result in higher customer attention, purchase intent, or engagement. Secondly, the interview results prove that overall consumer perceptions could influence consumers' purchasing intention. Particularly, the role of customer emotion in the live stream could be one of the main reasons motivating customers to purchase products. On this basis, consumers' perceived value can change or awaken consumer emotions. As consumer emotions play a decisive role in consumer attitudes, consumers' perceived value will stimulate their purchase intentions through their emotions.

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How customers' expectations and experiences towards global chain hotels be captured post-COVID-19? A netnographic perspective

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Type of manuscript: Extended abstract

Keywords: sentiment analysis; thematic analysis; COVID-19; customer experiences.

The current crisis of COVID-19 has changed the customer satisfaction and expectations metrics, giving way to an acute urgency for the hospitality practitioners to address the new expectations of the guests. With the COVID-19 outbreak, the service providers are experiencing a big challenge in providing services to the guests that not only have to meet the pre-COVID-19 era expectations but are also consistent with the new normal created due to the pandemic (Afaq et al., 2021). Guests need to feel safe and assured that their health is protected in this extraordinary situation created due to the pandemic. In this regard, tourism and hospitality management studies have suggested the need to analyse the user-generated content (UGC) available on the Internet to assimilate hotel guests' expectations and provide better hospitality (Yu et al., 2021). The review of the prior literature depicts that limited studies have analysed the UGC on social media platforms in the context of hotels after the outbreak of COVID-19 (Hu et al., 2021).
Furthermore, the studies carried out in the tourism and hospitality management domain to analyse the change in guests' behaviour post-outbreak of COVID-19 are based on a small sample size. Accordingly, the present study aims to explore and identify guests' attitudes towards the services provided by fifteen global chain hotels in South Asia, which leads to creating positive and negative opinions. Based on the above discussion, the current study aims to answer the following research questions.

- (RQ1) What are the sentiments of the guests towards the hotel's hospitality services?
- (RQ2) What are the hotel guests' experiences and expectations after the outburst of the COVID-19?

Methodology

The study adopted sentiment and thematic analysis to answer the research questions. First, sentiment analysis (SA) was carried out to evaluate guests' experiences and expectations towards the global chain hotels from a sentiment point of view. Python language is used for text mining and sentiment analysis. A package Textblob for SA contains extensive word documentation that can adequately manage all opinion tasks. The input data can be defined as the tweets extracted from the fifteen global chain hotels. Twitter handle of the hotels was used as the keywords, and the start and end dates were between January 1, 2020, to January 31, 2022. In the pre-processing data stage, all the unnecessary clutter from the unstructured data was removed.
Next, thematic analysis is performed to understand guests' experiences and expectations. Thematic analysis is widely used in netnographic marketing studies. Netnography is an advancement of ethnography and can be described as a tool for studying consumers' patterns of online behaviour. Different themes are identified wherein the guests shared

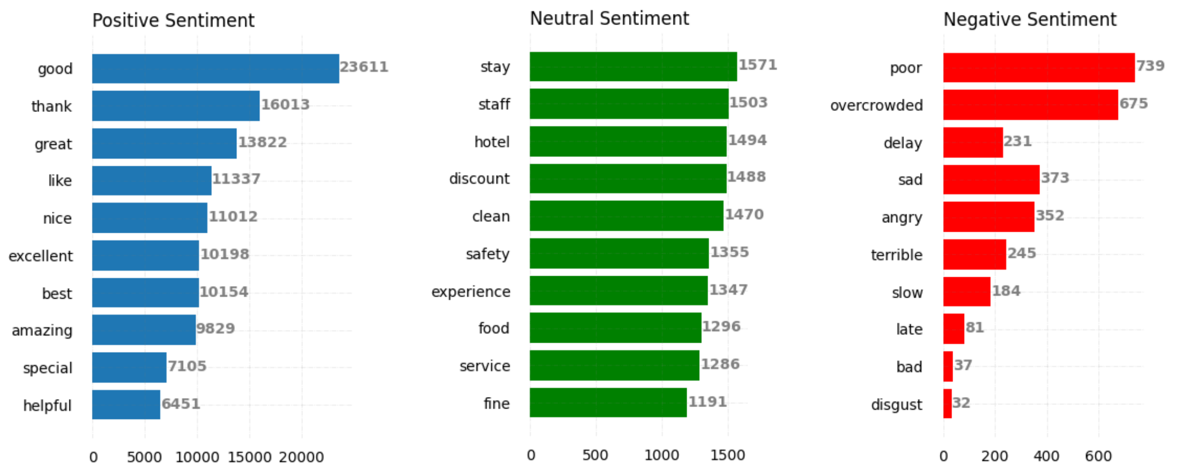
their expectations and experiences during the current crisis. For the study, it was important to perform thematic analysis along with SA because sentiment analysis cannot solely depict guests' experiences' and overall perspective. A sample of 20,000 tweets out of the total tweets was used for thematic analysis.

Results

Sentiment Analysis

Overall, 314193 tweets of the hotels were extracted for two years, 2020 and 2021. However, only 271086 tweets were utilised for SA as the other tweets were from the hotel companies and were primarily neutral. Overall, tweets depicting positive sentiments constituted 41.33% (n=112040). Tweets portraying negative sentiments constituted 21.84% (n=59205) and tweets representing neutral sentiments constituted 36.83% (n=99841). The results altogether portray a positive sentiment for the hospitality industry.

Figure 1. Sentiment Analysis across fifteen global chain hotels



Thematic Analysis

The most prominent themes are depicted below:

Sanitisation and fumigation of hotels- The hotels were questioned regarding the protocols being followed regarding the safety of guests and whether the rooms were sanitised after each check-out.

Food Safety- The dataset reflects the guests' curiosity about the disinfection and hygiene practices that are followed at the hotels for food preparation.

Contactless services at the hotels- A vital pattern widely seen in the dataset is the appreciation shown by guests towards the hotels for the contactless customer experiences like the use of hotel applications for check-in and check-out and keyless entry to rooms.

Follow up in case of service failure- The guests criticised the hotels for giving the wrong bills and unclean washrooms despite the hygienic stay labels. However, many tweets also highlighted the staff's attentiveness in handling the service failure.

Value for money- The low prices of the hotel rooms and other loyalty programs drove guests to return to their everyday life after the lockdowns. Many guests stated that their only reason for choosing a particular hotel was its discounted price compared to other hotels.

Smart safety measures at hotels- Many guests appreciated the hotel's on using thermal scanners and sanitiser stands at every stage within the hotel premises. However, many guests suggested the hotels adopt smart safety techniques like Robots for cleaning and disinfecting practices.

Conclusion

This study attempts to amplify the research on hotel guests' experiences and expectations post-COVID-19. Given its online context, the study is significant from the hospitality and tourism sector perspective as it provides plentiful insights about guests' service experiences.

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Emotional response of virtual assistants as an added value of an interactive product

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Keywords: interactive product; perceived privacy; emotional interactivity; emotional response; virtual assistants; personalization.

Context

Given the development of the Internet of Things and the increasing sophistication of Artificial Intelligence (AI), consumer products can offer new experiences in consumer interaction. Thus, smart products can adapt their responses to each user, learning from previous interactions and offering a better user experience, tailored to their preferences (Chen et al., 2021). This personalization can occur in a variety of functional and emotional ways. Thus, personalization can go further and achieve emotional adaptation, capable of reacting to users' emotions and thus eliciting emotional responses from them. Endowing virtual assistants with emotional capabilities is an important business challenge, insofar as these capabilities will allow assistants to interact with users in a way that is more like human relationships, adding a differentially competitive element of personalization that will result in greater added value for products based on this technology. For example, we have the case of Soul Machines' NADIA and companies such as Emotibot Technologies, which is developing robots that recognize emotions in a multimodal way to offer a more humanized conversation.

Literature review and research questions

Academic research on virtual assistants is still very recent (Du et al., 2022)and so far its analysis has mostly been approached from a functional and utilitarian perspective (McLean & Osei-Frimpong, 2019). Therefore, there is a need for studies that consider the emotional side of virtual assistants and analyze the influence of emotional aspects on interaction with people. Robotics science has succeeded in endowing robots with human characteristics, managing to emulate human behavior and emotions, however, questions regarding the added value that emotions bring to interactive products have hardly been addressed (Stock & Merkle, 2018) beyond those related to anthropomorphism.

With the help of facial emotion recognition, products can be personalized, enabling a two-way emotional interaction between the user and the technology. In this paper, an interactive product that adapts to user expressions detected by artificial intelligence is analyzed, and the contribution of this study is to examine and understand how such emotion-based adaptation or personalization a means is to connect the user and the product.

As existing technologies improve and new ones are developed, new forms of personalization (Cavdar Aksoy et al., 2021) are generated that can affect the user's emotional response. Therefore it is important to talk about emotional interactivity, which seeks to understand the user's needs, allowing products to stop being distant and reach the heart of users, and not only

that the interaction is based on a set of functions (Zhao & Chen, 2021). Some authors such as Gil et al. (2015) have pointed out that to improve the user experience it is necessary for objects to take into account the emotions of users, so developers of this type of product must try to achieve a more organic or human-like communication (Chen et al., 2021). Facial recognition is one of the technologies that can achieve this more effective communication with the user (Iannizzotto et al., 2018), although it would be interesting to integrate other mechanisms such as tone or message.
Depending on the emotions experienced by the user, we know that they will behave in one way or another (Jin & Oh, 2021). Furthermore, the impact that an interactive medium based on artificial intelligence can have on a person will be different depending on the emotions they have or stimulate at that moment (Jin & Oh, 2021), although as these authors state, there is still much to be studied about the impact of positive and negative emotions in the use of interactive media. On the other hand, given the very personal information that smart objects need to collect, it is necessary to explain to what extent the user's privacy feels invaded or not, as this is an important barrier to adoption (Sciarretta & Alimenti, 2021).
1. To what extent do people respond more positively to virtual assistants that offer emotional interactivity versus those that do not?
2. What differences are generated in the perception of a new emotional interactive product and a traditional product that does not have emotional interaction?
3. What factors lead people to respond more positively/negatively to the response of those virtual assistants that show emotional interactivity versus those that do not?
4. To what extent do privacy concerns affect emotional interactivity with virtual assistants?

Methodology proposed

On the one hand, an experiment will be carried out in laboratory conditions where we have an eye-tracker, a galvanic ring, and an EEG headset to collect the participant's signal. A short interview will also be conducted once the experiment is over, both to address the type of response expected from consumers to this technology and the factors that may influence the interpretation of the response offered by the interactive product. And as a second method, a survey will be carried out to collect data regarding the user's perceived attractiveness for a virtual assistant with emotional interaction, their attitude, and satisfaction with the interactive capability, their concern for privacy, etc. In the first part of the study, we intend to collect the necessary feedback to help us plan the second part of the study.

Expected results

It is expected that the results will help to understand the critical factors that affect the adoption of virtual assistants with emotional interactivity and provide companies with new knowledge that will allow them to improve these assistants to promote more humanized and complete communication. It is also expected that people will respond more positively to this type of interactive product than to more traditional ones and, at the same time, that privacy concerns will be a barrier to adoption.

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Digital companions in marketing: the crucial roles of perceived similarity and perceived humanlikeness in driving of customer outcomes

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Type of manuscript: Extended abstract

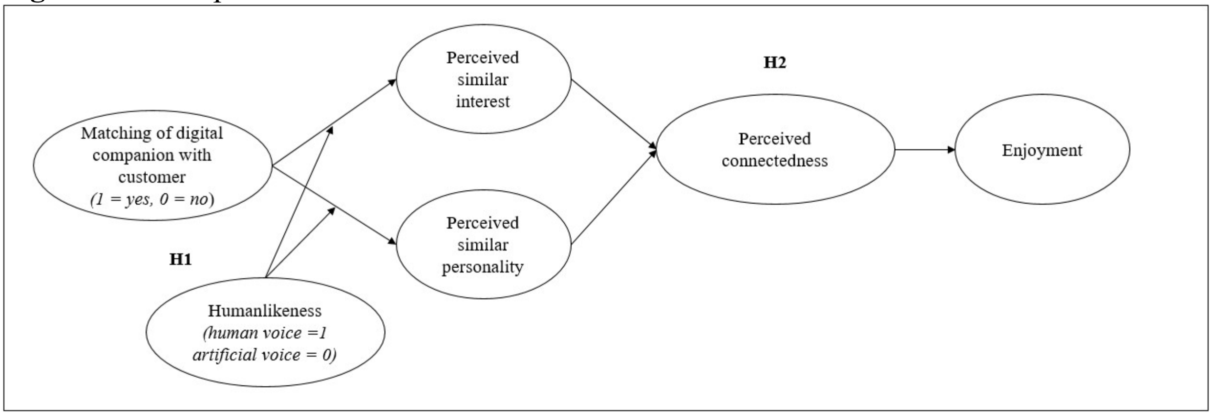
Keywords: digital companions; perceived similarity; humanlikeness.

Web-based service and consumption provides cost efficiencies for firms and convenience benefits for customers, but they also lack a human touch. Technologies 4.0 such as artificial intelligence (AI) are considered to help compensating for this lack (Puntoni *et al*., 2021). In particular, digital assistants (e.g., chatbots, shopping assistants, and other AI) are shown to serve this purpose, with perceived humanlikeness as the main driver of positive customer outcomes (Blut *et al*., 2021). At the core of this mechanism is the idea that driven by the desire for social connection, people tend to attribute human characteristics to nonhuman agents (Epley *et al.,* 2007), that is, they are able to consider smart agents as similar to humans.
Yet, are "being humanlike" and "being similar" interchangeable, as presumed in some research (Qui & Benbasat, 2009)? We argue that distinguishing between these two concepts is crucial, given that digital assistants have started to permeate everyday life and often take the role of digital companions that accompany people during their customer journey (e.g., Alexa, Siri, or
Replika). These companions often act like "buddies" rather than salespersons or service providers. Some companies also explicitly position their digital assistants as buddies such as German Autolabs promoting their digital assistants for drivers as "driving with a friend." In such a "friendship" framing, we argue that perceived similarity is key in driving positive customer responses, while perceived humanlikeness works as a necessary condition for similarity perceptions to occur.

We derive this proposition from similarity research in social psychology, where it is well established that the similarity between people positively affects interpersonal relationships (Byrne *et al.,* 1967). This can be explained by the similarity-attraction hypothesis (Byrne & Griffitt, 1969): We feel attracted by similar others based on a feeling of connectedness (McPherson *et al.,* 2001). Importantly, what counts is perceived, rather than actual, similarity (Montoya *et al*., 2008). These findings further shed light into consumer interactions in the marketing context: Similarity is an important driver of successful and long-lasting consumeremployee interactions (e.g., Jiang *et al.,* 2009), specifically sharing a common interest (Kleijnen *et al*., 2009) or personality (Dion *et al.,* 1995) with the salesperson. Prior work in the digital realm (Al-Natour *et al*., 2011) and research on human-robot interactions (Shahrezaie *et al.,* 2021) also support the beneficial effect of perceived similarity.
Yet, the interplay of perceived similarity and humanlikeness remains unclear. We argue that for digital companions, perceived similarity is key in fostering positive customer outcomes although perceived similarity still requires humanlikeness perceptions. This is because digital companions are framed as friends (rather than salespersons), which resembles a communal

(rather than an exchange) relationship, that is, a greater mutual concern (Clark, 1984). In light of this proximity, customers may only believe to share certain interests or their personality with a digital companion that is perceived as humanlike. We propose two main hypotheses. H1: Matching a digital companion with the customer fosters positive customer outcomes (enjoyment and positive WOM), mediated by perceived similarity and moderated by the humanlikeness of the companion. Specifically, the effect only occurs for a humanlike (but not for a non-humanlike) companion. H2: For a humanlike companion, the effect of matching on customer outcomes through perceived similarity is serially mediated by perceived connectedness (H2) (see Figure 1).

Figure 1. Conceptual framework.



We conducted two studies where participants used a wine learning platform that enabled them to travel online with a digital companion to several global wine regions. As an exploratory step, we conducted Study 1 to gain preliminary insights into the drivers of perceived similarity. We presented consumers with different digital companions and asked them to indicate whether and why they perceived them as similar or dissimilar to themselves. Results of a content analysis show that participants perceive a companion as similar when they believe to share the same interests or personality. Further, they perceive a companion as dissimilar when they consider it as not humanlike. These results suggest a match in interest and personality as a driving factor of perceived similarity and provide initial evidence that perceived humanlikeness may be a necessary but not a sufficient condition for perceived similarity to occur.

Based on these findings, we designed Study 2 with a 2 (matching: matching vs. not matching the digital companion with the customer in terms of interests and personality) x 2 (humanlikeness: humanlike vs. artificial voice of the companion) between-subjects experimental design. Hypotheses were tested with (moderated) mediation analyses using the PROCESS tool. The results support H1: Matching the digital companion and the customer increases customer outcomes (enjoyment, positive WOM), mediated by perceived similarity, but only in the human voice condition, not in the artificial voice condition. Further, the results support H2: The positive effect in the human voice group is fully mediated by consumers' felt connectedness to the digital companion. Interestingly, all effects occur because of perceived similarity in interests, not in personality.

Our research makes several contributions to the marketing literature. First, we show that perceived similarity and perceived humanlikeness of a digital companion are two different concepts, exerting distinct effects on customers. While perceived humanlikeness may be a

sufficient condition for digital assistants (i.e., digital salespersons) to exert positive effects on customer outcomes (e.g., Qui & Benbasat, 2009), this does not hold true for digital companions
(i.e., digital agents that take the role of "buddies"). Here, perceived similarity is key in driving positive customer outcomes, while humanlikeness is a necessary condition for perceived similarity to occur. Second, we extend a mechanism established in social psychology (people prefer similar others as friends because they feel more connected to them; McPherson *et al.,* 2001) to human-agent interactions in the digital realm. Third, although not specifically hypothesized, our findings reveal that perceived similarity in interests counts, while perceived similarity in personality is not as important, at least in the context of experiential learning.

Managerially, we present a viable and compelling strategy whereby perceived connectedness to digital companion leads to positive consumer outcomes: Firms should create/use digital companions that not only have a humanlike feature (such as a humanlike voice) but present them in a way that there is a shared interest between the consumer and the digital companion.

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Teaming up with chatbots: Creating an effective collaboration between human employee and digital employee to enhance customer experience

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Introduction
Augmented by artificial intelligence (AI), digital employees (or chatbots) (we call these agents as DEs hereafter) are gradually becoming the new competitive advantage for firms in that they could potentially augment the serving capacity of human employees (HEs) (Le *et al.,* 2022). For example, Avis Budget – a rental car agency, uses their DE to pre-process customer call details before transferring the calls to a HE, eliminating the need for customers to repeat this information (Kannan & Bernoff, 2019). The example represents a rising trend of utilizing the collaboration between HE and DE to improve customer service performance effectiveness.

Recent research has started to gain an interest in human-robot collaboration in marketing (Nobel *et al.,* 2022; Huang & Rust, 2021) and this area of research is still in its infancy (Wirtz *et al.,* 2018; Xiao & Kumar, 2021). Little research has been done to examine the effectiveness of the actual collaboration between HE and DE in the marketing literature. To address this challenge, we propose to examine the impact of "HE-DE collaboration" (HEDEC) on customer-perceived service satisfaction when being served by such hybrid team through the lens of interdependence (Le *et al.,* 2022).

Theoretical background
Researchers have focused in particular on structural and behavioral aspects of interdependence in organizational settings (Courtright *et al.,* 2015). The structural aspect is referred to as "features of the context that define a relationship between entities such that one affects (and is affected by) the other" (Wageman, 1999 p.198). Three important aspects of structural components of interdependence are joint workflow – the arrangement of work processes that required coordination; joint goal – shared customer-related objective between human and robot and joint decision-making authority – distribution of power between human and robot (Le, Sajtos, and Fernandez, 2022). These structural features set the stage for team-like behaviors to be emerged (Courtright *et al.,* 2015). We refer to such behaviors as behavioral interdependence – "the actual level of interaction between team members while doing taskwork" (Courtright *et al.,* 2015 p.1827). In the context of HEDEC, these three structural components set the stage for HE and DE to engage in team-like behaviors, in which they behave interdependently (e.g., coordinating with each other or one supervising the other) (Le, Sajtos, and Fernandez, 2022).
Ultimately, these behaviors convey the underlying structural configuration of collaborative process that dictates how HE and DE behave to the customers.
This study draws on the three structural components (joint workflow, goal and authority) to

advance two types of behavioral cues that convey the interdependence between DE and HE to the customers – workflow connection cues and entity connection cues. For each of these cues, we advance two components that aim to signal how HE and DE orchestrate taskwork and their relationship based on joint workflow, authority and goal.

In terms of workflow connection cues, we define social co-presence as *the sequence (co-presence or sequential presence) in which DE and HE present themselves to customers*. First, co-presence is where customers feel that they are being accompanied by HE and DE simultaneously. The second sequence is sequential presence, where customers perceive that they are being accompanied by one entity at a time and one after the other. We define planned coordination visibility as *the communication between the service agents (DE and HE) and customers about the coordination of the agents' allocated task in order to complete the service process in a way that is perceptible to customers*. This cue emphasizes the two-way communication between DE and HE that the customers witness.

In terms of entity connection cues, we define supervisory authority cue as *the signal which informs customers that either DE or HE is in charge of overseeing their partner during the entire service process*. We suggest that this component tells customers who (HE or DE) has more power than the other. We define team goal cue as *the communication between the service agents (DE and HE) and customers about a shared customer-related performance goal.* We emphasize that the shared goal must be customer-related because non-customer related goals (e.g., the number of inquiries handled by service agents) do not highlight the service team's motivation to serve the customers.

We consider two mechanisms that help explain the impact of workflow and entity connection cues on customer satisfaction and willingness to pay, which are process fluency – defined as the subjective experience of a process smoothness and team cohesion – the perceptibility of members bonding with each other. We particularly consider these two mechanisms in our study because they are attributes that help managers to understand better how to leverage HE-DE teamwork to influence customer experience.

Methodology

We tested the impact of workflow and entity connection cues in a series of four experimental studies. Study 1 (N=117) was a 2 (social co-presence: co-presence vs. sequential presence) x 2 (explicit coordination: presence vs. absence) between-subject design. Study 1 aimed to test the impact of workflow connection cue on customer experience. Study 2 (N=315) was a 2 (social co-presence: co-presence vs. sequential presence) x 2 (explicit coordination: presence vs. absence) x 2 (supervisory authority: HE vs. DE) between-subject design. Study 2 aimed to test the impact of entity connection cue (first component) on customer experience and replicated the results of study 1. Study 3A (N=294) was a 2 (Explicit coordination: Presence vs. Absence) x 2 (Supervisory authority: HE vs. DE) x 2 (Team goal: Presence vs. Absence) between-subject design *while holding the social co-presence as co-presence* constant across conditions. Study 3A aimed to test the impact of team goal and replicated the effect of previous studies. Lastly, study 3B (N=262) was a 2 (Explicit coordination: Presence vs. Absence) x 2 (Supervisory authority: HE vs. DE) x 2 (Team goal: Presence vs. Absence) between-subject design *while holding the social co-presence as sequential presence* constant across conditions. Study 3B aimed to replicate the result of previous study under a different workflow. We utilized this additive setup because these two cues likely exist in tandem in practice.

Findings overview and practical implications

Four experiments reveal that with workflow connection cues, the social co-presence does not affect the mechanisms, whereas planned coordination positively impacts both process fluency and team cohesion. In terms of entity connection cues, HE as supervisor has a positive impact on process fluency and team cohesion. However, these effects are only partially confirmed. Team goal cue has a strong positive impact on team cohesion and process fluency. Process fluency and team cohesion positively impact satisfaction.

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What's in a Name? Gender Suitability of Task-Specific Digital Assistants

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Type of manuscript: Extended abstract

Keywords: gender stereotypes; digital assistants; task-specific artificial intelligence.

Introduction

Names of digital assistants like Siri, Cortana, and Alexa are well known and easily recognizable. Digital assistant's name as well as it's form and look are a source of gender perceptions (van Tilburg et al., 2015). Genders provide a sense of pleasantness and commonality between the user and the digital assistant (Adam et al., 2021; Pfeuffer et al., 2019). Aside from improving interaction experience, extant evidence finds that the gender of a digital assistant embodies sufficient social characteristics to cue gender stereotyping (Chaves & Gerosa, 2020; Liew & Tan, 2021). While research concerning task stereotype cuing is prevalent in other AI domains (Dong et al., 2020; Eyssel & Kuchenbrandt, 2012; Kuchenbrandt et al., 2014), there are few exemplars for digital assistants. One exception is Pfeuffer et al. (2019) who investigate the role of gender in user perception of competence when carrying out tasks in math and finance. Yet this is an incomplete picture because tasks that require warmth and thus typically associated with gender stereotypes are not included (Cuddy et al., 2008). Therefore, this paper will examine *whether users apply gender stereotypes to task specific digital assistants***.** We conduct two studies. Study 1 assesses the suitability of female, male and non-binary names for use in digital assistants. Using the four most suitable names for each gender, Study 2 examines if the features of a task performed by a digital assistant cue gender stereotyping. Our paper contributes to the current state because we choose objective and subjective tasks and not just 'male' knowledge fields; objective and subjective tasks are based on findings specific to personal assistant domain;. and we widen gender choice to include non-binary.

Study 1: Suitability of gender for digital assistants

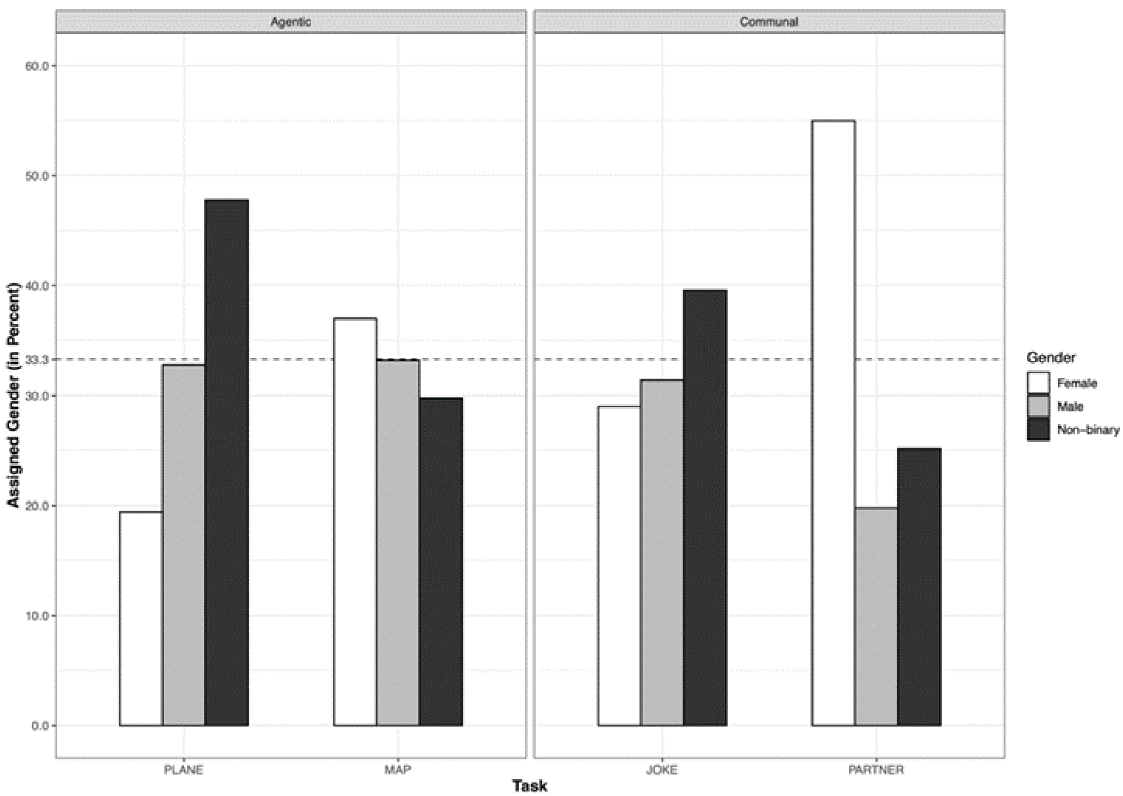
The most popular female, male and non-binary first names were retrieved from a US baby name website (https://babynames1000.com/). A pilot test was conducted from the results, the ten most suitable names from each gender were selected. Next, one hundred and fifty US participants (51.3% female; M_{age} = 40.9, SD = 12.3) were recruited through Amazon's Mechanical Turk. In exchange for monetary compensation, we asked participants to identify the gender of each name and rate its suitability as a name for a digital assistant. Participants from Study 1 were not allowed to participate in Study 2. We found that 60% of the participants perceived non-binary names as most suitable or extremely suitable, compared to 50% female names or 30% male names. As a check on the results, an analysis was carried out on how many participants had correctly identified each name's gender. The analysis found that 60.1% were correctly associated with gender as initially pre-defined from the website.

Study 2: Task-specific gender stereotyping of digital assistants

Here we explore whether a name for a digital assistant can lead to a stereotype categorization. Using Castelo's (2019) continuum of algorithmic tasks we select two objective tasks, i.e., piloting a plane and giving directions; and two subjective tasks, i.e., assessing the funniness of a joke and recommending a romantic partner. These tasks were selected because they are the best exemplars of objective or subjective tasks (Castelo, 2019). We posit that objective and subjective tasks are associated with competence (objective) and warmth (subjective) (Abele, 2003). Five hundred participants (51.2% female; M_{age} = 37.3, SD = 11.0) took part in an online survey through Amazon's Mechanical Turk. The names in both conditions were randomized, and following completion of the initial condition, participants answered the adjacent condition. Furthermore, when participants selected a name for a task, that name was no longer available as a choice.

Our results support a positive association between choice of names and the stereotyping of gender in particular tasks. There was a clear difference in participants' preferred suitability of gendered names, especially for the tasks piloting a plane and recommending a romantic partner. We believe Figure 1 illustrates a preference of non-binary names in objective tasks decreasing for subjective tasks, and the opposite for female names with a higher suitability for subjective tasks and decreasing for objective tasks. Male names were least suitable. Also, it was surprising for us that male names did not have higher suitability scores in objective tasks. We believe that the low-perceived suitability of male names reflects prior research indicating a greater preference for non-binary or female genders. In a sense, non-binary names replace male names in gender stereotyping in the domain of digital assistants.

Figure 1. Perceived suitability of names in task-specific digital assistants



Conclusion

The present research explores whether choice of names for digital assistants could produce gender stereotyping. Using the task continuum of objective and subjective algorithmic tasks, we found a general pattern of stereotyping where a non-binary gender was preferred for objective tasks and where a female gender was preferred for subjective tasks. We believe these are the first findings that confirm these preferences of gender for task specific digital assistants. These findings leads us to conclude that widening the genders available in digital assistants could present an exciting opportunity for both manufacturers and users alike. For example, evidence from the use of gendered digital assistants in education has that matching gender to students' own is particularly helpful for young female students, improving effort and performance (Arroyo et al., 2013). Thus, manufacturers should pay more attention to upstream design decisions as to how a gender should be represented, especially if doing so brings benefits downstream to users.

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Does chatbots establish humanness in customer purchase journey?

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Extended abstract

Artificial Intelligence (AI) is emerging to impact many marketing and other business interfaces (Belk, 2021; Puntoni et al., 2021). Natural language processing chatbots and other digital technologies (Quach et al., 2022) are the most common service mechanisms, which are also regarded as a growing AI function in marketing value chain activities (Balakrishnan & Dwivedi, 2021a; Flavián, 2021; Moriuchi, 2019). Balakrishnan and Dwivedi (2021a, p3) define chatbots as "A chatbot is a computer program that conducts a conversation in natural language and sends a response based on business rules and data tuned by the organization". Chatbots are gradually replacing human conversation in service space and other marketing functions such as in; online food delivery complains, online product enquiries, product delivery status enquiries, purchase enquiries. Notably, the applications of chatbot are spread across various stages of customer purchase funnel. Chatbots are more impactful in every stage of the consumer purchase journey (Grewal & Roggeveen, 2020). Despite the considerable expansion of AI based Chatbot in marketing, most research in this domain are in experimental stage (Balakrishnan & Dwivedi, 2021b). Most studies have investigated these chatbots' adoption and use behaviour (Blut et al., 2021). Still, no knowledge is available to understand the underlying factors behind user intention to recommend chatbots. More importantly, there is a lack of knowledge to investigate the cognitive and peripheral activities underlying these marketing chatbots at the three stages of the purchase funnel: pre-purchase, purchase, and post-purchase.
The activities and schemes involved in the chatbot interactions will differ across the purchase journey based on the customer expectations. The algorithmic information processing system in chatbots can incorporate both cognitive and peripheral conversations (Shin, 2021), similar to advertisements (Van den Broeck et al., 2019). The underlying cognitive and peripheral structure can also impact in humanness perceptions of the chatbot (Shin, 2021). Chatbot AI's can simulate a human voice and respond to users' statements just like a human, changing how people engage with computers. Previous research has investigated various human characteristics to simulate chatbot conversations (such as; voice modulations, gender tuning, contextual replies, etc.) to generate a human-like experience. However, these research has investigated chatbot conversations' speaking and listening aspects (Chang et al., 2018; Hu & Lu, 2021). But there are no conceptual or theoretical frameworks to understand the

humanness perception of this AI-based chatbot, primarily from a cognitive and peripheral way of conversation. Customers, though they might have enjoyed the AI experience of the chatbots, the humanness perceptions of the chatbots and their intention to recommend chatbots to others are yet to be explored. From the above discussion, the following gaps are proposed: (i) the cognitive and peripheral role of chatbot and its impact on humanness perception should be examined, (ii) the impact of perceived humanness in chatbots on recommendation behaviour among customers should be explored, (iii) the role of experience as an intervening variable should be tested, and (iv) the use of the above-proposed gaps in the three purchases stages can be tested.

Based on the identified gaps, the present research attempts to investigate the impact of cognitive and peripheral communication on AI experience and intention to recommend meditating through the humanness perceptions. This research uses a stimulus-organism-response (S-O-R) framework to develop the conceptual model by deriving the theoretical knowledge from Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986), psychological experience theories (Hoffman and Novak, 1996; Hassenzahl & Tractinsky, 2006), and humanness perception theories (Belanche et al., 2021). The elaboration likelihood model comprises two pathways (central and peripheral) that illustrate how a person's attitude evolves after receiving and processing a message through a communications platform. Though ELM has been used primarily in advertising studies, recent researches have applied this theory to technology-based marketing studies (Dwivedi et al., 2021; Shahab et al., 2021). This research conceptualizes humanness perceptions with three significant dimensions; human likeliness, competence, and warmth (Belanche et al., 2021). Based on the above discussion and gaps proposed, we formulate the following research questions.

RQ1: Does cognitive and peripheral conversations in chatbots build humanness perceptions in the three purchase stages?

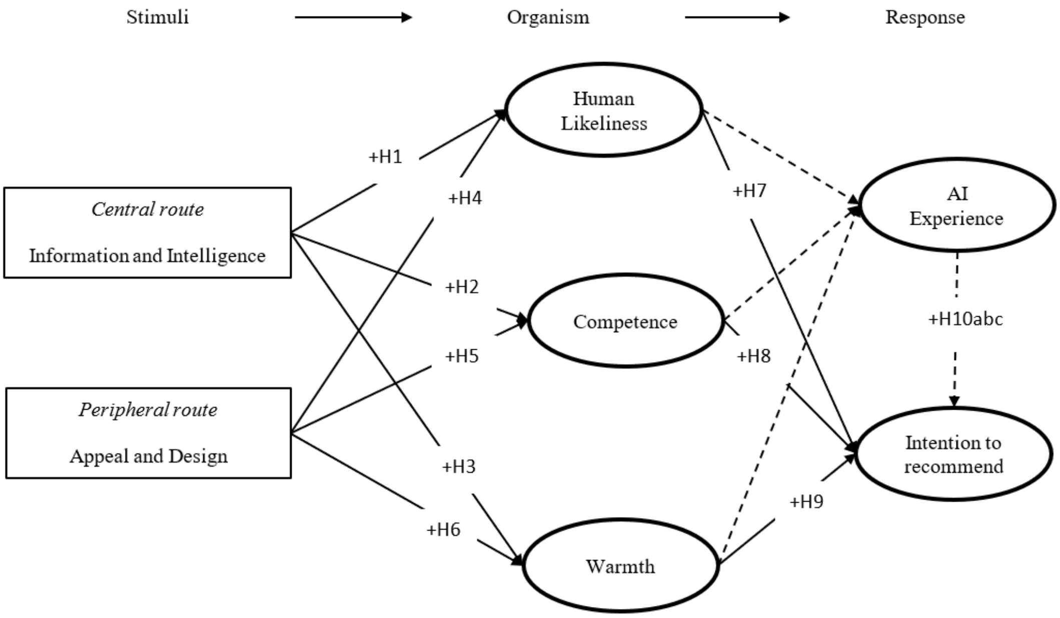
RQ2: Does AI experience intervene in the relationship of human likeliness, competence, and warmth to customer's intention to recommend chatbots to others?

By examining the research questions, the research can extend the theoretical knowledge in S-O-R (Stimulus-Organism-Response), Elaboration Likelihood Model (ELM; Petty & Cacioppo, 1986), psychological experience theories (Hoffman and Novak, 1996; Hassenzahl & Tractinsky, 2006), and humanness perception theories (Belanche et al., 2021). The research can aid in building a solid knowledge of the theories mentioned above and the literature concerned with psychology and marketing. Besides, the research results can also provide meaningful insights to marketing practitioners.

Study operationalization

The research will conduct three factorial designs operated in three broad experiments: pre-purchase stage (3x3), purchase stage (3x3), and post-purchase stage (3x3). The (3x3) factorial design in each experiment denotes the "High information-intelligence (3) - Low information-intelligence (2) framework" x "High appeal and design (3) – low appeal and design (3)". However, the conditions are different for the three experiments, as given in Table 1. The high information and high appeal states represent cognitive and peripheral elements of the proposed model. The experiment is a part of a consultancy activity with a first-party e-commerce company with both an offline and online presence. The experiment manipulation checks for each condition is conducted with 180 samples. The results indicate that the responses significantly differ across the three experiments' conditions. The final design of chatbots is in process for three experiments with nine blocks (3x3) each. A sample of 900 to 1100 customers is expected to be a part of the live experiment. Based on the theoretical underpinning and the experiment operationalisation, the conceptual model given in figure 1 will be tested using structural equation modelling with indirect effects.

Figure 1. Proposed Conceptual Model of the Study



Straight lines indicate direct paths; dotted lines indicate mediating path

Table 1. Conditions of the two experimental variables

<table>
<tr><td colspan="2">Central Route
(This variable deals with information search about the product prior to purchasing)</td><td rowspan="8">Pre-Purchase Stage (Experiment 1)</td></tr>
<tr><td>High (coded as 3)</td><td>In high condition, chatbots are designed with an option of nine answer options for the enquiries with the highest accuracy of answers.</td></tr>
<tr><td>Medium (coded as 2)</td><td>In medium conditions, chatbots are designed to have a response with six answer options for the enquiries with a medium level of accuracy.</td></tr>
<tr><td>Low (coded as 1)</td><td>The low condition is designed so that chatbots handle three answer options for the enquiries with a low level of accuracy.</td></tr>
<tr><td colspan="2">Peripheral route
(This variable deals with the attractive features in chatbots during the pre-purchase interaction)</td></tr>
<tr><td>High (coded as 3)</td><td>In high condition, the architecture of chatbots is more attractive in terms of colours and design.</td></tr>
<tr><td>Medium (coded as 2)</td><td>In the medium condition, the architecture of the chatbots is made attractive in terms of colour but was enabled with a static design.</td></tr>
<tr><td>Low (coded as 1)</td><td>In the low condition, the architecture of the chatbots is made less attractive in terms of colour and enabled with a static design.</td></tr>
<tr><td colspan="2">Central Route
(This variable deals with the information provided during the purchase stage)</td><td rowspan="8">Purchase Stage (Experiment 2)</td></tr>
<tr><td>High (coded as 3)</td><td>In high conditions, chatbots are enabled with important information about their purchase process with payment details with a faster response level minimising the effort of the customer</td></tr>
<tr><td>Medium (coded as 2)</td><td>In medium conditions, chatbots are enabled with low information with payment details with a medium response level minimising the effort of the customer</td></tr>
<tr><td>Low (coded as 1)</td><td>The low condition, chatbots are enabled with no information about the purchase process but with the payment details with a low response level minimising the effort of the customer</td></tr>
<tr><td colspan="2">Peripheral route
(This variable deals with the attractive features in chatbots during the purchase stage)</td></tr>
<tr><td>High (coded as 3)</td><td>In high condition, the design of the purchase chatbots are optimised with attractive design and colour</td></tr>
<tr><td>Medium (coded as 2)</td><td>The medium condition, the design of the purchase chatbots are optimised with attractive colour but with static design</td></tr>
<tr><td>Low (coded as 1)</td><td>The low condition, the design of the purchase chatbots are optimised with static colour and design</td></tr>
<tr><td colspan="2">Central Route
(This variable deals with information provided during post-purchase stage)</td><td rowspan="8">Post – Purchase Stage (Experiment 3)</td></tr>
<tr><td>High (coded as 3)</td><td>In high condition, chatbots are provided with more post-purchase options in chatbots namely, feedback/review, tracking information, service interaction, and recommendation information</td></tr>
<tr><td>Medium (coded as 2)</td><td>In medium condition, chatbots are provided with lesser post-purchase options in chatbots namely; feedback/review and tracking information</td></tr>
<tr><td>Low (coded as 1)</td><td>The low condition, chatbots are provided with only one post-purchase options in chatbots – feedback/review</td></tr>
<tr><td colspan="2">Peripheral route
(This variable deals with the attractive features in chatbots during the post-purchase stage)</td></tr>
<tr><td>High (coded as 3)</td><td>In high condition, the design of the purchase chatbots are optimised with attractive design and colour in post purchase stage</td></tr>
<tr><td>Medium (coded as 2)</td><td>The medium condition, the design of the purchase chatbots are optimised with attractive colour but with static design in post purchase stage</td></tr>
<tr><td>Low (coded as 1)</td><td>The low condition, the design of the purchase chatbots are optimised with static colour and design in post purchase stage</td></tr>
</table>

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The Effect of Autonomy Need Satisfaction and Escapism Motivation on Consumer's Variety-seeking Behavior in Metaverse

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Type of manuscript: Extended abstract

Keywords: metaverse; variety-seeking; autonomy need satisfaction; escapism motivation; positive affect.

Introduction

The metaverse, a group of virtual shared worlds, is rapidly growing (Collins, 2021) and many brands have created virtual product experiences in metaverse platforms (e.g., Roblox). However, if and how consumers possibly behave uniquely different in the metaverse is unknown. Because the physical laws governing the real world can be altered or ignored in the metaverse, consumers are likely to become adventurous and exploratory, which can encourage variety-seeking behaviors in the metaverse. Variety-seeking influences a wide range of consumer behaviors such as innovation adoption and exploration (McAlister & Pessemier, 1982), and can be a crucial consumer behavior in the metaverse. Based on the self-determination theory and theory of compensatory internet use, this study investigates consumers' psychological states (e.g., autonomy need satisfaction, escapism motivation, positive affect) to explain variety-seeking in the metaverse.

Theoretical Background

Variety-seeking refers to the propensity to seek diversity in product choices and can be motivated by both internal needs (e.g., stimulation) and external factors (e.g., retail environment) (McAlister & Pessemier, 1982). It is known that concerns regarding uncertain consequences of product choice (e.g., financial, social) suppress variety-seeking. The fact that the metaverse is virtual and illusory is likely to alleviate such concerns. Also, the users often use pseudonyms and thus are anonymous in the metaverse, which eliminates the social constraints of the real world (Collins, 2021). Thus, *in the metaverse (vs. real-world), individuals will seek more variety in their product choices (H1).*

The self-determination theory (Deci & Ryan, 2000) explains that three innate psychological human needs (i.e., competence, relatedness, autonomy) motivate behaviors. Autonomy needs, the desire for self-actualization and freedom of choice, is particularly relevant to the metaverse. As users navigate the virtual world exceeding the bounds of physical laws (Collins, 2021), the users can try out things that are impossible in real life and experience higher freedom of choice. Thus, *in the metaverse (vs. real-world), individuals will feel higher autonomy need satisfaction (H2).*

Studies identified that escapism is a critical motivation for engaging in the virtual world. According to the theory of compensatory internet use, people escape to an online world when they fail to deal with the psychological discomforts of real-life problems (Kardefelt-Winther, 2014). By escaping to a virtual world, users reduce the discrepancy between the actual and ideal self and can feel empowered. Because escapism motivation is closely connected to a lack of control in the real world, *the individuals with high (vs. low) escapism motivation will feel stronger autonomy need satisfaction in the metaverse (vs. real-world) (H3).*

When people's autonomy needs are satisfied, they feel positive affects (e.g., enjoyment, etc.) (Deci & Ryan, 2000). Thus, *autonomy need satisfaction will be positively associated with positive affect (H4).* Also, evidence suggests that positive affects heighten individuals' recognition of the differences among brands and motivates them to seek additional stimulation through variety-seeking regarding product choices (Kahn & Isen, 1993). Hence, *positive affect will increase variety-seeking intention (H5).*

Methods

A single-factor (real-world vs. metaverse) between-subjects online experiment was conducted (n=245, US consumers aged 18-39). The participants were randomly assigned to one of the two conditions. Participants were asked to imagine that they are shopping for fashion items in the offline store for themselves (real-world condition) or in the metaverse for their avatars (metaverse condition). They then answered a questionnaire that contains measures for the research variables. All measurement items were adapted from the previously validated instruments and measured on a 7-point Likert scale. Data were analyzed using SPSS and PROCESS SPSS Macro.

Results

Results demonstrated that the participants in the metaverse condition reported higher variety-seeking intention than the participants in the real world (M_{meta} = 5.00, SD = 1.62; M_{real} = 4.48, SD = 1.49; t = -2.65, p< .001), supporting H1. While, there was no difference in autonomy need satisfaction between the two conditions (p> .05, H2 rejected), escapism motivation moderated effects of the metaverse (vs. real-world) on autonomy need satisfaction (PROCESS Macro Model 1, n=5,000 resamples; β = .63***). Escapism motivation amplified the effects of metaverse (vs. real-world) experience on autonomy satisfaction (H3 supported). As hypothesized, autonomy need satisfaction positively influenced positive affect (H4: β = .67***) and positive affect positively influenced variety-seeking intention (H5: β = .21**).

Discussion, Conclusion, & Future Research Suggestions

This study extends the self-determination theory to the metaverse and has shown that the metaverse experience can increase consumers' variety-seeking behaviors by satisfying the users' autonomy needs. The significant moderating effect of escapism motivation emphasizes the importance of identifying user motivations. Considering the metaverse platforms are designed to dissociate the users from their reality, voluntary users of the metaverse are likely to present a high level of escapism. Thus, brands may develop strategies to utilize metaverse as a channel to experiment with new products or to expand their brand image or offerings using virtual products. Brands can even promote their goods with messages to heighten users' escapism motivation (e.g., "Try out this artsy skirt you may never wear at your workplace!"). Future research may recruit consumers from different age groups and use different product categories (e.g., furniture) to generalize the findings. Further research on characteristics of the metaverse (e.g., virtuality) that may contribute to variety-seeking behaviors is advised.

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Psychological ownership of virtual store experiences: the role of control

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Keywords: virtual experiences; virtual reality; psychological ownership.

Virtual Store Experiences

While consumers need concrete, tangible, multi-sensory shopping experiences, many times contextual restrictions (i.e. lockdowns or injuries) make them satisfice with digital (nonphysical) engagement. One of the most prominent of such engagement technologies, virtual reality (VR) is defined as a computer-generated simulation that includes the user who perceives it and communicates with it in a way that appears to be real through one or more senses (mainly vision, hearing, or touch) (Sherman & Craig, 2002), with or without a variety of hardware. A range of brands including Charlotte Tilbury, Clarins, Tommy Hilfiger, Farfetch, Intermix and American Eagle are all testing some form of virtual store technology. Similarly, the Covid-19 pandemic lockdowns *have given VR retail a new life*, *unlike experiments of past …exploring...virtual e-commerce experiences like Dior, Tommy Hilfiger and Diesel»* (McDowell, 2020). In an attempt to preserve social connectivity, the physical distance imposed by the pandemic facilitated the emergence of many virtual experiences (i.e., conferences, concerts, plays, travel, shopping) (Kirk & Rifkin, 2020). Vineyards are even offering virtual wine-tasting sessions since many tasting rooms are shut down (Freedman, 2021).

However, there is no guidance in the literature on how to strategically create VR experiences (de Regt et al. 2021). Literature differences strongly exist around the different aspects of customer behavior and perception using VR, calling for rigorous and theory-based studies in the field (Yung & Khoo-Lattimore, 2017). VR-related developments lead researchers to revisit current concepts and hypotheses in consumer behavior, including the analysis of what mechanisms mediate consumer responses to VR features and which features can be integrated as moderators into these models (Wedel, 2020).

Psychological Ownership of Virtual Store Experiences

One of the critical challenges posed by virtual retailing is disrupted psychological ownership (PO). Being one of the key drivers of positive consumer attitudes and behavior, PO is previously demonstrated to be lower in digital environments. In a recent JM-MSI Special Issue on "From Marketing Priorities to Research Agendas", PO has been under focus in the evolving landscape of consumption. Morewedge and others (2021) link the disruption of this vital concept to technological developments and the digitization of goods and services. On the contrary, several other researchers demonstrate high PO for digital experiences due to self-integration, self-identification, and positive self-signals (i.e., Kirk & Swain, 2018). In the light of conflicting findings, such as high PO in self-defining digital experiences, this research aims to investigate PO in various virtual retail experiences represent challenge & contribution #1.

The Role of Control in Psychological Ownership of Virtual Store Experiences

One of the major determinants of consumer PO is the consumer's sense of agency and control.

For example, in The Virtual Fan Experience of NBA, there are virtual seats so that the players can see or hear the virtual audience from those seats (Copans, 2020). Therefore, providing the customer with the ability to physically control and manipulate the form and content of the mediated environment is expected to positively impact telepresence, flow, PO, and other related positive outcomes (i.e., positive attitudes) in virtual environments.

While previous literature demonstrated that interactivity increases VR engagement (Sundar, Bellur, Oh, Jia, & Kim, 2016) and purchase intentions (Schlosser, 2003); Loureiro Krassmann et al. (2020) demonstrated the opposite, that greater interactivity in an instructional environment actually detracted from the learning performance of students. Therefore, one of the precursors of PO, control, and interactivity pose conflicting effects on the virtual experiences. Detailing and drawing the boundaries of the positive and negative sides of increasing customer control in virtual retailer experiences represent challenge & contribution #2.

To these ends, we hypothesize and test one mediator and two moderators in the following relationships:

H1: Real (vs. virtual) experiences lead to more positive responses towards the experience.

H2: Real (vs. virtual) experiences lead to more psychological ownership of the experience.

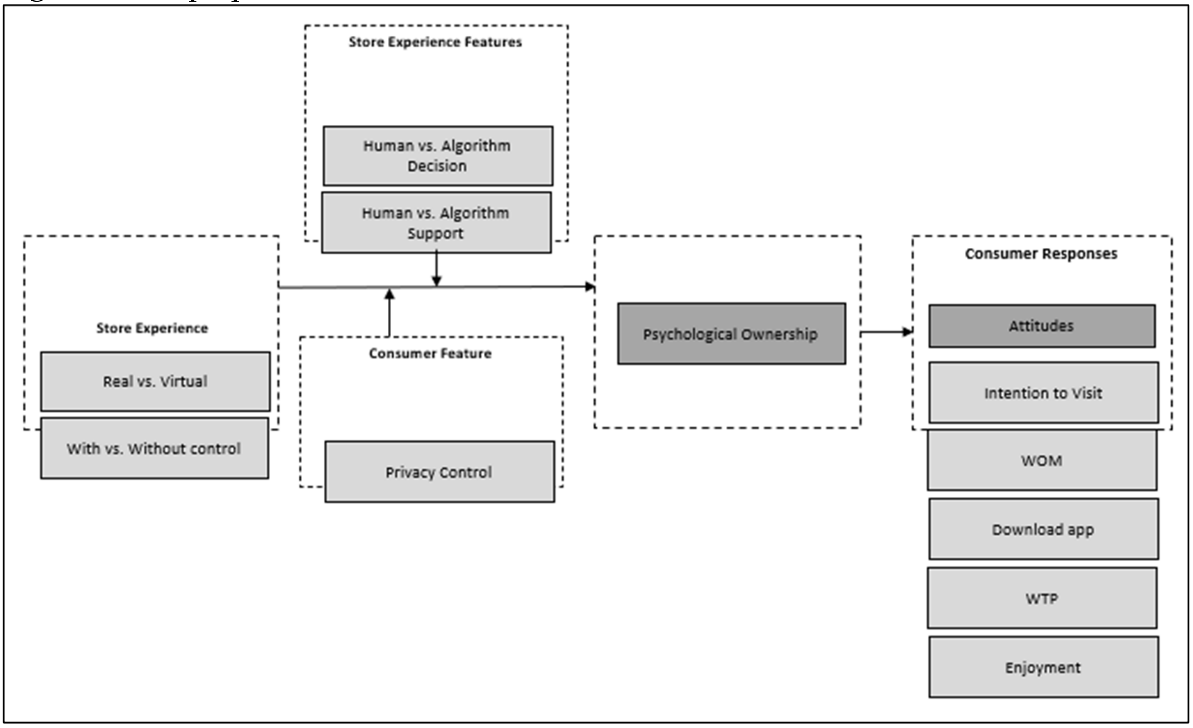
H3: Virtual experiences with perceived control (vs. without control) lead to more positive responses towards the experience through increased psychological ownership.

H4: Virtual experiences with perceived control (vs. without control) lead to more positive responses towards the experience through increased psychological ownership, only when the decision-maker is a human (vs. AI).

H5: Virtual experiences with perceived control (vs. without control) lead to more positive responses towards the experience through increased psychological ownership, only when the support is provided by a human (vs. AI).

Our proposed model is outlined in Figure 1.

Figure 1. The proposed model.



Methodology

In a series of field and online studies, we focus on we focus on online virtual realities, not requiring extra equipment, which may be accessed from anywhere over a device with an internet connection (Harz et al., 2021). Moreover, we implore the moderating effect of consumer characteristics such as privacy concerns as well as experience's algorithmic characteristics such as AI vs. human assistant and decision-maker, in forming these attitudes.
Pre-study, we have collected data from people who visited a certain sports brand's real store versus the virtual tour of a store of the same sports brand. We measured the attitudes towards the experience (Diehl, Zauberman, & Barasch, 2016; Keinan & Kivetz, 2010) and behavioral intentions (willingness to recommend, willingness to download the brand app, intention to visit the store in real/virtual). Preliminary results showed that PO of the store, the brand, and the experience were higher in the real store condition and mediated the effect of store type on behavioral intentions.

Findings from already conducted four preregistered experiments support the hypothesized effects. Virtual experiences with perceived control (vs. without control) lead to more positive responses towards the experience through increased psychological ownership. Moreover, consumers' responses to virtual experiences with perceived control (vs. not) are more negative when a human (vs. algorithm) supports the consumers in the experiment and when the decision to engage in interactive (vs. not) virtual experience is decided by a human (vs. algorithm). The findings extend the marketing literature on virtual experiences and the use of algorithms in marketing in a novel way and generate practical guidelines to improve virtual experiences.

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Metaverse: A Bibliometric Analysis

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Type of manuscript: Extended abstract

Keywords: metaverse; virtual reality; augmented reality; bibliographic analysis.

The advent of virtual reality and augmented reality technologies have pushed user's expectation for online experience to a new level. Social connections via texts alone can no longer satisfy appetite for the reality of virtual interaction. Subsequently, metaverse is invented to reimagine the way people work, play, socialize and live online (Xi et al., 2022). Metaverse is "the post-reality universe, a perpetual and persistent multiuser environment merging physical reality with digital virtuality" (Mystakidis, 2022). Following the rebranding of Facebook to Meta, there is a rapidly growing interest in the field of metaverse.

In this study, we use bibliometric analysis – the application of quantitative tools to bibliographic data (Broadus, 1987) to determine the current stage and avenues for future research of metaverse. Following the bibliometric methodology suggested by Donthu *et. al* (2021), we collected academic documents from Scopus database using the keyword "Metaverse", which results in a total of 151 related intellectual contributions. Metaverse is a novel field of research emerged in 2006 where the mutually constituted relations between avatars, space, and artifacts depicted in players' profile portraits were explored.

The performance analysis reveals number of publications since then has been low until 2020 when the figure increases to 6 before reaching 20 documents in 2021. Interestingly, 70 documents have been published between January to May 2022. Interestingly, even the most prolific author in the field only contributed 8 documents to date. Most publications originated from South Korea, United States, China, Japan, and United Kingdom with 32, 27, 20, 15, and 13 publications, respectively. This could be partially explained by the National Research Foundation of Korea being the main funding sponsor. As the field is still in its early phase, approximately half of the documents are conference papers. At present, the prominent field remains Computer Science and Engineering. These findings suggest vast possibilities for future research.

Topic modeling is also employed to discover the abstract topics that occur in the collection of keywords of the 151 documents. In particular, Latent Dirichlet Allocation (LDA) is used to classify them into topics based on the author keywords. Empirical results illustrate that there are currently two main topics in the field's current research: (1) experience in the metaverse (52.5% of documents) and (2) virtual reality and second life (47.5% of documents).

This study employs bibliometric analysis to explore the field of metaverse. The performance analysis demonstrates that the field is still in its early phase with great potential for growth in publications. Main directions for future research include improvement of experience in the augmented world and advancement in virtual reality technologies of the metaverse. Funding also proves to be a key driver for publications.

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A Process Model of Metaverse Immersion and Consumer Responses

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Type of manuscript: Extended abstract

Keywords: metaverse; NFT via blockchain; avatar digital human; educational knowledge-enhancement.

In this study, we examine the consumer metaverse platform immersion process and associated consumer responses. The metaverse is based on a virtual environment. As an extension of augmented reality (AR) and virtual reality (VR), VR and actual reality coevolve in the metaverse, which creates value by enabling social, economic, and cultural activities without face-to-face interaction (Acceleration Studies Foundation, 2007). Instead, such activities typically are facilitated by digital human characters (e.g., avatar). The 4th industrial revolution has facilitated the transition of the traditional digital world into a metaverse with various functions, including social media, an economic system (blockchain, purchasing, consumption), social interaction, and online e-commerce facilitated by advanced technologies such as AR, VR, and AI. According to SPRi (2021), the current metaverse in the consumer market has the following characteristics:

- Metaverse activities have shifted from games to B2C, B2B, and B2G transactions facilitated by user-led production and work platforms for real economic and social cultural activities (SPRi, 2021).
- Hardware is expanding beyond PCs, mobile devices, and consoles (e.g., Play Station) to VR headsets (e.g., Oculus) and head-mounted displays, and AR glasses, wristbands, rings, and gloves (theguru, 2021).
- Digital humans are being developed to function as social influencers, AI chatbots, and virtual assistants (Bradley, 2020).
- Luxury or popular brands are marketing to consumers in the metaverse. For example, Gucci, Louis Vuitton, Nike, and Disney have developed virtual fashion items for digital human avatars in Zepeto, LOL, and Fortnite.
- Economic activities are being facilitated by blockchain technology. Non-fungible tokens (NFTs) are used to secure asset ownership of user generated content (UGC) (SPRi, 2021). The size of NFT transactions in 2020 was 2.5 billion dollars.

Purpose
Our aim was to examine antecedents (platform compatibility, avatar- and NPC-human similarity, metaverse reality transportation) and consequences (educational knowledge-enhancement and revisit intentions) of metaverse immersion. In addition, we tested the moderation effects of gender, age group, and self-motivation in the relationships between metaverse immersion and consumer responses.

Methods
A marketing research firm collected survey data from 262 actual users of metaverse platforms such as Fortnite (40%), Horizon (26%), Roblox (25%), and Zepeto (19%) (some respondents used multiple platforms). To measure constructs associated with the immersion process (see Figure 1), we modified items from previous studies. Participants responded using 7-point Likert scales (1 = strongly disagree to 7 = strongly agree). To transform continuous variables into group variables (self-motivation and metaverse immersion), we categorized responses from 1 to 4 as low metaverse immersion and self-motivation, and responses from 5 to 7 as high metaverse immersion and self-motivation. We used PLS-SEM to analyze these data. In addition, we conducted ANOVAs for self-motivation (2x2: self-motivation level: high vs. low; metaverse immersion: high vs. low), gender (2x2: gender: men [53%] vs. women; metaverse immersion: high vs. low), and age groups (3x2: 20s [37%] vs. 30s [40%] vs. over 40 [22%]; metaverse immersion: high vs. low) to test main and moderating effects on consumer responses.

Results
Results for the PLS-SEM model are as follows:
- Metaverse platform compatibility ($\beta = .117$, $p < .05$), avatar-human similarity ($\beta = .385$, $p < .001$), and NPC-human similarity ($\beta = .388$, $p < .001$) positively influence metaverse-reality transformation, leading to metaverse immersion ($R^2 = .564$).
- Metaverse immersion positively influences education knowledge enhancement ($\beta = .597$, $p < .001$; $R^2 = .356$) and metaverse revisit intentions ($\beta = .495$, $p < .001$; $R^2 = .245$).
- In addition, we tested the main and moderating effects of gender, age, and self-motivation on consumer responses (i.e., educational knowledge-enhancement and revisit intentions,) in the metaverse. The results show that only self-motivation has main effects on consumer responses; no moderating effects are significant. The ANOVA results are as follows:
- Self-motivation has significant main effects on educational knowledge-enhancement (F [1, 258] = 15.590, $p < .001$, $\eta^2 = .057$; $M_{low} = 4.41$, SE = .14 vs. $M_{high} = 4.78$, SE = .07) and metaverse revisit intentions (F [1, 258] = 11.619, $p < .001$, $\eta^2 = .043$; $M_{low} = 4.60$, SE= .13 vs. $M_{high} = 5.11$, SE = .07)

Conclusion
We make important contributions to the literature by showing how metaverse platform compatibility and similarity between metaverse characters and humans influences metaverse immersion through metaverse-reality transformation. This in turn leads to educational knowledge enhancement and metaverse revisit intentions. Therefore, the metaverse platform has great potential as a platform for education and organizational training.
The results show no moderating effects of gender and age on educational knowledge-enhancement and revisit intentions. Thus, immersion in the metaverse platform consistently leads to positive consumer responses, regardless of gender and age.
In addition, consumer responses were positive for participants who were highly self-motivated. Thus, marketers should be able to easily target self-motivated consumers who are willing to learn by providing educational services in the metaverse. For example, marketers may be able to more effectively target consumers who want to learn foreign languages, seek professional development, or need specific training.

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Psychological impacts of digital travel shaped via immersive technology

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Type of manuscript: Extended abstract

Keywords: digital travel; immersive technology; COVID-19.

COVID-19 has severely hit the economy of the tourism industry. More importantly, people cannot easily restore their minds through the travel experience of visiting a natural destination abroad, namely restorative experiences. Attention restoration theory (ART) states that such restorative experiences are the key to maintaining people's daily mental health. In particular, the high coherence and compatibility between consumers and the natural environment reduce consumers' stress and mental fatigue (Kaplan and Kaplan, 1989; Kaplan, 1995). ART has pointed out that consumers need to perceive four elements of coherence, compatibility, being away, and fascination in the travel experience to shape restorative experiences in their psychology.

Digital travel shaped by immersive technology (such as augmented reality) can fully enable online consumers to have the same experience as visiting a natural destination in person, even if they cannot visit abroad (Chiang, Huang, & Chung, 2021; Tussyadiah *et al.*, 2018). In other words, digital travel created through highly immersive technology can not only shape a travel experience like a physical visit to a natural destination. More importantly, it enables digital journeys to more broadly meet people's desire to visit a natural destination abroad (Hedman, 2022; Huang, & Liu, 2021). Therefore, we can expect that digital travel created by highly immersive technology can effectively generate restorative experiences and positively affect the individual's physical and mental health. Therefore, while COVID-19 has caused people's physical and mental health to be deeply depressed, how to successfully shape restorative experiences through immersive technology has become the focus of current tourism research.

The experimental method in this study was used to verify the above research objectives. First, this research uses AR environmental embedding and somatosensory technology to shape the digital travel experience of the high immersive technology. In this context, the subject can select various objects (such as various scenes) on the computer screen by direct gestures to experience digital travel. Second, the subject could directly embed travel scenes around their body images with the press of a button. On the contrary, in the digital travel situation shaped by low-level immersive technology, the subject has no experience effect mentioned above. Finally, when the subject completed a purchase of a desired tourism product, he or she left the experience space.

The research results found that compared with the digital travel formed by low-level immersive technology, in the digital travel situation formed by high-level immersive technology online tourists can not only perceive higher coherence and compatibility between themselves and virtual tourism destinations but also intuitively explore virtual tourism destinations with lower cognitive resources (as in Table 1). In addition, compared with digital travel formed by low-level immersive technology, in the context of digital travel formed by high-level immersive technology online tourists have a stronger feeling of presence and the higher pleasure of escaping from reality. The results may help digital travel services select appropriate immersive technology that will incite tourists to reduce their stress and mental fatigue and enhance the effect of self-recovery.

Table 1. Psychological impacts of digital travel shaped via immersive technology

Psychological impacts	Types of the immersive technology	N	Mean	Standard deviation	T-value
Coherence	High-level immersive technology	142	3.8504	0.53929	9.565***
	Low-level immersive technology	159	3.2028	0.62527	
Compatibility	High-level immersive technology	142	3.6901	0.57146	11.29***
	Low-level immersive technology	159	2.8604	0.68943	
Being-away	High-level immersive technology	142	3.7521	0.63108	10.405***
	Low-level immersive technology	159	2.9421	0.71947	
Fascination	High-level immersive technology	142	3.9771	0.52983	10.872***
	Low-level immersive technology	159	3.2382	0.63657	

Notes: ** $p < 0.05$; *** $p < 0.01$

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AI-informed Transformative Service Research – Deploying AI Agents to Empower Vulnerable Consumers

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Type of manuscript: Extended abstract

Keywords: artificial intelligence; AI agents; consumer vulnerability; mind perception; transformative service research.

Transformative service research (TSR) calls to investigate extant frameworks and theories through the eyes of the vulnerable (Field et al., 2021; Ostrom et al., 2021; Rosenbaum et al., 2017), which are oftentimes overlooked but make up a nonnegligible part of the world population (Arnett, 2008; Henrich et al., 2010). Consumer vulnerability is "a state in which consumers are subject to harm because their access to and control over resources is restricted in ways that significantly inhibit their abilities to function in the marketplace" (Hill & Sharma, 2020, p. 554). This refers to consumers who "have stigmatizing personal or social characteristics" (Rosenbaum et al., 2017, p. 310) leading to disadvantages in service encounters. Therefore, vulnerable consumers often depend on the service provider to acknowledge these disadvantages and help them attain their desired goals (Rayburn, 2015).

Gartner (2019) recognizes vulnerable consumers' barriers to function in the marketplace and identifies the crucial role of artificial intelligence (AI) to help them overcome previously existing barriers. In line with prior research, we define AI as "programs, algorithms, systems or machines that demonstrate intelligence" (Shankar, 2018, p. vi). More specifically, AI-based agents can serve as a practicable and desirable means of service provision for vulnerable consumers. For example, "Woebot" supports individuals with mental anxiety disorders, for which appointments or waiting rooms represent typical barriers to seek help (Woebot Health, 2022). Moreover, the United Nations collaborate with Facebook to provide refugees with information through a chatbot, especially because call centers are often overloaded, hence making life-saving information more accessible (UNHCR, 2016).

Overall, AI agents seem to represent a promising opportunity for making services more accessible to vulnerable consumers. However, no research so far exists that informs on whether and if so why vulnerable consumers actually prefer contacting AI over human agents. We propose that vulnerable individuals might find solace in entrusting a life-less, therefore non-judging technology with their issues – whereas they might apprehend being socially devaluated by human service personnel. Our research calls on theory of mind perception (Gray et al., 2007) to conceptualize the underlying psychological process of appraising the service agent's suitability as a conversational partner. According to the theory, individuals make inferences about their counterpart's mental capacities in terms of agency, which refers to the capacity to intend and act, and experience, which refers to the capacity to sense or feel (Gray & Wegner, 2012). Extant research indicates that consumers attribute inferior mental capacities to AI than to human agents and are therefore less likely to rely on them (Kim et al., 2022; Lee et al., 2020). However, our work theorizes that for vulnerable consumers the opposite should be the case, in that they choose to rely on AI exactly because of its lower perceived capacities for agency and experience. We propose that the preference of vulnerable consumers for AI (vs. human) agents can be explained by the consumer's anticipated social devaluation (Harmeling et al., 2021) in the service encounter. Since individuals perceive lower mental capacities in AI agents, this should lead to lower anticipated social devaluation, and therefore, stronger preference of AI over human agents.

However, we note that this preference for AI agents vanishes when AI agents become increasingly human-like. As anthropomorphism increases mind perception (Uysal et al., 2022; Yam et al., 2021), it consequently increases anticipated social devaluation, possibly to the same extent as individuals fear devaluation by real humans. Notably, the dimension of agency seems to play a vital part in individuals' devaluation apprehension (Pitardi et al., 2022), as it makes up the capacity to make judgements – whereas the dimension of experience might even be appreciated in certain situations where vulnerable consumers seek a feeling, empathetic (but nonetheless nonhuman) conversational partner. Therefore, our research aims to shed light not only on humanizing AI agents as a whole, but disentangling different features that contribute to perceptions of agency vs. experience, which might have oppositional effects for vulnerable consumers.

Surprisingly, little research exists that sheds light on vulnerable consumers' preference for more or less human-like AI over human agents. In addition, prior work has neglected to extend typical firm-beneficial outcomes (e.g., purchase, satisfaction, or information disclosure) by outcomes beneficial for the consumers themselves (e.g., goal attainment, well-being), which is particularly desirable when consumer welfare is at stake and "advocacy" for consumers is key for firms and policymakers (Anderson & Ostrom, 2015; Blut et al., 2021). Therefore, the overarching goal of our research-in-progress is to investigate the effect of different types of AI agents vs. human agents on consumer- and firm-beneficial outcomes through anticipated social devaluation empirically in a series of scenario-based online experiments and a field study.

With the insights from our studies we plan to add knowledge on how vulnerable people act in a service landscape that is increasingly dominated by technology-driven interfaces, with AI agents assisting or even substituting human service employees (Huang & Rust, 2018; Larivière et al., 2017). We aim to advance the TSR stream through connecting it with the so far decoupled AI stream by investigating how vulnerable consumers experience technology-mediated service delivery. Based on existing theory and our empirical investigations, we expect to demonstrate that AI agents will be evaluated as a neutral audience, from which there is no risk of social devaluation, therefore emphasizing the significance of deploying AI agents to make services more accessible to a broader range of consumers. Furthermore, in exploring unintended negative consequences of humanizing AI, we challenge the oftentimes taken-for-granted assumption that human-like AI is desired by all consumers. However, if firms follow the general recommendation to anthropomorphize AI agents (Blut et al., 2021), they might unknowingly deter vulnerable consumers due to AI agents' resemblance to humans – which would create barriers for using the firm's services (Boenigk et al., 2021). Therefore, we provide insights on what types of AI agents are desired by vulnerable consumers, which not only enhances service provision by firms on the one hand, but further empowers vulnerable consumers attain their goals and contribute to their own well-being.

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Integrating AI into Customer Service: Improving the Actionability of Customer Feedback Analysis Using Machine Learning

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Keywords: user-generated content; customer service; machine learning.

Integrating artificial intelligence (AI) technologies into customer service is of great interest to firms that face a mass of feedback originating from multiple channels (Poser et al., 2022), including phone calls, emails, and social media. Particularly social media channels have increased their popularity in recent years as a notable channel of customer feedback. As such, firms require tools that can process these feedbacks at scale, including their effective prioritization. While prioritization of customer feedback has been considered from a requirements engineering perspective (Armacost et al., 1994; Haber & Fargnoli, 2019; Mastura et al., 2015; Olsson & Bosch, 2015), i.e., what features to prioritize in new product development (NPD), there has been considerably less work on prioritizing customer feedback in order to support the work of marketing and customer service. We focus on this gap.
Machine learning (ML), in particular, provides ample opportunities for supporting the marketing function of a firm (Salminen et al., 2019). Linguistic text analytics, such as opinion mining, sentiment analysis (Cambria et al., 2013), and unsupervised ML (Soriano, 2019), have proven useful for processing unstructured customer feedback in the wild, referred to as user-generated content (UGC) (Fader & Winer, 2012). Despite the general progress in the field of UGC analysis automation for marketing purposes, such as detecting word-of-mouth (Jansen et al., 2009), interpreting consumer sentiment for brands (Rambocas & Pacheco, 2018), and pain-point detection (Handfield & Steininger, 2005), there remains major work for research and development of models and systems that actually benefit firms. This benefit should take many forms: on the one hand, (i) assisting customer service personnel as well as marketing and sales staff to better perform their job duties (i.e., a direct support function of AI); on the other hand, (ii) systematically collecting UGC in data repositories and then mining these data to help firms in strategic planning, product and service position, and assessing the current level of customer satisfaction (i.e., indirect support function of AI). Focusing on the latter aspect, UGC has also been associated with open innovation and user-driven NPD (Von Hippel, 2009) that, in turn, can be seen as a realization of a high level of market orientation (Kohli & Jaworski, 1990) – an important strategic disposition for a firm.

Therefore, from a theoretical and practical perspective, it appears clear that the unstructured textual feedback given by customers online and on social media in particular (Kaplan & Haenlein, 2010) has tremendous potential and business value. Despite this potential, harnessing or capturing the value from data remains a persistent challenge in the field of Big Data analysis (Agarwal & Dhar, 2014). Partially, the problems are technical: methods for large-scale detection and analysis of feedback at scale have only recently achieved a level of adequacy. Other parts of the problem relate to forming actionable insights from these data (Hollis et al., 2017) and integrating data analysis outputs into corporate decision-making processes concerning strategy, NPD, and other use cases that require customer insights (Straker et al., 2021). At least the following operational challenges in processing UGC-based customer feedback remain (Baier et al., 2020; Kühl et al., 2020; Salminen et al., 2021):
(1) **detection of legitimate/useful feedback from noise/promotion/spam**;
(2) **aspect-based sentiment analysis:** e.g., first carry out unsupervised topic modeling to detect thematic issues, and then use sentiment analysis to "rank" how severe the mentioned issues are;
(3) **rank customer feedback by urgency/priority**. This uses human annotations to inform ML algorithms on the importance of a given customer comment.

The above challenges could be merged to form an ideal pipeline as follows: (1) the ML model detects if a tweet is constructive customer feedback or not; (2) for those that are, another ML model prioritizes them based on urgency/priority. Building on this rationale, our research aims at supporting customer service in processing large amounts of requests by automatically identifying those relevant requests (or parts of requests) to be addressed and used for product/service improvement, and those requests (or parts of requests) which are led by customer emotions and having no (or little) relevance for product/service improvement. In addition, we believe it will be helpful to support both customer service agents as well as marketing, e.g., improving customer touch points and improving or building new sales pipelines, chatbots, and customized email marketing. Depending on the domain and specificity of the available data, the proposed model can contribute to the development of the whole product or service. This is a novel approach, as it relies on estimating customer request constructiveness. We believe that such a focus is instrumental for identifying "signal from noise", which is a typical challenge in large-scale data mining problems (Kim et al., 2017).

Accordingly, communication with customers in both cases can be adjusted based on the request constructiveness (e.g., in determining urgency and priority of requests processing, in the formation of patterns for building a dialogue strategy with identified categories of customers) and further automated using chatbots, this way alleviating the work of the help desk. To this end, we apply randomized stratified sampling on a customer feedback dataset of ~4M tweets that contain mentions of 10 large global brands (e.g., Adidas, Nike, McDonalds, FedEx, etc.). We stratify this dataset by brand, randomly sampling 500 tweets where customers give feedback about the brand's products or services. The dataset is being cleaned and pre-processed to ensure its validity for testing purposes. Then we proceed with data coding, which involves extracting the following knowledge types from the tweets:

- **complaint**: By means of negative sentiment extended by the contextual topics;
- **suggestion**: Using specific keywords semantically indicating a suggestion/solution to the problem, e.g., "need", "propose", "suggest", modal verbs "could", "might";
- **situational context** (facts, history of the problem): Utilizing the tweet length, its informativeness (Zipf's law (Newman, 2005), unique nouns and verbs implying the most semantic load of the sentence);

- **positive experience**: Employing positive sentiment extended by the contextual topics;
- **contextless tweets**: Tweets that we cannot use, as they do not imply any useful information, e.g., very short tweets containing swearing words or emojis.

Every tweet will be analyzed according to the mentioned knowledge types. Depending on the presence or absence of certain knowledge types, the constructiveness level of the tweet will be determined. For instance, a tweet containing a complaint, a suggestion, and background information will be classified as "highly constructive", and a tweet containing only a complaint – "not constructive". The constructiveness can also be measured on a numeric scale, e.g., from 0 (totally unconstructive) to 5 (highly constructive). Based on such a classification, constructive customer feedback can be prioritized based on its urgency and considered by customer service for further actions. For the technical implementation of the knowledge extraction, we will use a semi-automated approach similar to the approach we used in our previous research (Rizun et al., 2019, 2021; Rizun & Revina, 2019). Our initial plan for the data analysis is the following. First, we apply the Structural Topic Model (STM) to the data sample to (i) identify the topics (aspects) and (ii) build the aspects' construct (taxonomy). Afterward, we use the topics' descriptive keywords to build the vocabularies (linguistic markers) for each of the knowledge types and "contextualize" our method. Second, identified knowledge types are used as linguistic features for further experiments with ML models. Whereas contextual marketing (Kartajaya et al., 2021) deals with the markers (and vocabularies) developed for specific purposes like targeting, to the best of our knowledge, ours is the first attempt to develop such a vocabulary for identifying the constructiveness of the feedback.

Our approach involves two lines of contribution: (1) conceptualization and extraction of qualitative insights from textual data, towards a theoretical understanding of what attributes make customer feedback constructive; (2) quantitative contribution focused on data modeling using ML experiments, towards the practical value of ML-based systems which support mission-critical business operations. Together, these efforts are synergistically combined in the research that advances the UGC application in marketing and addresses the call for using AI techniques for more elaborate customer analysis (Mustak et al., 2021). Although we focus on marketing, where UGC value and importance are indisputable, the potential of the proposed approach can be used in other sectors where the UGC can contribute to the improvement of the service or product.

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Learning Fintech from AI Chatbot: Two Dimensions of Trust on Financial Self-efficacy on Consumer Adoption of a Wealth Management App

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Introduction

An emerging trend in FinTech is to utilize the artificial intelligence (AI) based chatbot technology to offer financial advisory services to consumers (Huang & Lee, 2022). For example, Bank of America launched a wealth management mobile app, assisting their customers in investing their wealth powered by AI technology (Canzian & MacSween, 2021). Despite this recent trend, as Flavián and Casaló (2021) noted, marketing research on customers' services relevant to AI technology is still scarce. Our current understanding of the chatbot's financial advisory role and consumers' psychological adoption process is still unknown.

To fill the missing piece of the knowledge gap, this paper aims to examine consumers' psychological mechanisms as they adopt to use of an AI chatbot service. In financial services, trust is an essential element of customer service. Relevant literature on trust is divided into the dimensionality of trust: unidimensional or bi-dimensional dimensions (Doney & Cannon, 1997; Ganesan & Hess, 1997; Kumar et al., 1995). This research examines two dimensions of trust: (1) credibility—the belief that the trustee intends to and possesses the required capabilities to fulfill prior promises (Ganesan & Hess, 1997); and (2) benevolence—the belief that the trustee is genuinely interested in the trustor's welfare and motivated to undertake actions beneficial to the trustor (Doney & Cannon, 1997).

According to the social cognitive theory, human beings can learn behaviors by observing others, instead of directly experiencing themselves (Bandura, 1977; Im et al., 2007). This paper extends the theory from a human-human to a human-chatbot relationship. Specifically, we argue that the two dimensions of trust (i.e., credibility and benevolence) serve as significant sources of financial self-efficacy, which is defined as a consumer's belief in the ability to achieve their financial goal (Bandura, 1977; Chi et al., 2021; Henkens et al., 2021).

Furthermore, the recent Covid-19 pandemic has made a significant impact on consumers' lifestyles (Sheth, 2020), as well as on their interaction with chatbots (Huang & Kao, 2021). Thus, this paper examines the role of fear of Covid-19 as a boundary condition that facilitates individual reliance on a chatbot advisory service as a contactless, non-human agent. Altogether, this paper examines how the two dimensions of trust affect consumers' adoption of a chatbot service via increasing individual financial self-efficacy, and the moderating role of fear of Covid-19 in the dynamics.

Method

We designed a scenario-based online survey as this technique is commonly used in consumer research (Bleier & Eisenbeiss, 2015, Fisher & Dubé, 2005; Park et al., 2021). To facilitate participants' involvement levels, a picture of a chatbot providing financial advisory service to its customer was presented. Then, participants submitted their answers regarding the two dimensions of trust (Ganesan & Hess, 1997; Toufaily et al., 2013), financial self-efficacy (Chen et al., 2021), fear of Covid-19 (Witte, 1994), intention to adopt chatbot-based mobile app (Venkatesh et al., 2012), and control variables including privacy concerns and familiarity levels (Kim et al., 2008). The results remain the same whether the control variables are included or not. Items of Covid-19 fear were measured on a seven-point scale (1 = "not at all", 7 = "extremely much"), while all other items were measured on a five-point Likert scale.

Results

A total of 400 participants were collected in the US through Amazon Mechanical Turk to draw a pool from a generalizable population. Among them, valid responses obtained from 361 participants were examined in the following analysis ($M_{\text{age}} = 40.17$, $SD = 11.93$; Female = 65.4%). First, we test for common method variance following a latent construct approach (Podsakoff et al., 2003). Then, we examined the measurement model, in which the results of Cronbach's alpha (> .70) and the average variance extracted (AVE) (> .50) presented reliability and convergent validity. Also, all AVE values were greater than the correlations of each construct, showing discriminant validity.

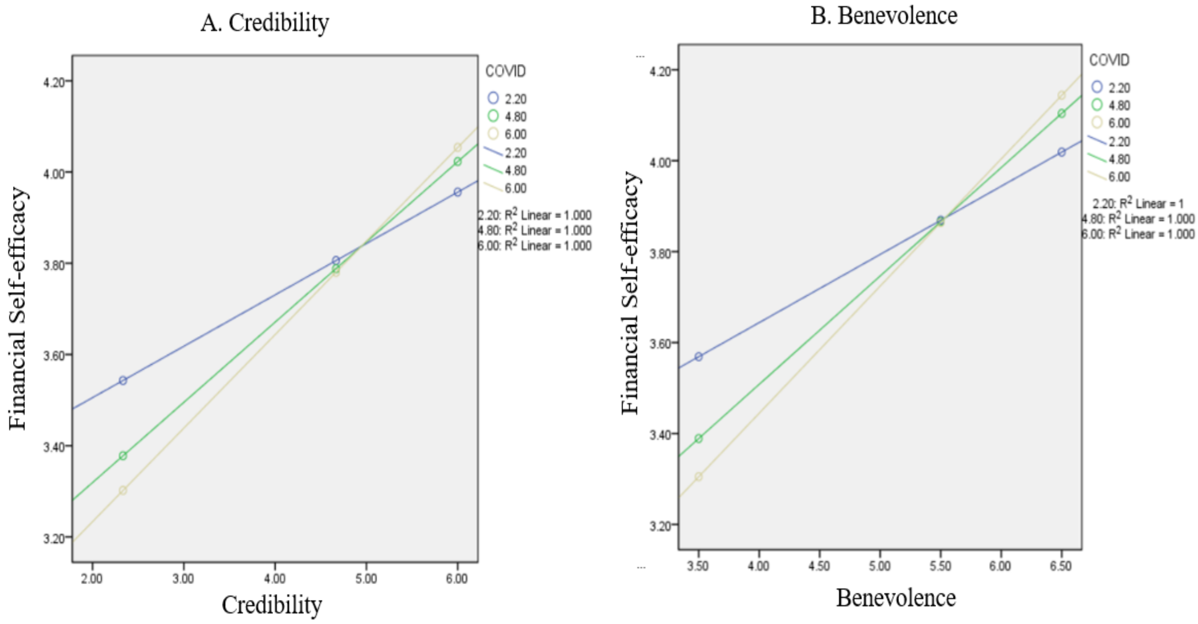
Next, we assessed the structural model using AMOS. The overall results showed a good model fit ($\chi^2 = 292.51$, $df = 16$, $\chi^2 / df = 2.76$, $p < .05$, CFI = .95, GFI = .92, NFI = .93, RMSEA = .07). The path from the benevolence to financial efficacy was significant ($\beta = .373$, $p < .001$). However, the path from credibility to financial efficacy was not significant ($\beta < 1$, $p > .05$). Also, the direct path from credibility to the mobile app adoption was significant ($\beta = .220$, $p < .001$). Yet, the path from benevolence to the mobile app adoption was not significant ($\beta < 1$, $p > .05$). The path from financial efficacy to mobile app adoption was significant ($\beta = .330$, $p < .001$).

Lastly, we examined the moderating effect of Covid-19 fear using model 1 of Hayes's (2018) PROCESS macro in SPSS. The fear significantly moderated (a) the path between credibility and financial efficacy ($\beta = 0.024$, $p < .05$), and (b) the path between benevolence and financial efficacy ($\beta = 0.034$, $p < .05$). The moderating effect is plotted in Figure 1.

Discussion

In summary, our results indicate diverging effects of trust depending on its two dimensions that when consumers trust the AI chatbot, they would have a higher adoption intention of wealth management apps because the trust increases consumers' financial self-efficacy. Building upon social cognition theory (Bandura, 1977), we extend the current consumer-chatbot research by showing that consumers can also learn from non-human agents, chatbots. Also, our findings add to the chatbot literature by showing that consumers' fear of the Covid-19 pandemic strengthens the relationship between trust in the AI chatbot and financial self-efficacy. Thus, our findings provide managers with a practical lesson to utilize a new type of contactless customer service through AI chatbots.

Figure 1. Plotting the moderating effect of Covid-19 fear on the impact of credibility and benevolence on financial self-efficacy



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The Interplay Between Robot Design, Customer Perceptions and Service Outcomes: A fsQCA Perspective

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Objectives and background
An increasing number of companies are using service robots to interact with their customers. Service robots are autonomous agents with the purpose of providing services to customers by performing a variety of physical and nonphysical tasks (Jörling *et al*. 2019). Not surprisingly, there is a vast market potential associated with these robots, which is expected to grow to 87 billion by 2025 (BCG, 2017). Service robots can physically embodied or virtual (e.g., chatbots) (Blut *et al*., 2021). Although virtual service robots have the advantage that they are not restricted to one physical location, there are also reasons why a physically embodied service robot should be used. For example, to physically manipulate an object, physical presence is necessary (e.g., moving packages, delivering food). Moreover, physical presence is also integral in social interactions with humans (Blut *et al*., 2021). Indeed, Belanche *et al*. (2021) show that robots physical appearance (i.e., physical human-likeness) improves customer expectations of service value (i.e., functional, social, monetary and emotional). Furthermore, these service values mediate the effect of human-likeness on loyalty intentions in a hospitality setting. Chuah *et al*. (2021) further argue that rather than one particular factor, combinations of human-like, technology related expectations, and consumer characteristics are associated with intent to use service robots. Meanwhile, robots can be categorized as playful robots, androids, and humanoid robots. Playful robots are seen as likable, submissive, non-threatening, and not very human-like, while displaying somewhat mechanical appearance (Rosenthal-Von Der Pütten & Krämer, 2014). Androids are robots exhibiting appearance that is very close to a real human appearance. Humanoid robots are not as human-like in their appearance and are rather perceived as a robot, while showing stylized, simplified or cartoon-like human-like features (Belanche *et al*., 2021)
More importantly, their design influences if people perceive a robot as human-like (high anthropomorphism), animate, likeable, intelligent, safe, warm, and trustworthy, which can determine the consumer acceptance of a robot, and specifically attitude formation (Bartneck *et al*., 2009; Castro-Gonzalez *et al*., 2016; Ivanov *et al*., 2018; Rosenthal-Von Der Pütten & Krämer, 2014). This raises the question *which robot type a company should use to evoke the most positive perceptions that will positively influence attitudes toward a robot in a service setting*? By exploring this question, our study aims to bring knowledge forward in two ways.
First, building on prior research we extend knowledge on how different robot designs evoke consumer perceptions (e.g., Rosenthal-Von Der Puetten & Kramer, 2014; Belanche *et al*., 2021) by considering the subsequent influence of these perceptions (e.g., trust, safety) on attitude toward the robot. In doing so, we build on conceptual articles (Gonzalez-Jimenez, 2018; Van Doorn *et al*., 2017; Wirtz *et al*., 2018), and few empirical studies, to offer

evidence on how these consumer perceptions of service robots influence service-related outcomes (i.e., attitude toward the robot "working" in the store).

Second, in real-life contexts, human perceptions and behavior are rarely linear in terms of antecedent-outcome relationships. Indeed, complexity theory focuses on complex systems that operate in a nonlinear fashion, suggesting that outcomes are the result of interactions from various antecedents (Woodside *et al.,* 2015; Olya & Akhshik, 2019; Pappas, 2019). In other words, rather than a clear direct path, it is often a combination of various antecedents that can lead to a particular outcome (Ragin, 2008). Following Woodside (2014), adopting complexity theory allows to account for the fact that when numerous variables interact, there can be a nearly unlimited number of scenarios – like in the real world - that can lead to a specific attitude toward the robot in a service setting. In the context of our study, applying complexity theory allows us to explore the effect of multiple evoked perceptions on attitude toward the robot when comparing different robot design types. Specifically, we aim to explore the following two propositions.

Evidence suggests that service robot acceptance is the result of various factors such as perceived human likeness, safety, trust, and usefulness, just to name a few (e.g., Belanche *et al*., 2021; Blut *et al*., 2021; Chua *et al*., 2021; Rosenthal-Von Der Pütten & Krämer, 2014). Coupled with complexity theory, it is likely that various configurations of consumer perceptions may lead to positive attitude toward the robot. Accordingly:

Proposition 1: *No sole consumer perception of robots (e.g,, anthropomorphism, safety, warmth) leads to high attitude toward robot service. Instead, there are multiple configurations of consumer perceptions for the three different robot types that lead to high attitude toward robot service.*

Furthermore, the literature suggests that individuals´ demographic characteristics can influence their perceptions and behaviors in consumer settings (Papadopoulou *et al*. 2019). Differing perceptions can also apply to robotics (Kaplan *et al*., 2019) and these can be the result of characteristics such as gender, age, or income (e.g., Blut *et al*., 2021; Ivanov *et al*., 2018; May *et al*., 2017). Accordingly:

Proposition 2: *The obtained optimal consumer perception configurations per robot type in P1 may be perceived differently by different users (e.g. age, gender, income).*

Moreover, our insights also have implications for practitioners. For instance, robot designers may be in a better position to equip their robots with hardware and software features that elicit a particular set of perceptions (e.g., high degree of safety or trust) that will lead to positive service perceptions in retail settings. In addition, if marketers know that users prefer in service settings robots that, for instance, are perceived as very trustworthy and safe, they can emphasize these aspects in their communications, thus potentially contributing to a user´s perception.

Methodology

To date we have conducted a pre-test (n=38) to select a service setting for the main study where the use of service robots may be relevant to consumers. This pre-test consisted of two steps. First, we asked participants to rate the likelihood that service robots are used, or will be used, in the near future in various settings (e.g., retail, hospitality, public administration). Second, we asked participants to rank the service-related locations where they would expect service robots to be present now or in the near future. Both, retail and hospitality settings received the highest mean scores during the first test. Interestingly, findings showed the same mean scores for both settings (5.89/7). However, in the rank order test, 13 (34%) participants ranked retail settings as their top choice, ahead of hospitality settings, which were selected by 8 (21%) participants as their top choice. As a result, the main study will focus on retail settings. We expect to conduct the main study in June-July 2022. We will use on online survey in to collect data from Chinese consumers. Based on work by Rosenthal-Von Der Pütten and Krämer (2014) the main study will show pictures of three different robot types (Humanoid: Atlas; Playful: Pepper; Android: HRP-4C) as stimuli. Next, we will adopt measures by Bartneck *et al*. (2009) to measure consumer perceptions in terms of *Anthromorphism, Animacy, Likeability, Intelligence, Safety, Trust, and Warmth*, as a response to the three different robot types. Finally, we will measure *attitude towards the robot* service by adapting the scale by Heerink *et al*. (2010). To account for the complexity of the "real world" this study will rely on a set-theoretic method, "fuzzy-set qualitative comparative analysis" (fsQCA; Ragin, 2000). fsQCA allows the analysis of complex combinations of causal conditions leading to an outcome in question (Woodside, 2015). As outlined above, fsQCA will enable us to explore the effect of multiple evoked perceptions (e.g., trust, warmth, animacy) on attitude toward the robot when comparing different robot design types. We expect to have preliminary findings available for the conference.

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The emerging "we" tribe of human-robot partners in consumption spaces

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Several sectors have embraced service robots to support the tribal need to congregate intra-pandemic. This research identifies the growing "we" tribe of human-robot partners in consuming situations due to the Covid-19 pandemic. Through a series of in-depth interviews with robotic service providers as well as consumers, we unpack major reflections on the cobotic teams[2]. Surprisingly, while the Covid-19 era encouraged social isolation, it also fostered new connections between human and nonhuman communities to keep us connected. Following the development of the major features of human-robot tribes, we conclude with recommendations to reevaluate the marketing mix framework that would account for the new customer journey to better speak to the relevant marketing theory.

Frontier robot teams developed in the manufacturing and defense industries were based in remote areas far apart from everyday social life. With the onset of the Covid-19 pandemic, human-robot teams started to co-exist and co-form social interactions in services and other consumption spaces. With this progress, the role of "cobotic" (Peshkin & Colgate, 1999) tribes in allowing robots to assume leadership roles seems crucial (Shanks et al., 2021). Despite various reactions from interacting humans, robot-led cobotic teams were used to combat the involved risks to humans with the airborne infectiousness. Another factor bolstering robot leadership is the increasing diagnostic capabilities and accuracy of AI-powered medical robots (e.g., IBM Watson), which may threaten traditional decision-making.

Robots made their long-awaited debut in servicescapes in the physically shattered revisited new normal. Whether as postmodern ensembles or post-pandemic tribes, we are likely to notice and feel the new "we." Rituals, comprising verbal, physical, and emotional features, bind consumer tribes together (Pekkanen, Närvänen, & Tuominen, 2017). These elements are shared by the intra-pandemic human-robot tribes, as explained below.

It is impossible to exaggerate the importance of verbal communication in establishing and preserving a tribe. According to a new study, humans expect the same conversational style from human service staff and service robots but not from service kiosks (Choi, Liu, & Mattila, 2019). The cobotic tribe employs verbal communication akin to ordinary language in terms of its richness, as opposed to a pre-set of commands to support other linked technologies in service situations. The revisited new normal appears to link robots with

[2] *In-depth interviews are continuing together with data analysis running in parallel - planned date of completion October 2022*

human actors rather than machines in a servicescape in this regard.

Mitigating loneliness intra-pandemic facilitates another important emotional function of tribes: social support. Not merely utilitarian but also socially motivated (delivering joy, friendship, courtship, dating, or sexual pleasure). Robots have historically been objects of love, sex, or desire (i.e., the movie "Her," the Netflix series "Love, Death, and Robots," anthropomorphic sex robots like Synthea Amatus's Samantha and RealBotix's Harmony). On the other hand, the post-pandemic new normal creates conditions for a more balanced distribution of social power, with humans and machines on nearly equal footing. Odekerken-Schröder et al. (2020) identify three possible connections for companion robots in their netnography, ranging from personal helper to relational peer to "intimate friend." In an intimate buddy relationship, the person thoroughly anthropomorphizes the robot, gives it a social identity, and develops a strong attachment to it. The growing close pals are not only consequences of isolation as non-pharmaceutical pandemic solutions but also an expedited answer to the postmodern society's acute loneliness and social isolation problems.

Cobotic tribes are becoming physically evident as the robot tribe becomes more human-like. The tendency to incorporate human-like qualities, motivations, intents, or sentiments into nonhuman actors' real or imagined actions is known as anthropomorphism (Epley et al., 2007, p.864). With the growth of social isolation and virtual immersion during the pandemic, there was an immense desire than ever for anthropomorphic yet noninfectious social creatures. Consumers adapt, adjust, and learn to suit their environment through cycles of reflexive consumption (Beckett & Nayak, 2008). When humans lack physical interactions, they may adjust by anthropomorphizing inanimate phenomena (e.g., growing belief in anthropomorphized religious forces or their pets) (Epley et al., 2008). As a result, the revisited new normal provides anthropomorphized robots a big stage with its rather blurred (in)animacy lines.

Marketing theorists' position in the new normal appears crucial at a time when face-to-face (f2f) marketplaces suffer existential crises that promote new norms and normality. The services marketing mix must be revisited to account for the re-invented "we" within the new face-to-face normalcy.

In the new normal, cobotic service providers created new approaches. For example, QR code stickers placed on tables replaced restaurant menus. The humanless delivery of orders to the tables was facilitated by some robotic waiters. Finally, the dispersed table layout rendered the communal meal experience a distant memory. Thus, the involved customer journey was reformatted, reformulated, and reinvented. It is in this scope that we implemented a grounded approach to conduct in-depth interviews for unpacking the relevant mechanisms[3].

As our preliminary conclusions from the ongoing field work made evident, the implemented measures not only stopped Covid-19 from spreading but also inhibited socializing. Less social interaction gradually became the appropriate thing to do. Robotic waiters have completely replaced human waiters in some circumstances. Preferences and attractiveness questions altered in lockstep; for example, the pre-pandemic appeal of a busy restaurant was replaced by a desire to avoid crowds. Similarly, by replacing the risky infectiousness bearing human touch with a robotic receptionist's greeting at hotel check-in, a new piece of physical proof for some excellent service design arose.

The services marketing mix's "people," "physical evidence," and "processes" have all been altered to varying degrees intra-pandemic. Other entities in the servicescape are no longer limited to "people" as robotic service providers join cobotic teams. Furthermore, the pre-pandemic limited perspective fails to account for cobotic groups' verbal communication and emotional support. Robots have become one of the most sought-after "physical evidence" in servicescapes due to their involvement in reducing loneliness. Finally, with the cobotic service teams, new intra-pandemic "processes" emerged. Such shifts in the services marketing mix are expected to continue in the post-pandemic era. As a result, the expanding "we" tribe of human-robot co-consumers needs a rather inclusive review of the relevant marketing theory.

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Traveling in the post-COVID era: The role of intelligent technologies in enhancing travelers' service experience

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Keywords: artificial intelligence; customer experience; traveler journey; tourism industry.

Relevance of research
In a recent study on experience quality in service settings by PwC (Clarke & Kinghorn, 2018) civil aviation industry was among the sectors with the biggest mismatch between expectations and perceived customer experience (CX). When asking customers about places that offer extraordinary CX, airports are highly unlikely to make the list (Duncan *et al.*, 2017).

At the same time, artificial intelligence (AI) is fundamentally changing the landscape of service provision resulting in new kinds of CX (Ameen *et al.*, 2021). In civil aviation industry, technologies like self-service check-ins and biometric solutions offer numerous benefits to service providers while providing a seamless and compelling service experience to customers. In the (post-) COVID-19 era these technologies more and more replace human service employees, thereby reducing interhuman communication but helping to minimize the spread of diseases. However, only little research exists that explores the role of artificial intelligence technologies in enhancing CX.

This demonstrates the urgency of addressing the questions on how, when, and where AI can effectively and meaningfully contribute to CX enhancement in service settings (Grewal *et al.*, 2020).

Research objectives and research question
Against this background, this research seeks to answer the following research question:

> *How and when does AI-infusion into airport service encounters enhance travelers' service experience?*

To narrow this research question down and make it more approachable and assessable during our empirical design, we further established one guiding question for each of our three empirical studies (see "methodology" below) to facilitate the course of our multi-study research. These guiding questions helped us collect the relevant insights and knowledge to successively answer the research question given above.

These guiding questions were:
(1) What are the major experiential pain points in travelers' airport service journey?

(2) How do service providers account for travelers' service experience when designing AI-enhanced touchpoints at the airport?
(3) How do travelers perceive, use, and evaluate AI-enhanced service interactions along their personal traveler journey?

Research methodology
The methodological approach acknowledges the lack of conceptual underpinnings regarding the impact of AI on the service experience in the service-centered aviation industry. We use an exploratory research design with three complimentary studies to (1) understand what constitutes the service experience for travelers throughout their service journey and (2) determine how artificial intelligence infusion into service encounters influences travelers' perception, usage, and evaluation of these service encounters as compared to the human alternative.

The first study (narrative interviews with flight travelers, n=33) identifies contributing components of travelers' service experience at crucial encounters throughout the travel journey. It especially reveals experiential pain points that cause a friction in travelers' seamless experience at the airport. Study two takes the service provider perspective to understand how firms contributing to touchpoints throughout travelers' airport journey account for the service experience when designing service encounters involving AI technologies. For that purpose, 24 expert interviews were conducted with airport operators and service companies contributing to one or multiple service encounters in the travelers' airport journey. Finally, study three was designed as a problem-centered exploratory research approach counting on frequent travelers (n=17) experienced in interacting with artificial intelligence services as part of their travel journey. It addressed the question of how travelers perceive, use, and evaluate AI-enhanced service interactions along their personal traveler journey.

All interviews were transcribed verbatim and checked for correctness and accuracy and then exported to atlas.ti 22, a qualitative data analysis software. We followed a systematic stepwise recursive process in the thematic analysis of the data (Boyatzis, 1998). Transcripts were coded independently by both members of the research team. A code system was established and built inductively, based on the in-depth textual analysis. New codes were created in an iterative fashion to capture the meaning of initial code groups (Thomas & Harden, 2008). Co-occurrence matrices in atlas.ti were applied to hierarchically organize individual codes in the shape of a coding tree. In an iterative process, the data material was merged, and the two members of the research team independently formed the main categories, discussed the content and labeling and, after several rounds, agreed on a final set of themes.

Preliminary findings
The findings decode the major experiential pain points faced by travelers going through airport service encounters along their personal traveler journey. Based on the current (first) step of analysis, the major sources of experiential pain stem from the interplay of (1) individual, customer-related attitudes, and behaviors, (2) process-related frictions increasing complexity and (3) service-related factors resulting in insufficient satisfaction of travelers' transactional and/or relational performance expectations. The potential of AI systems to address these experiential pain points and enhance travelers' service experience largely depends on the type of service (information-processing vs. people-processing service), the source of the pain to be addressed, and the level of AI infusion used to address the issue. The

goal is to establish a comprehensive framework of AI-enhanced service provision with straightforward propositions on how to account for the service experience when designing AI-powered service encounters in the airport journey.

Originality of the paper

This research is among the first to identify critical components of traveler's service experience and present boundaries and opportunities for enhancing the CX through the application of specialized AI technologies. There is no doubt that AI will have significant effects on CX in the aviation journey and that customers are aware of this effect and open to changes. However, there are boundary conditions and barriers to be identified in customer-AI interactions to ensure positive customer evaluations. However, scholarly (re)search for determinants and interdependencies of meaningful and delighting service experiences with AI technologies is still in its infancy. This research thus motivates scholars to strive for a better understanding of the barriers and drivers of meaningful service experience through sophisticated implementation of AI in the traveler journey. It reveals interdependencies of personal, technological, and encounter-specific determinants to collectively define the traveler experience, thereby providing practitioners with avenues for intelligent service encounter optimization.

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Marketing 5.0 and its business applications: a bet on the future

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In the new context in which companies have to face the digital transformation of business and the changing behavior of customers, the Marketing 5.0 approach is likely to provide companies with a way to integrate the latest advances that the evolution of technology has brought with the changes in consumer behavior that have been observed in recent times (Kotler, Kartajaya and Setiawan, 2021), many of which have been reinforced due to the pandemic situation. It is therefore to be expected that the implementation of the Marketing 5.0 approach will enable company managers to respond to customer needs in the most convenient way possible, thus making a difference in a continuously changing world.

Marketing 5.0 builds on the foundation of its closest and most recent predecessor, Marketing 4.0, with the addition of emerging precepts related to the Internet of Things (IoT) and the Internet of Bodies (IoB) and Artificial Intelligence (AI) algorithms. One of the major differences between Marketing 5.0 and Marketing 4.0 is that while the latter approach tried to combine the best of the traditional physical environment with the online environment (aiming at competitiveness in both worlds), the Marketing 5.0 approach, on the contrary, proposes for the first time to focus on mastering the digital environment, so that under this approach being competitive means becoming a complete digital agent (Zozul'ov and Tsarova, 2020; Amato, 2021). In Marketing 5.0, the consumer is in the driver's seat; he or she is immersed in an entirely digital, intelligent and flexible environment, engaging in full interaction with the IA. Moreover, Marketing 5.0 is characterized by several fundamental aspects, which make it unique from previous approaches, as detailed below (Zozul'ov and Tsarova, 2020).

First of all, it allows to create the illusion of a valuable virtual existence, in which the environment is able to influence all senses and all organs human being. Thus, all actions of potential consumers can be fixed at the same time, from their emotional state (e.g., through the analysis of the content being consumed) to the analysis of the consumer's appearance (e.g., through various neuromarketing techniques, such as the recognition of emotions and gestures).

Secondly, it favors the continuous emergence of new possibilities for real-time consumer research. So that their current and past actions can be studied, and the necessary changes and parallel monitoring of results can be carried out on an ongoing basis. In addition, marketing strategies can be implemented "24/7" - i.e. 24 hours a day, 7 days a week.

Thirdly, it leads to the emergence of countless possibilities for implementing segmentation strategies - even on an individual level. This is due both to the total transparency of all actions carried out by the company and to the immersion of the consumer in a digital environment. In this context, information and communication technologies (hereinafter ICT) will allow direct interaction with the consumer, through the development of individual messages that have been elaborated on the basis of the analysis of large databases.

Fourthly, it is important to comment on how Marketing 5.0 promotes the presence of the IA in the entire marketing process, so that it can partly assume the functions of the company offering the services, as well as some of the decisions to be made by consumers.

Fifth, it enables the incorporation of a multitude of new technologies, which come to replace ordinary reality with digital reality, all facilitated by the fact that the IA becomes a partner in mutual relationships (e.g., i.e., it can adopt various roles, such as that of a helper, a vendor, etc.).

Sixth, it fosters the emergence of various IoT devices, capable of regulating and managing the interaction between various market players, their operation and cooperation.

And finally, it makes it possible for the business model to take on a "everything can be offered as a service" style. In this model, traditional goods can be replaced by services, which means that the efforts required to operate with traditional products (and the problems associated with their maintenance) are considerably reduced.
It is important to note that all these advantages can be obtained in practice with quite low costs, as well as with great ease and simplicity, which is possible thanks to the evolution of ICT (Öz and Arslan, 2019). In particular, the adoption of Marketing 5.0 in general is likely to provide great benefits to companies in their relationship with end-customer management. It has been years since ICTs began to enable companies to establish direct and collaborative relationships with customers, with the latter acquiring a more important role. In fact, this led to consumers starting to show active behavior, as evidenced, among other things, by the amount of useful feedback comments they sent to companies (Prahalad and Ramaswamy, 2004).
With these ideas in mind, the aim of this paper is to analyze the three generations of Internet of Bodies (Marr, 2019), Body external, Body internal and Body embedded and its relationship with the Technology Acceptance Model. According to this, this paper examines the factors influencing customer’s intention to use different devices that are ingested, implanted or connected to the body physically or internally.

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Does the cognitive style influence user experience? A comparative analysis of website and virtual reality in a hotel choice setting

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Type of manuscript: Extended abstract

Keywords: virtual reality; hotel choice; user experience; cognitive style; neuroscience.

Recent technological developments are dramatically changing the consumer's experience of tourism and hospitality services. Hotel managers and booking marketplaces use virtual reality (VR) to offer their customers with realistic pre-experiences to give them clear and vivid impressions of how the real experiences might turn out (Flavián, Ibáñez-Sánchez, & Orús, 2021). VR provides the potential of bringing individuals' imagination and dreams closer to that of reality, and therefore, research scholars are devoting increased attention in the business spheres and, particularly, in tourism research (Beck, Rainoldi & Egger, 2019; Fan, Jiang, & Deng, 2022; Wei, 2019). Studies have demonstrated that the sense of presence and immersion provided by VR could have a positive effect on consumer experience and enjoyment (De Gauquier et al., 2018) and brand advocacy (De Regt, Plangger, & Barnes, 2021).

Tourism and hospitality services have seen the rise in VR applications designed to hotel bookings and enhance tourism experiences (Israel, Zerres, & Tscheulin, 2019; McLean & Barhorst, 2021; Yoon et al., 2021), with a research interest in analyzing the effects of preview modes (Bogicevic et al., 2019), the post-purchase stage and consumer information processing models (Loureiro et al., 2019; Wedel, Bigné, & Zhang, 2020).

The aim of this study is to analyse how the type of environment (2D website, 360º website vs virtual reality) affects the customer experience of hotel choice. Our theoretical background suggests research hypotheses to analyse (i) the effects of type of environment on users' experience (presence and enjoyment), (ii) the effects of users' experience on attitudes and behavioural intentions, and (iii) the moderator role of cognitive style in the influence of types of environments on users' experience.

An experimental design was conducted to individuals who participated in a neuromarketing and virtual reality laboratory study from a large European university from the end of April 2022 to mid-June 2022. Each scenario showed at the cover five choice attributes (rooms, facilities, price, location, and online ratings) that were selected as their importance in booking urban hotels. Three types of data were gathered: (i) behavioural data from which criteria were used for booking and in which order participants looked at each criterion before their decision making; (ii) implicit data gathered from neuroscientific measurements such as eye tracking, heart rate variability, electrodermal reaction and electroencephalography; (iii) explicit measures were gathered from a questionnaire filled right after the experiment. After booking the hotel, the participants were asked to complete a post-experimental questionnaire. The questionnaire consists of the study main constructs and socio-demographics.

Our experimental design aims to address the research hypotheses. More specifically, we aim to delineate the moderation role of the cognitive style delivered in each scenario. Our future results may provide interesting findings in two directions. From a theoretical point of view, we aim to test the validity of the proposed model and its hypotheses. From a managerial point of view, we expect to provide helpful insight for hotel managers in designing effective digital content for tourists.

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Uses and gratifications of chatbots: their influence on consumer experience and purchase intention

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Type of manuscript: Extended abstract

Keywords: chatbot; customer experience; purchase intention; uses and gratifications theory; e-commerce.

Introduction

E-commerce is gaining importance in the context of business activity. At the same time, consumers are increasingly demanding and expectant of their online experience (Emplifi, 2022). To satisfy such requirements companies have opted for the development and implementation of virtual assistants. Chatbots, also designated as conversational agents (Kerly et al., 2007), can be described as an application or software that establishes a personalized dialogue and interaction with the user (Dale, 2016) by mimicking a human conversation (Yen & Chiang, 2021).

Chatbots can provide positive experiences to customers, and incorporate factors that motivate their use. In this context, one of the theoretical frameworks that allow understanding the motivations for consumers to use chatbots is the "Uses and Gratifications Theory". This theory seeks to explain the reasons why individuals use a particular media, or technological system, to satisfy specific communication needs (Brandtzaeg & Følstad, 2017). Cheng and Jiang (2020) listed the dimensions that can be considered as motivators for the use of chatbots, namely Information, Entertainment, Media Capability (or Media Appeal), Social Presence, and also an inhibitor: Privacy Risk.

Despite the significant boom in the use of chatbots and the increased interest of researchers in their study (e.g., Jenneboer et al., 2022; Chen et al., 2022; Rese et al., 2020), the existing literature is limited in terms of exploring the potential of chatbots in business communication (Cheng & Jiang, 2020). In particular, the empirical study on the marketing activities of chatbots and their effectiveness in the Spanish market, the context in which this study is developed, has been scarcely studied in the marketing literature (e.g., Illescas et al., 2021).

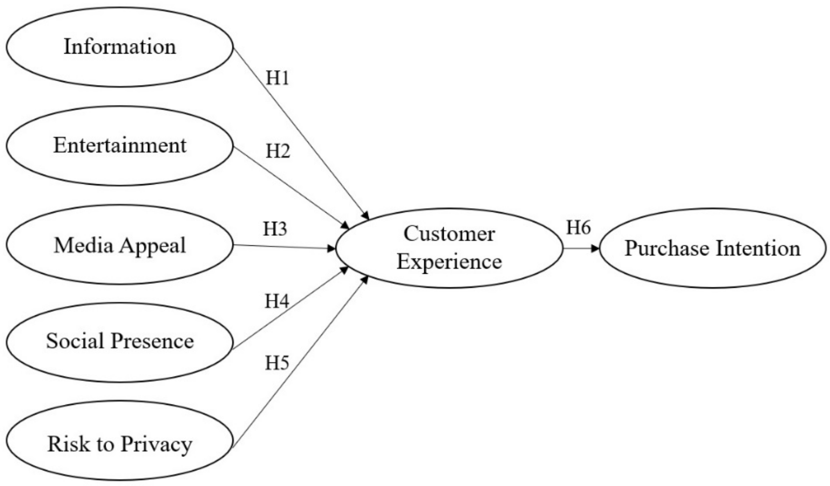
In this context, the present study aims to analyze consumer perception of chatbots as customer service applications. More specifically, it intends to verify the impact of the dimensions of Information, Entertainment, Media Capability, Social Presence and Risk for Privacy on the Customer Experience and the latter on the Purchase Intention. The theoretical framework is built on the Uses and Gratifications Theory.

Research hypotheses

Based on the literature review that has been conducted, the following research hypotheses are proposed (Figure 1):

H1: "Information" has a positive impact on "Customer Experience".
H2: "Entertainment" has a positive impact on "Customer Experience".
H3: The "Media Appeal" has a positive impact on the "Customer Experience".
H4: The "Social Presence" has a positive impact on the "Customer Experience".
H5: "Risk to Privacy" has a negative impact on "Customer Experience".
H6: "Customer Experience" has a positive impact on "Purchase Intention".

Figure 1: Conceptual model



Research method

The empirical component of this study was conducted in Spain, a country that has had a significant number of e-commerce users in recent years (Statista, 2021) and that has reinvigorated the percentage of companies using chatbots (Ontsi, 2021).
To develop the quantitative study, a convenience sample, composed of university students, was used in an online survey. The participants were asked to fulfil a structured questionnaire with 33 questions that covered demographic details and items to measure the dimensions incorporated in the conceptual model (Figure 1). Participants were asked to think of the last experience with chatbots they remember and to answer the questions based on that experience.
The data collection instrument was structured based on instruments used in previous research works. The dimensions related to the theory of uses and gratifications (Information, Entertainment, Media Appeal, the Social Presence and Risk for Privacy) were constituted by items used by Cheng and Jiang (2020). The items of the “Consumer Experience” dimension were inspired by the instrument used by Trivedi (2019). And the "Purchase Intention" dimension was elaborated from the instrument used by Yen and Chiang (2021). A five-point Likert scale (Chen et al., 2021) was employed to measure all constructs included in the questionnaire. Finally, after rejecting cases with missing data, 173 responses were obtained.
The data statistical analysis will be conducted with R software through the package lavaan. Specifically, to validate the measurement scale, we will carry out a confirmatory factor analysis (CFA) and we will consider the usual measures for reliability, convergent validity and discriminant validity. Next, to test the hypotheses from the conceptual model (Figure 1), we will adopt a structural equation modelling approach due to its advantages over other traditional methods, such as multiple regression (Bagozzi & Yi, 1989).

Expected contributions

The main objective of this work will be to develop and validate a model to extend the understanding of the customer purchase intention in an e-commerce context through the customer experience with the use of chatbots. Based on previous studies (Cheng & Jiang, 2020), our model contemplates the theory of uses and gratifications to combine several constructs and customer experience to achieve a better knowledge of purchase intention and, therefore, provide some contributions.

Firstly, our work aims to extend previous studies on how technological advances and the use of artificial intelligence allow brands and companies to strengthen their relationships with customers (Ameen et al., 2021).

Secondly, our work may provide new empirical evidence of how the uses and gratifications theory explains the adoption of a new technological advance.

Third, with this proposal, we intend to provide insights into the dimensions of chatbots that improve online customer experience (Chen et al., 2021). Thus, the considered model incorporates the dimensions of Information, Entertainment, Media Capacity, Social Presence and Risk for Privacy which previously had not been jointly considered in previous studies on e-service agents.

Finally, the present study is a new contribution to a better understanding of antecedents and outcomes of online customer experiences. The investigation also attends to show that the customer experience with chatbots is a key factor in driving sales in e-commerce by fully mediating the effect of dimensions included in the model on the purchase intention, a relationship that has been little considered in the previous literature about chatbots (Yen & Chiang, 2021). Consequently, results from this study aim to capture the main characteristics of chatbots that can support brands to effectively develop their virtual assistants to promote their sales strategies.

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May I suggest these products to you? Effects of recommender and product types on expected quality of product recommendations.

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Type of manuscript: Extended abstract

Keywords: artificial intelligence; human characteristics; retail service.

Introduction

Non-human service encounters are becoming increasingly popular as technologies such as self-service technologies and service robots are implemented in retail stores (van Pinxteren et al., 2019; Wirtz et al., 2018). These technologies not only can be very effective in providing quality service to customers at a reduced cost (van Pinxteren et al., 2019) but also became necessary during the COVID-19 pandemic. One of the most important services in retail is product recommendations and the current store technologies can offer personalize product recommendations effectively using AI. However, finding appropriate recommendations can be very complex and often requires understanding of social and personal context (e.g., finding a dress for a wedding). Consequently, consumers may doubt how well AI can emulate the human capability in generating appropriate recommendations, especially when recommendations seem to require consideration of various factors (e.g., product knowledge, social situation, personal taste, social approval). Thus, the current study aims to investigate how much consumers' perception of human vs. non-human characteristics influences their evaluation of AI recommendation services.

Literature review & hypotheses development

Making appropriate recommendations to customers requires the expertise of the salesperson and understanding of the individual customer's needs. While consumers recognize that AI can easily manage a large amount of data, they also believe that comparing complex options while considering people's individual situations is a unique human capability (Longoni et al., 2019). This belief of unique human characteristics or capability is likely to influence how consumers evaluate whether the recommendations made by AI will be as good as ones made by humans. While AI can process and compute a vast amount of information very efficiently (and thus highly competent in some tasks), creating good recommendations requires some traits only humans are believed to possess (e.g., creativity, ability to consider individual's unique situations). Therefore, it is likely that consumers will (H1a) expect a higher level of service quality from sales associates (vs. AI kiosks) and (H1b) accept recommendations more when they are made by a salesperson (vs. AI kiosks).

Theoretically, stereotyping may explain this pro-human bias. The stereotype content model (Cuddy et al., 2008) states that people quickly evaluate others using two fundamental dimensions of social perception, warmth and competence judgments. Warmth reflects traits such as friendliness, helpfulness, sincerity, and trustworthiness, whereas competence is related to intelligence, skill, and efficacy (Fiske et al., 2007). Combination of these two judgments activate implicit biases and stereotypes and determine one's cognitive, emotional, and behavioral reactions to the other person (Güntürkün et al., 2020). As a universal social perception principle, consumers are likely to use these warmth and competence judgments to assess the ability of salespeople in retail stores.

In the context of human vs. machine, people have developed stereotypes that characterize and distinguish humans from machine. Humans (but not machines) are believed to have affective and warm qualities and to have ability to consider the complex facts in a nuanced way. Therefore, it is likely that the effect of the recommender type (human vs. AI) will be explained by (H2a) warmth and (H2b) competence, which in turn increases the expected level of service quality.

The human characteristics are likely to be more important for symbolic and self-expressive (vs. utilitarian) products because the appropriateness of the recommendations depends on human-to-human interactions. Warmth is particularly relevant as qualities like sincerity, friendliness, and trustworthiness and will be critically important for product categories that consumers use to signal their self, feelings, or social information. Thus, it is predicted that the mediating effect of warmth, but not competence, on expected service quality and willingness to accept recommendations will be moderated by the product type (H3).

Methods & Results

A 2(recommender: AI self-service kiosk vs. sales associate) x 2(product: utilitarian vs. symbolic) between-subjects online experiment was conducted. Based on the previous literature, computer and clothing were selected as a utilitarian and symbolic product, respectively. Participants were asked to imagine receiving recommendations from a sales associate or AI self-service kiosk while shopping in a clothing or computer store. Then, they responded to the questionnaire containing instruments for the study variables and manipulation check items. All measurements were adapted from the previous studies and showed high inter-item reliabilities.

384 US adult consumers were recruited through Amazon Mturk (M_{age}=40.59, SD=12.97; Male: 58.3%). Manipulation of product type was successful ($p<.001$). MANCOVA revealed the significant main effect of recommender type ($F(376, 4)=52.48$, $p<.001$, partial $\eta^2=.36$) and product type ($F=5.45$, $p<.001$, partial $\eta^2=.06$). The sales associate (vs. AI self-service kiosk) was rated as significantly warmer (M=5.55 vs. 3.91, $p<.001$) and more competent (M=5.71 vs. 5.23, $p<.001$). Consistent with H1, expected service quality (M=5.70 vs. 4.92, $p<.001$) and willingness to accept recommendations (5.44 vs. 4.98, $p<.001$) were higher in the sales associate (vs. AI) condition. Serial mediation analysis (SPSS PROCESS macro, model 6) revealed warmth and expected service quality (effect: .65, 95% CI=[.4726, .8480]) and competence and expected service quality (effect: .21, 95% CI=[.0961, .3503]) serially mediated the recommender type effect on willingness to accept recommendations (H2 supported). Lastly, we tested the moderating effect of the product type (PROCESS model 14). The product type moderated the mediating effect of warmth (index: -.3439, 95% CI=[-.6161, -.0936]), but not of competence (index: -.0270, 95% CI=[-.1281, .0432]), supporting H3.

Discussion & Conclusion

The current study demonstrated consumers build different expectations from the preexisting human and machine stereotypes. This result is largely consistent with the previous study which found AI is perceived to be less effective in considering individual unique circumstances (Longoni, 2018). Yet, this study contributes to the literature by validating that the stereotypes contents model in a new context and showing the human stereotypes are particularly important for symbolic products. The findings suggest that retailers should consider factors such as product category when implementing AI self-service kiosks.

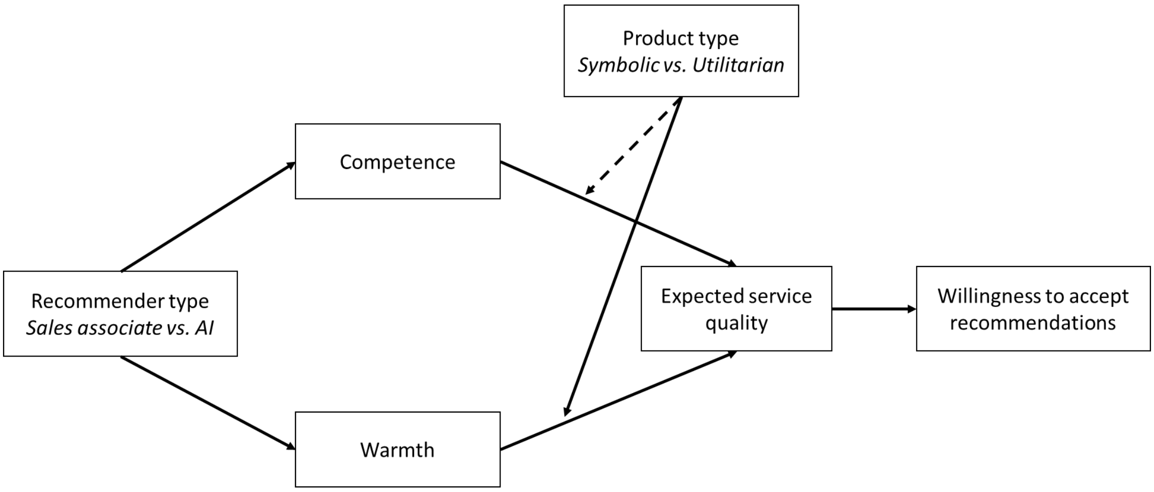

Figure 1. Research model

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Understanding the impact of pre-existing online reviews upon customer intention to review the products on fashion e-commerce websites

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Type of manuscript: Extended abstract

Keywords: online reviews; uses and gratifications; intention to review; fashion e-commerce.

This study aims to evaluate the role of gratifications sought from online reviews in affecting intention to review products on B2C fashion e-commerce websites. The cross-sectional data was collected online from Indian e-commerce shoppers. The validity and reliability of data was analysed using confirmatory factor analysis. Finally, to test the hypotheses structural equation modelling was applied. It was found that the gratifications of entertainment seeking and information seeking from reviews significantly affected the customer intention to review the products. The results also demonstrated that the dissimilar product risk negatively moderated the relationship of advice seeking with intention to review the products. These results have important academic and industrial implications by demonstrating the importance of encouraging online reviews and reducing the risk of receiving dissimilar products online.

Introduction

The objective of this research is to evaluate the role of gratifications sought from online reviews in affecting the intention to review the products on B2C fashion e-commerce websites. The reasons for undertaking the study of online reviews in fashion e-commerce context are as follows. Online reviews are becoming increasingly important in e-commerce shopping, with more than 93% of customers reading reviews to make shopping decisions (Statista, 2022). As per the extant qualitative investigations based upon uses and gratifications theory, customers read reviews on fashion e-commerce websites to seek gratifications like advice seeking, convenience seeking, entertainment seeking, and information seeking (Athwal et al. 2019 and Nelson et al. 2019). However, empirical validation of these gratifications is missing in the fashion e-commerce literature. Further, the gratifications achieved from reading reviews may impact intention to contribute back to the system.

Further, this study undertakes fashion e-commerce as a study context for following reasons. The share of B2C e-commerce in overall retail is expanding each year, reaching 18% of total retail sales at 4.28 trillion USD as of 2020 (Statista, 2021a). Interestingly, fashion is the biggest category within broader e-commerce, with a sale of USD 665.6 billion in 2020 alone, with further potential for expansion (Hootsuite, 2021, p. 232). Given the popularity of the fashion category among e-commerce shoppers, and corresponding business opportunities available for the retailers, it is paramount to investigate the intricacies of online reviews in influencing the customer intentions in this domain.

Further, B2C e-commerce shopping, in general, is fraught with uncertainties regarding financial transactions, privacy, and overall look of the products displayed on the website (Bashir et al., 2021). Particularly, customers on fashion e-commerce portals perceive risk of products mismatch in terms of fit, feel, and appearance (Bashir et al., 2021). Such risk of receiving products that are not similar to those being sold on the website is termed as dissimilar product risk (Bashir et al., 2021). The risk of receiving dissimilar products may inhibit customer intention to review the genuine products. Thus, this study examines dissimilar product risk as a potential moderator in this study.

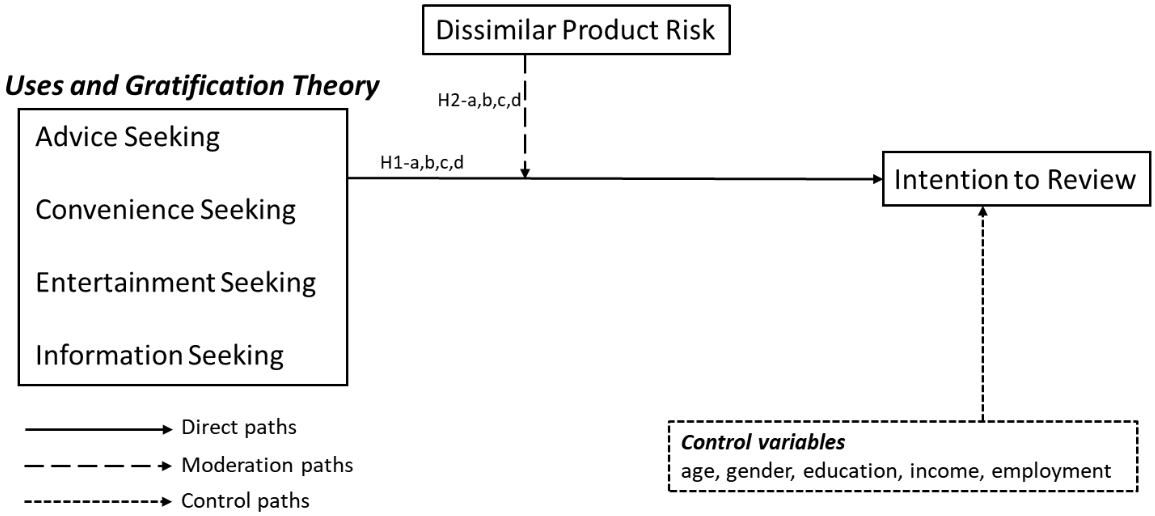
Hypotheses

Based upon the line of thought in the introduction section, the relationships hypothesized in this study are:

H1. The gratifications from reading online reviews: H1a) advice seeking; H1b) convenience seeking; H1c) entertainment seeking; H1d) information seeking positively affect intention to review the products.

H2. Dissimilar product risk negatively moderates the relationship between H2a) advice seeking; H2b) convenience seeking; H2c) entertainment seeking; H2d) information seeking; and intention to review the products.

Figure 1. Research model.



Method

Data collection

To test the hypothesized relationships, a cross-sectional study was undertaken by distributing questionnaire via email lists and social media channels among Indian e-commerce shoppers. The items to measure respective variables were adapted from the existing literature and anchored on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). In total, 283 valid responses were collected out of which majority respondents were aged 26-35 years (53.07%), males (70%), and belonged to the high-income group (46.6%).

Data analysis

The convergent and discriminant validity was determined using confirmatory factor analysis (CFA) under Lavaan using the maximum likelihood mean adjusted estimation (MLM) estimator to overcome the limitation of multi-variate non-normality (Rosseel, 2012; Lai, 2018). Further, a covariance-based structural equation modelling (CB-SEM) was applied to test the hypotheses.

Results

Common method bias

First, the common method bias was assessed using Harman's single factor test. The results demonstrated that a single constrained factor accounted for 32% of variance, well below the threshold of 50%, thus ruling out the possibility of common method bias in the dataset (Sreen et al., 2021).

Validity and reliability

The items were subjected to CFA using MLM estimator. A decent model fit got demonstrated ($\chi2/df = 1.568$, CFI = 0.960, TLI = 0.955, and RMSEA = 0.048) (Hair et al., 2010). All the AVE values and factor loadings were well above 0.50, establishing the convergent validity. Additionally, the HTMT ratios were less than 0.85 and inter-construct correlations less than square root of AVEs, establishing discriminant validity. Further, the McDonald's omega and Cronbach's alpha values were well over 0.70, establishing the internal reliability. Hence, all the conditions required for validity and reliability were satisfactorily achieved (Nunnally, 1978; Fornell & Larcker, 1981; Henseler et al., 2015). Further, there was nothing worrying about multicollinearity with all VIF values less than 4 (Hair et al., 2010). Table 1 and Table 2 list out all the validity and reliability measures.

Table 1. Convergent validity and reliability.

Variable	Adapted from	Item	M	SD	Loading	Cronbach's-α	McDonald's-ω	AVE	VIF
Advice seeking (AS)	Hennig-Thurau et al. (2004)	AS1	5.198	1.536	0.862	0.865	0.865	0.762	2.018
		AS2	5.223	1.465	0.884				
Convenience seeking (CS)	Ko et al. (2005)	CS1	5.254	1.436	0.850	0.928	0.930	0.765	1.869
		CS2	5.106	1.377	0.827				
		CS3	5.191	1.355	0.918				
		CS4	5.269	1.331	0.904				
Entertainment seeking (ES)	Ko et al. (2005)	ES1	2.463	1.618	0.786	0.917	0.910	0.696	1.045
		ES2	2.880	1.806	0.805				
		ES3	2.908	1.732	0.972				
		ES4	2.936	1.727	0.956				
		ES5	3.403	1.883	0.635				
Information seeking (IS)	Luo (2002)	IS1	5.297	1.292	0.816	0.926	0.927	0.716	2.268
		IS2	5.311	1.247	0.876				
		IS3	5.307	1.345	0.864				
		IS4	5.428	1.202	0.897				
		IS5	5.286	1.331	0.783				
Intention to Review (IR)	Dixit et al. (2019)	IR1	4.569	1.575	0.920	0.956	0.957	0.879	1.305
		IR2	4.587	1.563	0.961				
		IR3	4.519	1.540	0.931				
Dissimilar Product Risk (DPR)	Bashir et al. (2021)	DPR1	5.110	1.274	0.855	0.882	0.883	0.654	1.211
		DPR2	4.936	1.362	0.853				
		DPR3	5.053	1.324	0.879				
		DPR4	4.413	1.531	0.673				

Table 2. Discriminant validity.

Variable	AS	CS	ES	IS	IR	DPR
AS	**0.873**	0.616	0.060	0.658	0.360	0.292
CS	0.609	**0.875**	0.101	0.645	0.288	0.341
ES	0.059	0.097	**0.834**	0.107	0.189	0.195
IS	0.656	0.619	0.095	**0.846**	0.454	0.366
IR	0.359	0.272	0.178	0.443	**0.938**	0.276
DPR	0.297	0.326	0.134	0.375	0.266	**0.809**

Note. AVEs' square roots are showcased in bold on the main diagonal.
The matrix below the diagonal displays correlations among constructs as per the Fornell-Larcker criterion, while heterotrait-monotrait (HTMT) ratio is displayed above the main diagonal.

Control variables

The control variables were age, gender, education, employment, and income. First, all the control variables were linked to intention to review during CFA. It emerged that no control variable confounded intention to review. Thus, all these control variables were removed at the SEM stage.

Hypothesis testing

The proposed hypotheses were tested using CB-SEM (MLM estimation). A decent model fit was achieved ($\chi2/df = 1.526$, CFI = 0.980, TLI = 0.976, and RMSEA = 0.049) (Hair et al., 2010). The results revealed that the antecedents explained 22.5% variance for intention to review. The results in table 3 demonstrate that entertainment seeking and information seeking significantly effect intention to review. Further, the results in table 4 demonstrate negative moderation effect of dissimilar product risk in the relationship between advice seeking and intention to review.

Table 3. Direct effects.

Hypothesis	Effect	Coefficient	*p*-value
H1a	Advice Seeking (AS) → Intention to Review (IR)	0.156	>0.05
H1b	Convenience Seeking (CS) → IR	-0.069	>0.05
H1c	Entertainment Seeking (ES) → IR	0.159	<0.05
H1d	Information Seeking (IS) → IR	0.511	<0.05

Table 4. Moderation effects.

Hypothesis	Relationship	Coefficient	*p*-value	Moderation?
H2a	AS → IR	0.318	<0.01	Yes
	Risk → IR	0.160	<0.05	
	ASXRisk → IR	-0.137	<0.05	
H2b	CS → IR	0.182	<0.05	No
	Risk → IR	0.193	<0.01	
	CSXRisk → IR	-0.112	>0.05	
H2c	ES → IR	0.129	<0.05	No
	Risk → IR	0.272	<0.01	
	ESXRisk → IR	0.106	>0.05	
H2d	IS → IR	0.432	<0.01	No
	Risk → IR	0.127	>0.05	
	ISXRisk → IR	-0.038	>0.05	

Discussion and conclusion

The results demonstrate that information seeking and entertainment seeking from online reviews can enhance intention to review the products. Thus, brands should encourage existing customers to review the products as higher number of reviews increase the tendency of new customers to get relevant product related information from reviews apart from the general entertainment derived by customers on reading reviews. Further, the results demonstrate negative moderating effect of dissimilar product risk in the relationship between advice seeking and intention to review. Thus, brands should ensure adequate quality checks to ensure similarity between displayed and the shipped products. However, the insignificant relationships demand further exploration from the future researchers. Additionally, this study is fraught with certain limitations like its focus only on Indian e-commerce market and fashion e-commerce. These limitations can be overcome in future studies by expanding the context to broader B2C e-commerce across multiple geographies. However, despite some of these limitations, this study offers important academic and managerial insights.

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Micro-level and cross-level moderating effects on customer satisfaction in social commerce platform: A multilevel analysis in the hospitality industry

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Extended abstract
Social commerce is developing rapidly in tandem with the electronic commerce evolution (Han et al., 2018). The rise of social commerce dramatically impacts customer satisfaction (Mou & Benyoucef, 2021). Researchers have found that rating from social commerce platforms is a more significant predictor than the traditional survey-based measure of customer satisfaction for explaining hotel performance (W. G. Kim & Park, 2017). Statistics show that 72% of travellers read customer reviews on social commerce platforms before booking restaurant reservations (HotelTechReport, 2022). Customer reviews reflect customers' perceptions toward the products and services, which provide clues for firms to better understand their customers and make the corresponding improvement (Berezina et al., 2016; Xu, 2020). As a measure of customer satisfaction, rating from customer reviews on social commerce platforms enhances customer loyalty (Branch et al., 2018; Kandampully & Suhartanto, 2011; M. R. Kim et al., 2015), review helpfulness (Fang et al., 2016; Filieri et al., 2019), social well-being (Altinay et al., 2019), brand power (Branch et al., 2018), and financial performance (K. A. Sun & Kim, 2013) in the hospitality industry.
Due to the importance of customer satisfaction in social commerce platforms, researchers in hospitality have conducted a series of studies to explore the determinants that drive customer satisfaction. At the micro-level, researchers have found that terms (Berezina et al., 2016; Kostromitina et al., 2021; Xiang et al., 2015; Xu & Li, 2016), sentiment (Geetha et al., 2017; He et al., 2017; Tian et al., 2021; Zhu et al., 2020), and technical attributes (Zhao et al., 2019) in the text of customer reviews affect customer satisfaction. Moreover, researchers have found that macro-level factors, including regional consumption, economic condition, and population density, moderate the relationship between service quality and customer satisfaction (Zhang et al., 2013).
Despite the rich empirical evidence regarding the impact of customer reviews on customer satisfaction on social commerce platforms, several research gaps are noted.
First, although previous evidence suggests that some micro-level factors, including attributes of both text and image cues in customer reviews, affect review enjoyment (Yang et al., 2017), their impact on customer satisfaction is unclear. On the one hand, informativeness in the text of customer review has been identified as an essential factor in influencing helpfulness votes on social commerce platforms (Cai et al., 2022; X. Sun et al., 2019; Yi & Oh, 2021). However, the relationship between review informativeness and customer satisfaction is underexplored. On the other hand, media richness, such as images in customer reviews, reduces customers' cost of information search (Maity & Dass, 2018) and increases product

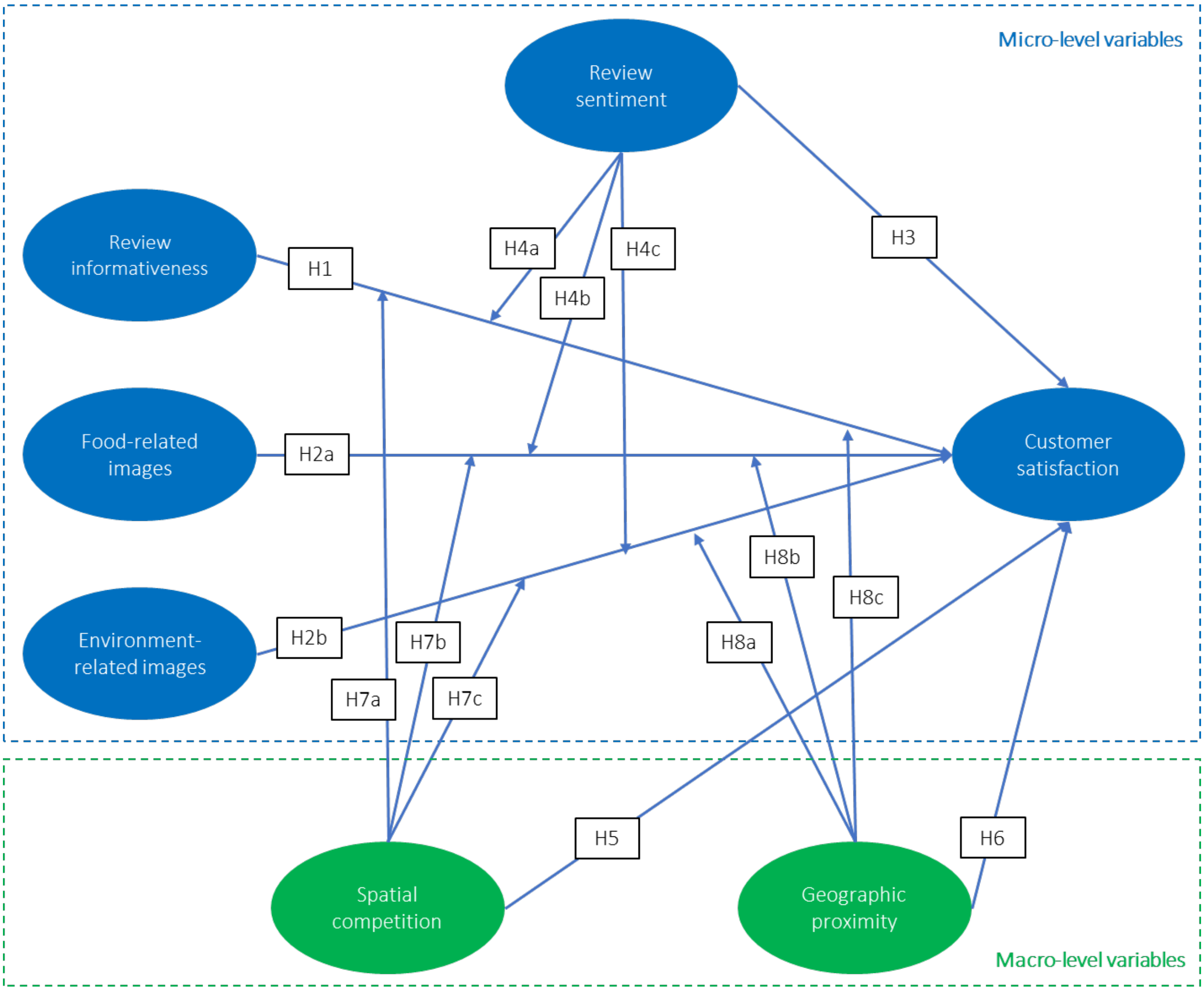
sales (Cai et al., 2022) on social commerce platforms. Nevertheless, the relationship between media richness and customer satisfaction remains to be studied.
Second, the relationship between review sentiment and customer satisfaction is well studied (Geetha et al., 2017; He et al., 2017; Tian et al., 2021). Additionally, previous evidence suggests that negative sentiment in customer reviews tend to decrease the informative value of the reviews (Junyong Kim & Gupta, 2012). Nevertheless, we still do not know whether sentiment interacts with other micro-level determinants, including review informativeness and multimedia richness, that affect customer satisfaction.
Third, researchers have identified that some macro-level socioeconomic factors, including per capita GDP, per capita retail sales, and population density, moderate the relationships between catering service quality and customer satisfaction (Zhang et al., 2013). Moreover, researchers have found that a macro-level geographic factor, spatial dependency, influences customer satisfaction in low-end and high-end restaurants (Jaewook Kim et al., 2022). Nevertheless, the evidence of macro-level factors on customer satisfaction in the hospitality industry is still scant (Zhang et al., 2013). For instance, the influence of other critical macro-level geographic factors, such as spatial competition (Gravelle et al., 2019) and geographic proximity (Iofrida et al., 2022), on customer satisfaction remains unexplored.

Therefore, this research aims to verify:

1. the direct influence of the micro-level factors, including review informativeness and multimedia richness, on customer satisfaction.
2. the moderating role of a micro-level factor, review sentiment, between the micro-level factors (review informativeness and multimedia richness) and customer satisfaction.
3. the direct influence of the macro-level geographic factors, including spatial competition and geographic proximity, on customer satisfaction.
4. The moderating role of macro-level geographic factors, including spatial competition and geographic proximity, between the micro-level factors (review informativeness and multimedia richness) and customer satisfaction.

To achieve the mentioned goals, we created a conceptual framework based on the Service-Food-Environment-Region (SFER) framework (Zhang et al., 2013). According to the SFER (Zhang et al., 2013), customer satisfaction is driven by both micro-level and macro-level factors. At the micro-level, service, food, and environment jointly influence customer satisfaction (Pantelidis, 2010; Reuland et al., 1985; Wall & Berry, 2007; Zhang et al., 2013). At the macro-level, socioeconomic factors, including per capita GDP, per capita retail sales, and population density, moderate the relationships between catering service quality and customer satisfaction (Zhang et al., 2013). In our adapted SFER framework, which we name as the Service-Food-Environment-Location (SFEL) framework (See Figure 1), we advocate that the influence of service, food, and environment is moderated by both micro-level (review sentiment) and macro-level geographic (spatial competition and geographic proximity) factors.

Figure 2: Conceptual framework.



To test the hypotheses in our conceptual framework, we collected restaurant review data from Google Maps using a third-party API service. Then, we operationalised the constructs and measured the variables. We developed a lexicon in the context of the catering service based on bigram, which serves to measure review informativeness. We called the *Rekognition* API from the Amazon Web Services (AWS) to classify the food-related and environment-related images from customer reviews. Besides, we called the *Comprehend* API from the AWS to measure review sentiment. We measured the spatial competition and geographic proximity with the assistance of Google Maps API. Table 1 summarises the measurement of the variables. Finally, we estimated the empirical model using the multilevel regression model. In terms of the software environment, we implemented the API application to obtain Google Map data using Python in Spyder. Moreover, we called the requests from *Comprehend* and *Rekognition* APIs and conducted the early data analysis using R in RStudio.

Table 1. Measurement of the variables.

Level	Concept	Measurement	Description
Micro-level variables (Customer-level)	Review informativeness	Number of service-related attributes	Matching the text of customer reviews with the custom lexicons of catering service attributes.
	Food-related images	Food/Beverage images	Total number of food and beverage images identified by the Amazon Rekognition API.
	Environment-related images	Physical environment images	Total number of physical environment images identified by the Amazon Rekognition API.
	Review sentiment	Review valence	Valence in customer reviews identified by the Amazon Comprehend API.
	Customer satisfaction	Rating	Rating in customer reviews.
Macro-level variables (Restaurant-level)	Spatial competition	Number of competitors in the area	Number of any rival restaurants within 0.25 miles (about 400 meters) of walking distance.
	Geographic proximity	Distance to the nearest attraction	Shortest route between the restaurant and the attraction returned by the Google Maps API.

This research makes several contributions to the social commerce literature and practitioners in the hospitality industry. On the theoretical side, in line with the authors of the SFER framework (Zhang et al., 2013), our SFEL framework also challenges the dominant position of the Expectancy-Disconfirmation Model (EDM) (Yüksel & Yüksel, 2001) in the hospitality literature. The EDM has been criticised because it assumes that customers should have expectations of the products/services they are about to receive in every consumption situation, which is rarely realistic (Yüksel & Yüksel, 2001). Moreover, this study extends the original SFER framework (Zhang et al., 2013) by incorporating both micro-level (review sentiment) and macro-level geographic (spatial competition and geographic proximity) moderators. On the practical side, empirical evidence in this study will guide managers in the hospitality industry to further understand their customers and enhance their marketing strategies on social commerce platforms. Moreover, the results highlight the impact of geographic factors on customer satisfaction, which provide empirical support for restaurant owners when choosing the location for their new business or relocating the existing business. Moreover, as a product of the research process, we developed the lexicons of catering service attributes, which helps practitioners and researchers to understand and further study these attributes in the hospitality industry.

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Virtual influencers: generation of trust, loyalty and purchase intentions

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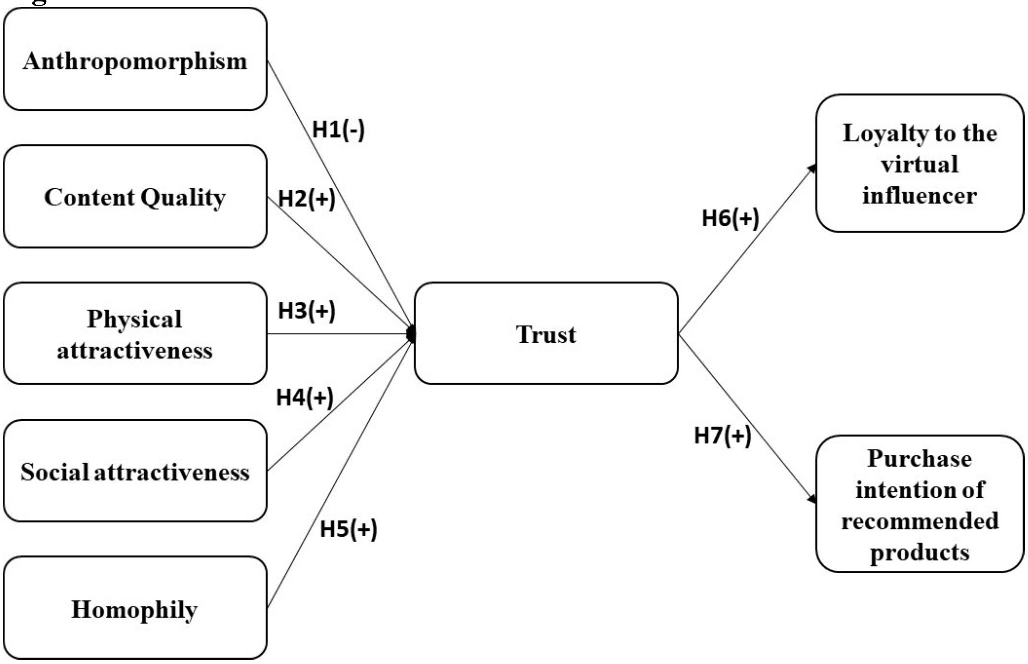
Keywords: virtual influencer; trust; purchase intention.

In recent years, companies have increased their use of influencer marketing because they generate content valued by consumers (Casaló et al., 2020; Ge & Gretzel, 2018). In 2022, it is expected that that the industry will grow by 17 billion dollars, representing an increase of investment of 70% on the part of e-commerce professionals (Werner, 2022). Influencer marketing is defined as the use of opinion leaders, famous or not, who have many followers on social platforms, to evoke positive attitudes and behaviours in these followers in the interests of brands (Martínez-López *et al.*, 2020a). They are considered to be prescribers, sources of advice and opinion leaders (Casaló et al, 2020), and to generate trust (Balaji et al., 2021).

In this context, a new type of influencer has emerged: the virtual influencer (Arsenyan & Mirowska, 2021). They are artificial images, or interactive avatars, that resemble human influencers in a number of their functionalities (e.g., they post content online, and can be followed), but they are not human (Arsenyan & Mirowska, 2021). Virtual influencers create and disseminate online content, and have the capacity to persuade (Arsenyan & Mirowska, 2021). Unlike human influencers, their non-human characters lead them to "stick to the script" and project an image of perfection (Appel et al., 2020). Appel et al. (2020) argued that advances in computing power and artificial intelligence algorithms will make virtual influencers even more prominent in the near future. While the marketing literature on influencers is extensive (see Belanche et al., 2020; Casaló et al., 2020; Kim & Kim, 2020; Martínez-López et al., 2020a, b; Sokolova & Kefi, 2020), few studies have examined the effects of using virtual influencers (Arsenyan & Mirowska, 2021; Kim & Kim, 2021).

The objective of this research is to explore the processes of the generation of trust and purchase intentions among followers of virtual influencers. Although this work is still ongoing, this extended abstract proposes and evaluates a model based on the theory of social exchange and its principle of reciprocity (Kim & Kim, 2021). The model presents five antecedents of trust widely accepted in public influencer marketing research (see Filieri et al., 2015; Kim & Kim, 2021; Masuda et al, 2022) four being content quality, physical attractiveness, social attractiveness and homophily; in addition, anthropomorphism is included as an antecedent variable of trust given that it has been identified as important in interactions between people and artificial intelligence-enabled service devices (Melián-González et al., 2019). As outcomes the model evaluates the influence of trust on loyalty to the influencer and on intentions to buy the products recommended by "him/her" (Figure 1).

Figure 1. Virtual influencer theoretical model.



During October and November 2021, an online survey was distributed among active Instagram users who follow LilMiquela (Figure 2). LilMiquela is a virtual influencer with a very human appearance, indeed, difficult to distinguish from a real person. "She" has 3 million followers, and has collaborated with brands such as Calvin Klein and Prada. Previous studies have specifically studied this virtual influencer (e.g. Lee, 2021). The model variables were measured using 7-point Likert-type scales validated in previous studies. Physical attractiveness, trust, loyalty to the influencer and purchase intentions were adapted from Kim and Kim (2021), social attractiveness and homophily from Masuda et al. (2022), content quality from Filieri et al. (2015) and anthropomorphism from Melián-González et al. (2019).

Figure 2. Image of the virtual influencer LilMiquela.

A total of 167 valid responses were obtained. The sample consisted mainly of women (65.3%), aged between 18 and 35 years (85.1%), having university studies (69.5%). The model was evaluated using the PLS-SEM technique, with SmartPLS software, version 3.3.3 (Henseler et al., 2018; Ringle & Sarstedt, 2016). The model meets the reliability and convergent validity criteria. All factor loads are greater than 0.70. Cronbach's alpha (CA) and composite reliability (CR) in all cases exceed the minimum value 0.8 suggested by Nunnally (1978). The average variance extracted (AVE) values exceed the minimum recommended level of 0.5 (Fornell and Larcker, 1981). Discriminant validity was verified using the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the heterotrait-monotrait ratio (HTMT) (<0.9) (Henseler et al., 2016). The values are all within the recommended limits.

Table 1. Reliability and validity of the measurement scales

Construct	CA	CR	AVE
Anthropomorphism	0.917	0.941	0.799
Social Attractiveness	0.859	0.904	0.702
Physical Attractiveness	0.929	0.950	0.825
Trust	0.852	0.900	0.692
Content Quality	0.907	0.929	0.686
Homophily	0.891	0.925	0.755
Purchase Intentions	0.933	0.957	0.882
Loyalty	0.907	0.935	0.782

The Bootstrapping method, with 5,000 subsamples, was used to evaluate the structural models (Dijkstra & Henseler, 2015). The results showed that the data support five of the seven model hypotheses (Table 2). In particular, the effects of content quality, social attractiveness and homophily on trust, and of trust on loyalty and purchase intentions are statistically significant. On the other hand, the effects of anthropomorphism and physical attractiveness on trust cannot be accepted.

Table 2. Results of the hypotheses testing

Hypothesis	Path coefficient	t-value	p-value	Supported
H1. Anthropomorphism → Trust	-0.061	0.946	0.172	No
H2. Content Quality → Trust	0.328	4.832	0.000	Yes
H3. Physical Attractiveness → Trust	0.078	1.166	0.122	No
H4. Social Attractiveness → Trust	0.218	2.119	0.017	Yes
H5. Homophily → Trust	0.328	3.173	0.001	Yes
H6. Trust → Loyalty to the Influencer	0.774	21.804	0.000	Yes
H7. Trust → Purchase Intentions	0.683	13.854	0.000	Yes
Trust			R^2	0.617
Purchase intentions			R^2	0.463
Influencer loyalty			R^2	0.596

Content quality is the variable with the greatest effect on trust, followed by homophily and social attractiveness. Unlike studies into human influencers that have highlighted the key roles of their physical and social attractiveness, this research into virtual influencers highlights the key role of their ability to generate quality content. This may be because Instagram users accept their messages, but are aware they are not real people. Thus, they do not attach importance to the virtual influencer being more or less physically attractive, while the impact of social attractiveness is reduced (β = 0. 218). That is, influencers need to exercise social interrelation skills with their audiences (Rapp et al., 2013). However, Instagram users do not place their trust in these figures because of their beauty, attractiveness or sensuality (Kim & Kim, 2021). This fact could also be explained by the uncanny valley theory, whereby anthropomorphism can provoke rejection in users of AI systems (Martin et al. 2020). Homophily is understood as being the similarity that followers perceive between their beliefs, values, experiences and lifestyles, and those of their influencers; it strengthens trust by creating good feelings and reduced uncertainty among followers, as occurs in communication between humans. Finally, the negative effect of high anthropomorphism is not statistically significant. In the literature this is a controversial topic with very different results, so further study is needed to arrive at more reliable conclusions.

This work in progress has several limitations. First, a specific influencer, specialising in fashion and lifestyle products, was used as the stimulus. It would be advisable to evaluate the model's relationships based on influencers with different characteristics and in other sectors. The convenience sample was obtained from Spanish Instagram users. Future work should use samples from other cultures and, if possible, random sampling. Finally, although the explanatory capacity of the model is acceptable, its power could be increased by adding other variables, such as perceived experience and satisfaction.

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Looking at embarrassment in consumer-technology interactions

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Type of manuscript: Extended abstract

Keywords: consumer technology; embarrassment; consumer behavioral responses.

Embarrassment is a social emotion in which a person experiences an adverse state of shame and chagrin as a result of unintentional mistakes or social situations (Miller, 1995; Modigliani, 1968). Although embarrassment can occur in private or public, by self-appraisal or othersappraisal (Krishna et al., 2019), consumer research mostly considers public embarrassment which necessitates the observation and assessment of actual or imaginary audiences (e.g., Brumbaugh and Rosa, 2009; Kilian et al., 2018; Verbeke and Bagozzi, 2022; Wang et al., 2017). Moreover, marketing and consumer research concentrate on examining public embarrassment situations that occur due to salespeople or customers' inappropriate or offensive attitudes and behaviors (e.g., Brumbaugh and Rosa, 2009; Grace, 2007, 2009; Kilian et al., 2018; Verbeke and Bagozzi, 2002, 2003), due to being in uncomfortable environments such as luxurious stores (e.g., Lunardo and Mouangue, 2019), due to watching socially sensitive advertisements (e.g., Puntoni et al., 2015), or due to buying/consuming sensitive products such as condoms (e.g., Dahl et al., 2001), hearing aids (e.g., Iacobucci et al., 2003), self-help books (e.g., Kumar, 2008), and products featuring lucky charms (e.g., Wang et al., 2017).

However, concerning embarrassment due to consumer-technology interaction (CTI), we noticed a lack of information and investigations. In this context, in embarrassing service encounters, Pitardi et al. (2022) suggest that service robots (compared to frontline employees) mitigated consumer embarrassment because they do not have feelings and are incapable of making moral or social judgements. The authors of this study thus suggest that technology is a solution for embarrassing service encounters.

However, we believe that technology can also be a cause of embarrassment. In this vein, Liu and Mattila (2019), investigating Apple Pay as a payment method, found that embarrassment and coolness mediate the relationship between payment method and satisfaction. The study also considers the moderating role of encounter outcome (payment success vs. failure). Although this study investigates a CTI embarrassing situation, (1) it is done at the level of payment methods comparing Apple Pay to card payments, hence, more research should consider consumer embarrassment at the level of more advanced technologies such as artificial intelligence (AI) powered assistants (e.g., Alexa and Siri) which became a part of people daily life and include longer-time interactions, (2) the study does not look to many variables such as consumer personality, relationship closeness with the observer, gender of the observer, and experience of using such technologies. For example, Kilian et al. (2018) have considered some of these variables but at the level of service encounters that do not include technology presence.

Based on the above discussion, the current study aims to:

- Identify the main antecedents and behavioral outcomes of embarrassing situations that occur due to consumer interaction with technologies such as AI-powered virtual assistants.
- Identify the potential factors that can play a role in changing the relationship between CTI embarrassing situations and behavioral responses to this technology.
- Examine the moderating role of these potential factors.

Figure 1. Initial research model.

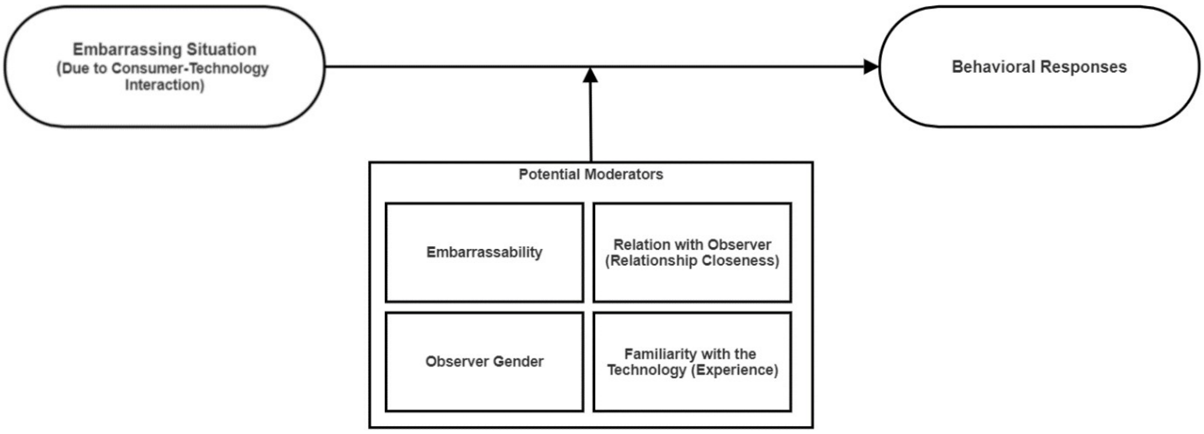

Figure 1 demonstrates our initial research model. To test this model, the following empirical studies (some, all, or more) will be conducted:

- Pilot study. Relying on the Critical Incident Technique (CIT) (Flanagan, 1954), we will ask several individuals to report embarrassing stories that occurred to them due to interaction with technologies such as AI-powered virtual assistants, AR, VR, or smart screens. Based on this study, we will be able to identify embarrassing situations to use in our experiments, moreover, we will be able to identify the main behavioral responses to consider as well (satisfaction, attitude, behavioral intention towards technology, etc.).
- Empirical studies. These studies will be online scenario-based or offline lab experiments where individuals will see or be subject to embarrassing situations due to CTI, based on that the relationship between embarrassing situations and behavioral responses will be investigated. In addition to that, we will test the moderating effect of factors such as embarrassability, relation with the observer, gender of the observer, and familiarity with technology (experience).

Based on the findings, theoretical contributions will be discussed, and managerial implications on how to design technologies that consider mitigating the negative effect of embarrassment will be provided. As applications for AI-powered and voice-based virtual assistants grow and become more diverse, it is important to deepen our understanding of human-AI assistants' interactions.

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Artificial Intelligence and Value Creation: Present Research Focus and Future Research Agenda

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Type of manuscript: Full paper

Keywords: artificial intelligence; value creation; industry 5.0

Purpose
Disruptive technologies are fueling tremendous business growth. The potential of Artificial Intelligence has revolutionized the concept of creating value for end users. The emergence of Industry 5.0 has given rise to the idea of humanizing technology. AI is the technology with promising prospects to contribute to organizational success.

Research Methodology
This paper follows the systematic literature review approach by following Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) protocol, framework.

Findings
Smart service ecosystem development and business model is the most established theme for research as majority of research was focused upon them, while business intelligent system, AI applications and AI innovations were the emergent themes.

Originality
The context of value creation in the AI domain is innovative, but there is a need to define the significance of value by recognizing the context of AI applicability in diverse settings and industries.

Limitation
This review also recognizes that adhering to the methodology may exclude some studies, as the criteria have been set out and cannot be changed as these criteria represent the selected context.

Managerial implications
The emergence of platform economy revolution contributes the development of scalable AI organizations. In order to encourage sustainability, business leaders must now understand the fundamental significance of value creation.

To explain, or not to explain, that is the question. Do we need explainable artificial intelligence (XAI) in consumer neuroscience?

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Type of manuscript: Extended abstract

Keywords: explainable artificial intelligence (XAI); consumer neuroscience; interpretable brain models.

Framework

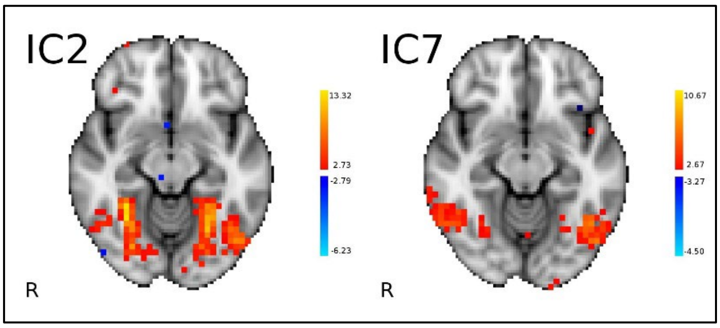
The advancements of artificial intelligence (AI) have been prompting visible improvements in many fields of science, technique, and daily life. Such advances have been intensively considering three concepts: hit rate, accuracy, and precision. The result is commonly a high performing "black box" (de Oña & Garrido, 2014; Olden et al., 2004; Paliwal & Kumar, 2011), i.e., a model with increased hit rate (and accuracies and precisions) but opaque in what it concerns the underlying rationale, logic, or decision path. Such opacity has precluded the adoption AI in assorted fields, such as health (Samek & Müller, 2019; Tjoa & Guan, 2021). Which physician on Earth would rely on a suggestion from a black box? Which physician would adopt an AI-based decision-aided software without knowing its supporting scientific knowledge and techniques?

Faced with users' discomfort, AI experts have been starting to understand the machine learning algorithms and converging around explainable artificial intelligence, XAI (Adadi & Berrada, 2018; Samek & Müller, 2019; Tjoa & Guan, 2021). XAI aims to bring trust and transparency to machine learning calculations and predictions. The mission, however, is not easy. A deep neural network for classification may have ten hidden layers, each with twenty nodes, i.e., totalizing 200 nodes and 4,000 connections, not counting the input nodes and their connections to the first hidden layer. To increase complexity, in each node, the activation function may be "tansig", "ReLU", "sigmoid", "softmax", "linear", or even more kinds. Neural networks may be accurate, but rather complex structures.

Time traveling to 20th century closure, one may already find applications of data mining to predict consumers' choices (Van den Poel & Piasta, 1998). Such applications continue nowadays, for example predicting consumer actions in a webshop (Lang & Rettenmeier, 2017). The objective, however, is to deliver accurate predictions irrespectively of the black box computations. Although it was already foreseen (Smidts et al., 2014), it seems that there is some resistance to conducting studies using machine learning algorithms with neuroscientific data for consumer behavior modeling. However, its benefits were recently

outlined (Lei et al., 2020). Hakim et al. (2021) find that machine learning and neuroscientific data predict consumer choice better than machine learning and self-reporting in a questionnaire, whereas Zeng et al. (2022) achieve 94.22% accuracy using EEG data in liking/disliking footwear.
Nonetheless, the focus is systematically on prediction accuracy relying on an impenetrable black box. So far, to our knowledge, only one published study has tried to uncover the underlying processes during consumer choice besides the prediction rate. Using an artificial neural network (ANN), Marques dos Santos et al. (2014) classified above randomness images of human faces, objects, and preferred and indifferent brand logos. The intriguingly finding is that the analysis of the hidden nodes and the inputs reveal critical participation of brain networks located in the fusiform gyri and the lateral occipital cortex in the psychological process, as depicted in Figure 1, which contradicts the mainstream theories of decision-making, which tend to locate such processes in the prefrontal cortex (Grabenhorst & Rolls, 2011; Murray & Rudebeck, 2018). Such aspect answers the question in the title of this paper: yes, consumer neuroscience needs machine-learning-based analyses, and machine learning-based models need explainability to reveal and understand underlying processes besides the correlational methods that dominate the current panorama.

Figure 3. Participation of the fusiform gyri and the lateral occipital cortex in choosing preferred and indifferent brand logos **(**Marques dos Santos et al., 2014**).**



Explainability versus Interpretability
Although explainability and interpretability are intimately connected, at least in machine learning, they are not the same. Interpretability is usually related to the whole model, how a human may understand its components and mutual relations, i.e., which are the "mechanics" of the model so one can make sense of how it works (Roscher et al., 2020). On the other hand, explainability searches backwards from the decision to understand how certain features produced it (Roscher et al., 2020). According to Montavon et al. (2018, p. 2), "An explanation is the collection of features of the interpretable domain, that have contributed for a given example to produce a decision (e.g. classification or regression)". Adadi and Berrada (2018) find four reasons for needing explainable AI:

- explain to justify decisions;
- explain to control, i.e., to rule, manage, and superintend the process;
- explain to improve the model;
- explain to discover.

Consumer neuroscience needs them all.

Ranking the inputs
To explore deeper a well-performing model, Garson (1991) proposed a procedure to rank the input nodes according to the influence over a specific output in a classification neural

network. Together with the method proposed by Olden et al. (2004), they are the "gold standard" in explaining decisions based on input ranking. The rationale is that if one knows how changes in an independent variable influence the outcomes, one may control the system and improve it. The neural networks, however, keep complex and challenging to interpret (Roscher et al., 2020). Nonetheless, such decoupling between explainability and interpretability burdens and limits control and improvements.

Neural network lightening and path weight analysis

Marques dos Santos et al. (2014) analyzed the inputs' importance in interpreting the hidden nodes and all connection weights in a cognitive paradigm exempt from motor influence. They controlled complexity using a shallow neural network (SNN) designed with six nodes in the hidden layer. There is a "discovery", the participation of the fusiform gyri in a brand decision process, but the procedure was not validated yet against known inputs, outputs, and mediating processes. Furthermore, cognitive activity spreads across the brain, and the neural bases of decision-making are far from being established. Therefore, we use fMRI data from the motor paradigm of a publicly accessible database, the Human Connectome Project (Elam et al., 2021) and an SNN (10 nodes in one hidden layer) to classify the five types of stimuli:

- squeeze the left foot (LF);
- tap the left-hand fingers (LH);
- squeeze the right foot (RF);
- tap the right-hand fingers (RH);
- move the tongue (T).

The proposed method lightens the network by depleting the less important path weights. The concept "path weight" is defined as:

$$path\ weight_{\ ijk} = |w_{I_iH_j} \times w_{H_jO_k}| \tag{1}$$

where $w_{I_iH_j}$ is the weight between the input node I_i and the hidden node H_j, and $w_{H_jO_k}$ is the weight between the hidden node H_j and the output node O_k. Therefore, $path\ weight_{\ ijk}$ is the module of the product of the weights found in the path from input I_i to output O_k, passing by the hidden node H_j. The analysis of the path weights aims to identify which magnitudes are further from zero, i.e., contribute more to the decision and, thus, are more important in the model.

Table 1 and Table 2 report the predictions and global and partial accuracies and precisions of the initial SNN and the lightened SNN (considering the top 10 path weights per output only). Table 3 compares the initial SNN, the lightened SNN (top 10), and the SNN lightened considering the ten higher-ranked inputs using Garson (1991) method. Figure 2 depicts the statistical parametric maps of the four most contributing brain networks (inputs) for the motor-based decision task.

Table 2. Confusion matrix of the predictions of the neural network based on the test data, including the partial and global accuracies and precisions.

Stimulus		Prediction LF	LH	RF	RH	T	Total
Input	LF	27	1	6	5	1	40
	LH	3	36	0	1	0	40
	RF	8	0	31	1	0	40
	RH	0	2	1	37	0	40
	T	4	0	1	0	35	40
Total		42	39	39	44	36	200
Accuracy (%)		67.5	90.0	77.5	92.5	87.5	83.0

Precision (%)	64.3	92.3	79.5	84.1	97.2

Table 3. Confusion matrix of the predictions of the top 10 path weights per neural network output, including the partial and global accuracies and precisions.

Stimulus		Prediction					Total
		LF	LH	RF	RH	T	
Input	LF	19	1	9	2	9	40
	LH	1	31	4	4	0	40
	RF	5	0	17	8	10	40
	RH	0	1	2	36	1	40
	T	7	1	3	4	25	40
Total		32	34	35	54	45	200
Accuracy (%)		47.5	77.5	42.5	90.0	62.5	64.0
Precision (%)		59.4	91.2	48.6	66.7	55.6	

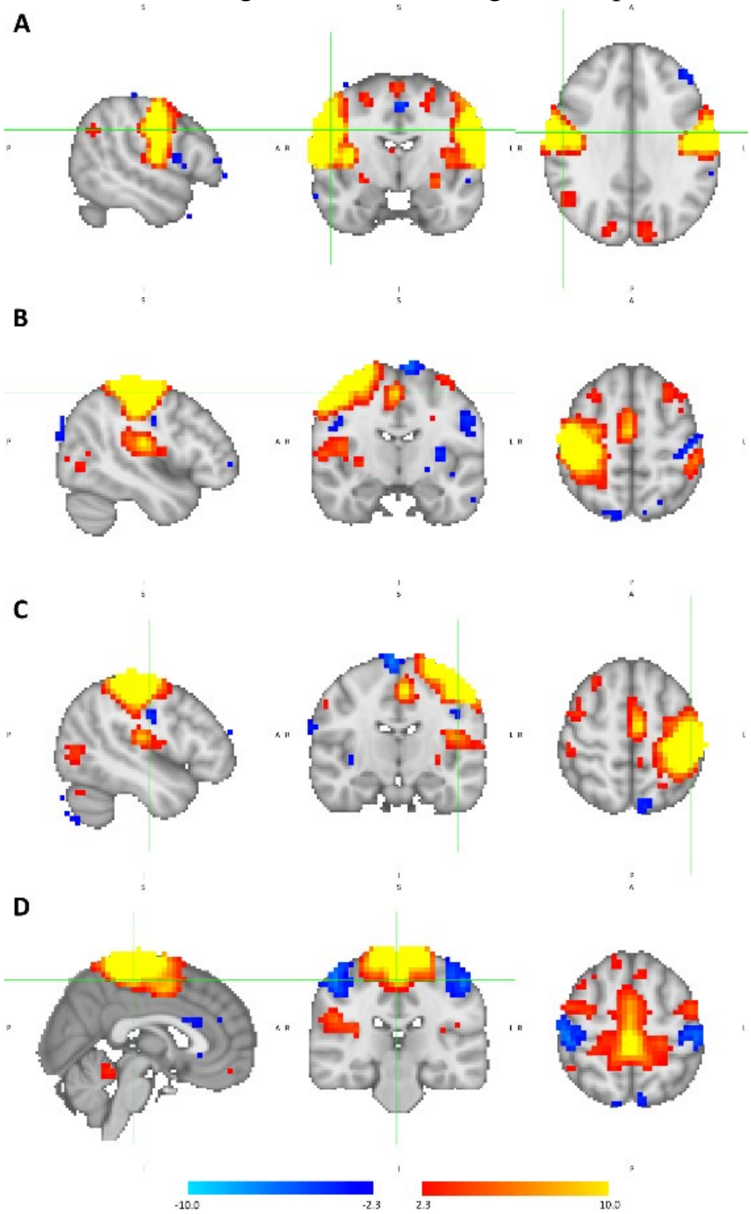
Table 4. Global accuracies and network complexity (number of connections).

Network	Connections	Hits	Hits per connection	Global Accuracy (%)
Initial network	510	166	0.325	83.0
Path weights (top 10)	36	128	3.556	64.0
Garson (top 10)	170	154	0.906	77.0

Discussion and conclusions

The lightened SNN balances predictive ability, interpretability, and explainability. With 36 connections, it retains 128/166 = 77.1% of the predictions of the initial SNN, and it is still well above the randomness level (64.0 % versus 20.0% (1 out 5 possible choices)). However, the outputs are explainable with the inputs because the former are triggered by known motor networks identified in the latter. This procedure may now be extended to cognitive processes, in the case of consumer neuroscience, those that support decision behavior and preferences. There is then an opportunity to control consumption processes, improve them, and, hopefully, discover new ones.

Figure 4. Selected sagittal, coronal, and axial views of the main network inputs. A: IC 5 depicted in the plans x=54, y=-6, z=32; B: IC 7 depicted in the plans x=46, y=-10, z=56; C: IC 11 depicted in the plans x=-46, y=-14, z=56; D: IC 12 depicted in the plans x=2, y=-26, z=56. MNI152 coordinates. Radiological convention: right hemisphere on left.



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Relationship quality in customer-service robot interactions: An analysis of value recipes

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Keywords: service robots; relationship quality; fsQCA, social exchange theory.

Robots play an increasingly key role in the management of customer services (Holthöwer and van Doorn, 2022). It is clear that customers, in some cases, interact with smart inanimate objects much the same way they would with other people (Epley, 2018). "But it is also clear that smart objects are very different from conventional brands and products, and that these differences will require some expanded thinking about the nature of relationships consumers have with smart objects (Novak and Hoffman, 2019, p. 217; see also Huang and Rust, 2017)." Such expanded thinking and novel theorizing is particularly needed in the context of understanding the boundary conditions that determine the quality of interactions between people and robots in service encounters. Much leeway has been made in the literature on service robots and the technology behind these robots including machine learning, deep learning, natural language processing and so forth (Rust, 2020). Service robots are usually seen as "information technology in a physical embodiment, providing customized services by performing physical as well as nonphysical tasks with a high degree of autonomy" (Jörling et al., 2019 p. 2). Problematically, however, much remains unknown about the factors that determine the nature of these interactions, and that of the relationship quality that ensues between consumers and robots in a service context.

Broadly speaking, a high-quality relationship between customers and service robots is one where customers' perceptions of the relevant interaction costs are less than the perceived benefits (Sirdeshmukh et al., 2002; Zeithaml, 1988). With this in mind, the following research question motivated our study: *What value dimensions facilitate, or stand in the way of, a high-quality relationship between customers and service robots?* To address this question, and explore value dimensions we put forth three propositions. These propositions are theoretically grounded in Leroi-Wereld's (2019) value typology (both positive and negative value types). Leroi-Wereld's (2019) value typology is an evolved conceptualisation of value that takes into account the infusion of technological advancements into businesses including the use of service robots.

Since individual value dimensions will have complex trade-off effects and only certain combinations of value dimensions will unveil the complex value patterns contributing to relationship quality between customers and service robots, we work with value recipes. Value recipes describe multiple, distinct, and different combinations of positive and negative values (Leroi-Werelds, 2019) that affect the quality of relationships between customers and service robots.

Theoretical Underpinning
In addition to value recipes, we ground our propositions in social exchange theory, which posits that customers tend to reciprocate positive thoughts, feelings, and behaviours toward a service robot upon receiving specific benefits from the relationship (Blau, 1964). We also use the complexity theory approach to design research propositions as causal recipes to put forth different associations between variables, and theoretically specify which should be present or absent from the mentioned value recipe (Woodside, 2014).
Based on these theoretical underpinnings, we propose:

Proposition 1: The presence of both positive values (such as convenience, excellence and others) and negative values (such as effort, security risk and others) is a necessary condition (for a value recipe) to predict the relationship quality of human-robot interactions in a retail setting.

Proposition 2: The combination of positive and negative values in different combinations are sufficient to determine the relationship quality, but each one alone is insufficient because the human-robot interaction is influenced by different values, which means the positive and negative values jointly, in different combinations (value recipes), predict the relationship quality.

Proposition 3: The combined presence of positive and negative service values (value recipe) can either increase or decrease the relationship quality because each value component has a different contribution to the human-robot relationship quality in a retail environment.

Methodology
The proposed propositions are addressed by performing configurational analysis using fuzzy set qualitative comparative analysis (fsQCA) (Ragin, 2009)

Data Collection
To explore the propositions, a purpose-made questionnaire was developed. The target sample included customers who had accessed retail services and used service robots. The study used a realistic and validated written scenario to help consumers visualise the use of service robots. A web-based survey was administered using a panel provider. A sample of 326 customers was evaluated for this research.

Results and Contribution
Results reveal configurations that may enhance or hamper customers' relationship quality with service robots. Results support all three propositions. Specifically, the configuration having positive values, namely, relational benefit, novelty, control, personalization, excellence, and convenience, is the most desirable and it is indeed a necessary and sufficient configuration to enhance the relationship quality between customers and robots. The results show that personalization and excellence are necessary conditions to enhance relationship quality. But these factors will not enhance the outcome when combined with a negation of other positive values. Hence, our data suggest that relationship benefit, novelty, control and convenience are the core positive ingredients in the value recipe. Our results also reveal that out of the explored negative values, effort needs to be managed judiciously as it is a condition that can undermine relationship quality as well as enhance it. The study results show that there are no specific configurations of positive and negative values that will significantly impede relationship quality. Hence, we conclude that customers' negative values, associated with

costs and sacrifices, have the potential to undermine relationship quality, but can be dealt with through an increase in the level of positive value components. Our results empirically validate Moliner et al.'s (2007) and Leroi-Werelds's (2019) value conceptualizations. Also, our study echoes prior studies that identified value components as antecedents for relationship quality (e.g., Wisker, 2020).

Overall, two distinctive influence configurations show all the necessary conditions of value recipes to enhance the relationship quality between service robots and customers. The first one is the combination of a low level of perceived effort, performance and privacy risk combined with a high level of relational benefit, novelty, control, personalization, enjoyment, excellence, and convenience. The other combination shows a low level of effort and privacy risks along with a high level of benefit, novelty, control, personalization, enjoyment, excellence, and convenience. We contribute to the literature by shedding some light on the value recipes capable of fostering or standing in the way of high-quality relationships between service robots and customers (e.g., Leroi-Werelds, 2019; Zeithaml et al., 2020). Broadly speaking, our findings go some way toward showing the significance of the many boundary conditions managers should heed when working with service robots.

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Citizen Science and Photovoice technique to assess Food Waste Perceptions: An AI-driven approach

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Keywords: food waste; sustainability; citizen science; photovoice, artificial intelligence.

Introduction

Presented research attempts to understand the secondary school students' perception of food waste by involving them in the research process. It is a critical problem and a threat to global food security. In 2015, the UN set ambitious sustainable development goals, i.e., Zero Hunger and Sustainable Consumption and Production by the year 2030. However, we don't appear to be on a trajectory to achieve the same (United Nations, 2022).

Food waste, a multibillion-dollar loss is an economic consequence (Vilariño et al., 2017). A single person produces 0.75 Kg of food waste per day and though this range varies in different parts of the world, two billion tons of solid waste arise around the globe every year. While global wastage has become a serious environmental concern (Kumar & Agrawal, 2020) subsequently, it is enough to feed 2 billion people around the world; where one person in nine is a victim of chronic hunger (WHO, 2019). Pursuant to Martínez & Pachón-Ariza (2014) in developing countries, food waste has become a social, economic, and political problem. Hence, this study aims to gather data on the perception of food waste and to assess possible solutions that can also be replicated in other developing nations.

Review of Literature

'Food Loss, Food Waste, and Food Wastage' are the terms researchers use around the globe to address the phenomena. According to WBCSD (2021), all the terminologies have different meanings.

Food Loss refers to discarding food due to a loss of nutritional value. Probable reasons are poor management of the food supply chain. *Food Waste* is concerned with discarding addible and quality food. This happens when people purchase excess food, keep it beyond its perishable date, and then throw it away. *Food Wastage* is a combination of food waste and food loss. In this research, the authors shall focus on the food which is edible and safe for consumption but still being discarded.

Global Waste Management Outlook (2016) suggests that high-income and middle-income countries generate high organic waste, whereas low-income countries produce lower organic waste (Poças Ribeiro et al., 2019). In consonance with Parfitt et al. (2010) in high-income countries, accessibility and palatability are the cause, whereas, in mid-level or low-income countries, poor management of the food throughout the food supply chain is a probable factor. Food waste patterns and causes also differ with demographics. Considering age as a factor, children-related factors of food waste are its taste and palatability, while adults waste food because of over-purchasing and excess cooking (Scaglioni et al., 2018). In the case of developing countries like Pakistan, the cost of food insecurity is USD 7.6 billion a year (World Food Programme, 2017) whereas, the waste collection rate is merely 50 percent which has serious environmental consequences (Akmal & Jamil, 2021). Indistinguishably, people are not aware of the issue, wasting a huge amount of food by which 43% of the population of the country can be fed. Schanes et al. (2018) established that at the consumption level, food waste includes households, the hospitality industry, schools, and offices where 85% of the waste happens in the household (ReFED, 2020). This research will predominantly focus on household-level food waste.

Research Methodology

The research method will embed citizen science as its backbone (Kasperowski et al., 2017), aligned with Photovoice (Budig et al., 2018) for data collection. This study will involve Secondary school students following ethical and data protection guidelines. Citizen science is an approach involving community volunteers to resolve a social problem. Participants shall collect data from photos, audio, and documents to achieve a common goal (Schaefer et al., 2021) to offer multiple perspectives (Roche et al., 2020). As the proposed study called for the understanding of behavioral aspects (Jordan et al., 2011) amateur scientists were involved in participatory monitoring (Kasten et al., 2021).

Photovoice is a participatory method that will provide the participant with a sense of association with the cause (food waste) to come up with innovative strategies to address that problem (Yen et al., 2022). At a later stage, the researchers will conduct focus group interviews with young students about their respective perceptions and emotions on food waste and its social, environmental, and personal impact.

The study assumed a normal distribution of 50% and based on a large population size with a Confidence Level of 85% & Margin of Error of 7% sample size of 105 was calculated (Morse, 2000). After data collection; analytical processing will be carried out using Artificial Intelligence (A.I.) for both the photos and voice content to generate unbiased insights (Krishna et al., 2019). To achieve the same, the voice will be transcribed to be fed for Qualitative Content Analysis. This would be fulfilled using the Natural Language Processing of AI (Ning, 2022). Concurrently, the Photos will be subjected to Image Processing to generate valuable insights relevant to the food waste scenario (Zhang, 2022).

Findings:

The State of Food Security and Nutrition report (2021) identified that low affordability affects billions that cannot eat healthily or nutritiously. Hence, the findings of this paper will give us insights into the perception of Secondary School students about food wastage. This study will also provide the strategies developed by young minds regarding food waste and inculcate their creative approach to addressing this societal problem.

Contribution:

This research extends the prior notions with secondary school children as argentic consumers who can shape food waste solutions in school. These findings can be used by local educators to develop their solutions to reduce food waste on school premises. The methodology of the study would likely provoke children to examine their attitude toward food and develop environmental consciousness.

This study would further encourage school students to record their perceptions and understanding of the problem of food waste and develop innovative solutions. Research design would embed their perception and scientific dimensions to draw valuable insights via citizen science. The researcher further believes using these insights, a technology-driven mechanism could be developed in the near future that can be utilized to nudge people to minimize food loss.

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Artificial Intelligence Applications. Challenges for Cultural Institutions

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Keywords*: artificial intelligence; Industry 5.0; Industry 4.0; user service experiences; cultural institutions; user experience; users; managers.*

Introduction

The Fourth Industrial Revolution, often known as Industry 4.0, refers to the use of technology to automate industrial manufacturing processes (Xu et al., 2018). Industry 4.0 (Lu, 2017) is primarily reliant on information and communication technology (ICT), which paves the way for further technologies such as cloud computing, the Internet of Things, and social media to assist with production and data-driven decision-making (Autio et al., 2018; Para et al., 2018). Lately, the use of artificial intelligence (AI) applications in the service sector have been linked to what is known as 'Industry 5.0'. It has been derived from an impulse of technology adoption provoked, among other phenomena, by the COVID-19 pandemic. Considered the next industrial revolution, Industry 5.0 takes advantage of the creativity of human beings in collaboration with efficient, intelligent and precise machines to obtain efficient resources and solutions adapted to the user (Maddikunta et al., 2021).

The tourism sector has gradually adopted Industry 4.0 tools, as well as technologies such as robots, artificial intelligence, and service automation (Ivanov & Webster, 2017; Tussyadia, 2020; Belanche et al., 2021). However, the tourism sector requires taking a step further toward Industry 5.0 tools (Calero-Sanz et al., 2022). Cultural institutions are embracing ICT to co-create and provide services that better respond to customer preferences in the experience society (Hanafiah & Zulkifly, 2019; Marasco et al., 2018). The use of these tools in cultural institutions presents an inclination to attract tourists as well as young visitors (Bonacini and Giaccone, 2021; Hausmann and Schuhbauer, 2021).
Tussyadiah (2020) considers AI as a system that thinks or acts humanly or rationally. Despite the fact that robots and other AI technologies have been employed in cultural institutions and museums for more than a decade (Polishuk et al., 2011), their potential for creating interactive experiences with users has yet to be explored. They can create collaborative experiences that make it easier to customize the technology's functioning and adapt it to unique requirements. In addition, AI has a significant impact on how tourists interact with art galleries and museums (Singh and Atta, 2021).

The aim of this paper is to analyse the potential of artificial intelligence (AI) implementation in the services experience provided by cultural institutions (e.g., museums, exhibition halls, and cultural spaces). The study considers two different perspectives using the Industry 5.0 approach: experts and tourists as users.

Methodology

Considering previous studies, this research is focused on conducting a deductive analysis considering the different dimensions of user–AI interactions to explain the user interactions with AI applications (Tussyadiah & Park, 2018; Primawati, 2018), which can be classified into three groups: functional, contact, and co-experience dimensions.

The study was carried out in a qualitative manner, with the material acquired from two roundtable talks with specialists and tourists as users being analysed. The roundtable discussions were organised to obtain information from two different type of participants: professionals from cultural institutions and visitors of cultural institutions. The roundtable discussions were held on 11 November 2021 and each one lasted a mean of 105 minutes.

Preliminary findings

The main findings show that AI helps cultural institutions engage with users, which is important since it allows institutions to learn more about their users and create a more integrated and immersive experience. Furthermore, AI is crucial in developing and maintaining a community on a regular basis. As a result, AI is more than a tool; it is an essential component of the whole experience.

Conclusions

The originality of this research resides in the theoretical model proposed. It includes the three dimensions considered under the Industry 5.0 approach: functional, contact, and co-experience dimensions. It also includes three different stages of the visit to these institutions (pre-visit; visit and post-visit) where AI can be applied to enhance experiences and also management.

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What if we took a holiday? Enriching Advertising with Intelligent Voice Assistants

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Type of manuscript: Extended abstract

Keywords: artificial intelligence; parasocial relationship; advertising value.

Introduction

For several decades, the entertainment industry has created an imaginary relationship between human and non-human beings like robots, humanoids, or other artificial intelligent (AI) devices, some of which could perfectly hold a fluent conversation and respond to voice instructions. AMELIA, the conversational AI, is the current market-leading solution that incorporates the main elements of human interaction (e.g., expressions, emotions, logical conversation, and understanding), enabling digital employees creation and delivering the "most engaging user experiences" (Amelia, 2022). The Intelligent Voice Assistants (VAs) are the most prominent technology and a fast-evolving disruption on human-computer interaction (Moriuchi, 2019). This technology has become of paramount importance on smart devices and is exponentially rising worldwide with over 8.4 billion VAs expected in 2024 (Laricchia, 2022).

Given the spreading technological development, VAs will certainly play a major role for marketers on brands' communication strategies, advertising effectiveness and purchase intentions. In fact, with the communication automation process, VAs sophistication growth is leading to personalized and assertive recommendations, contextualized conversations with consumers, which will certainly enhance consumer engagement with the brand (Hoy, 2018; McLean *et al*., 2021; Tassiello *et al*., 2021). However, how will advertising value be influenced by AI attributes?

Theoretical Background

Previous studies highlighted the relevance of future research on AI assistant features, such as human-like features (McLean *et al*., 2021; McLean & Osei-Frimpong, 2019; Schanke *et al*., 2021) or social presence (Park *et al*., 2022). Despite the attention given to in-home VAs, studies concerning the practice of advertisements through AI assistants are still in an early stage (Cho *et al*., 2019; Park *et al*., 2022; Paxton, 2019; Romero *et al*., 2021). Therefore, this study aims to overcoming this gap by conducting a study on the use of advertising through an AI assistant, the inherent effects and value perception, in the tourism context.

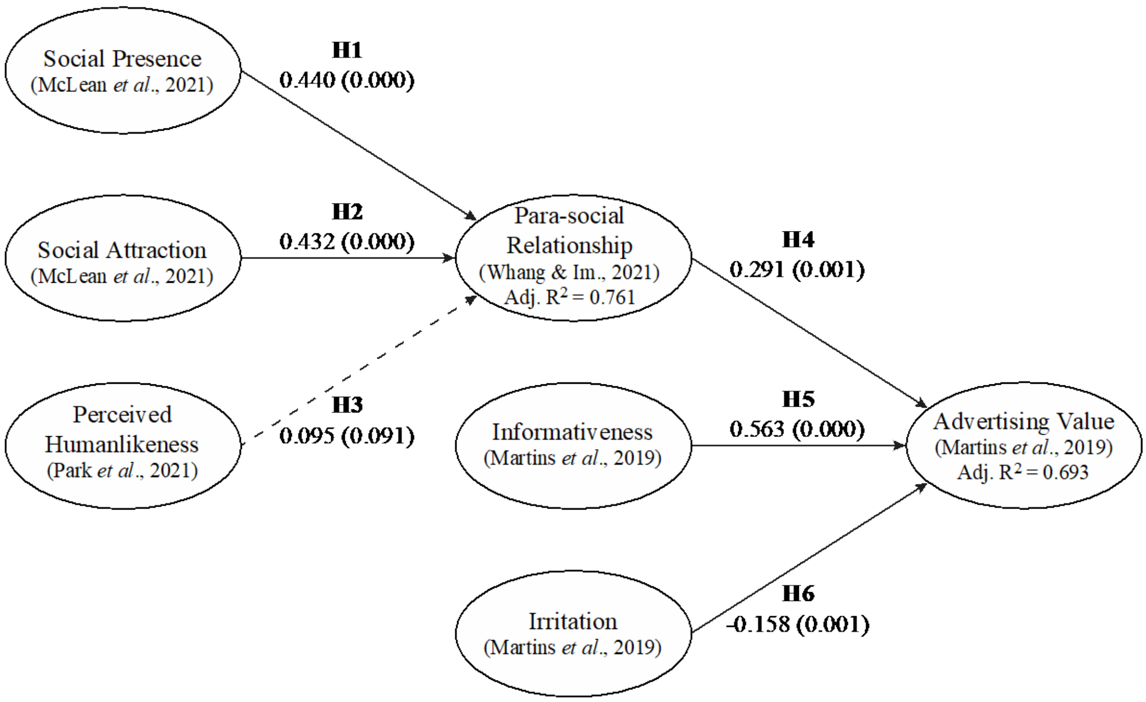
As VAs rely on human voice-based conversational interactions, users easily tend to anthropomorphize them (Whang & Im, 2021), eliciting social responses, including a sense of social presence defined by the degree of perceived presence of a communication partner (Biocca *et al*., 2003; Jacob *et al*., 2021). These human similarity cues, based on the "similarity-attraction" principle may convey social presence in the form of social attraction

(McLean *et al*., 2021; Nass & Moon, 2000). While imbuing the smart devices with human qualities, the non-human partner is perceived as humanlike (Park *et al*., 2021), a significant VA attribute and a prerequisite to parasocial relationship (Whang & Im, 2021). Parasocial relationships are gradually developed upon illusory human-to-human interactions (parasocial interactions) with the device (Horton & Wohl, 1956), creating a delusional interpersonal relationship such as friendship or of more intimacy. Hence, we suggest that VAs attributes such as social presence (**H1**), social attraction (**H2**), and perceived humanlikeness (**H3**) positively influence with parasocial relationship. Whang and Im (2021) established that consumers' decisions are significantly influenced by VAs product recommendations once a strong relationship is created, so we can posit that also the advertising value is positively influenced by parasocial relationship (**H4**). Grounded on Ducoffe's (1995, 1996) web advertising model, and by Martins *et al*. (2019), the informativeness (**H5**) is conceptualized as positively affecting advertising value, while irritation (**H6**) assumes a negative effect.

Methodology

For this study, a total of 142 Amazon Mechanical Turk (MTurk) VA users volunteered for survey in exchange for a monetary compensation. All constructs' measurement scales were adapted from previous research (see Figure 1), and the hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) on SmartPLS 3 (Hair *et al*., 2010).
The measurement model revealed itself as complying with the minimum thresholds, upon checking items' reliability (loadings higher than 0.7) and constructs' reliability (both Cronbach's alpha (CA) and composite reliability (CR) higher than 0.7) (Henseler *et al*., 2009). The convergent validity was evaluated by calculating the average variance extracted (AVE) being higher than 0.5 (Hair *et al*., 2010). For discriminant validity assessment, the Fornell-Larcker criterion (Fornell & Larcker, 1981), the cross-loadings comparison (Chin, 1998), and the Heterotrait-Monotrait ratio (HTMT) (Henseler *et al*., 2015) were analyzed. In this case, the authors opted to also confirm the discriminant validity results by calculating the new measure HTMT2 proposed by Roemer *et al*. (2021). The measure HTMT2 allows items' loadings of a construct to be different from each other, which turns out as more likely to hold in most scales, while HTMT does not, hence providing more accurate estimations of the correlations between latent variables. All HTMT2 values are below the 0.90 threshold, which supports the discriminant validity condition. For model's goodness-of-fit assessment, the absolute measure Standardized Root Mean Square Residual (SRMR) was calculated obtaining a value of 0.07, hence considered a good fit (Henseler *et al*., 2014; Hu & Bentler, 1998).
To test the structural model, the bootstrapping technique of 5,000 subsamples was used to estimate the statistical significance of model's path coefficients (Martins *et al*., 2019). The path coefficients ($\hat{\beta}$) and p-values are included in Figure 1.

Figure 1. Conceptual model and structural model results.



Results

Social presence ($\hat{\beta} = 0.440$, $p < 0.001$), social attraction ($\hat{\beta} = 0.432$, $p < 0.001$), and perceived humanlikeness ($\hat{\beta} = 0.095$, $p > 0.050$) explain 76.1% of parasocial relationship, even though perceived humanlikeness stands as non-significant. As for the advertising value, it is explained in 69.3% by parasocial relationship ($\hat{\beta} = 0.291$, $p < 0.010$), informativeness ($\hat{\beta} = 0.563$, $p < 0.001$), and irritation ($\hat{\beta} = -0.158$, $p < 0.010$). Advertising value is negatively influenced by irritation revealing itself as an inhibitor of the former.
This study intends to develop a framework to better understand the perceived value of advertising through intelligent VAs, and how the human voice as the anthropomorphic cue is reflected on AI attributes, and how their relationship with advertising value is mediated by parasocial relationship. Practically, this research aims to give insights to practitioners on how to build effective advertising strategies using VAs. In the tourism context, it is important to enhance to what extent this assertive technology can be used to advertise and recommend tourist destinations only voice-based, that mostly rely on visual cues to attract consumers.

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Chatbots as service recovery agent: the role of chatbot disclosure on perceived justice and forgiveness

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Type of manuscript: Extended abstract

Keywords: chatbot disclosure; service recovery; forgiveness.

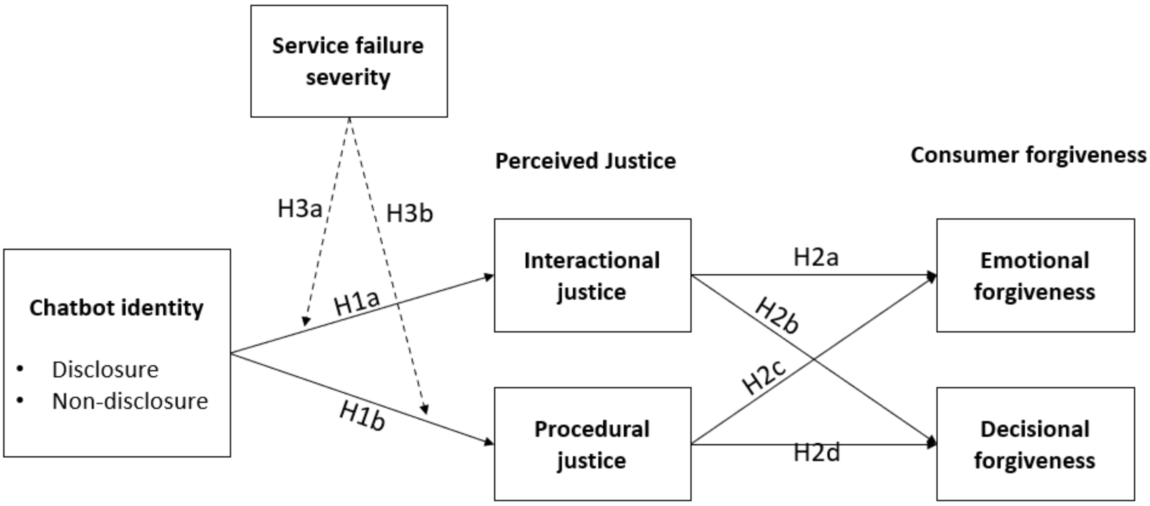
Chatbots have been increasingly implemented in online customer service settings such as retail (Cheng et al., 2021), hospitality (Um et al., 2020) and healthcare (Nadarzynski et al., 2019). While in the past chatbots were limited to answer Frequently Asked Questions they can now respond to complex situations or identify customers' emotions (Suhaili et al., 2021). Research has studied chatbots in various contexts through different stages of the customer journey, including customer experience (Chen et al., 2021), customer perceived values (Presti et al., 2021) and usage intentions (Park et al., 2021). However, limited literature has discussed how customers perceive the role of chatbots in the context of service recovery or post-purchasing.

Customers' perceived justice, especially procedural and interactional justice, directly impacts customer forgiveness. The more justice a customer perceives, the higher the likelihood for customers to forgive the fault parties (Muhammad, 2020). Therefore, we argue that interacting with a chatbot during service recovery might lower perceived justice and in turn lead to lower levels of forgiveness. However, when interacting with a highly anthropomorphic chatbot, customers might not be able to identify the machine identity and hence perceive the conversational partner as human staff, which could have different impacts on customer perceived justice and forgiveness. This raises the question whether the identity of chatbots should be disclosed and what impact disclosure may have in the service recovery context

However, companies are facing a dilemma of chatbot disclosure. On the one hand, scholars argue that the interaction process between chatbots and customers should be ethically transparent (Luo et al., 2019), which can reduce uncertainty and over-expectations (Leo & Huh, 2020). On the other hand, disclosing chatbots' identities has negative impacts on customer experience by reducing trust and social presence (Mozafari et al., 2020).

Only a few studies have discussed the role of chatbots in the service recovery context (McLean & Osei-Frimpong, 2019; Um et al., 2020), among which few studies covered chatbot disclosure, and service recovery is not their central topic of work (Cheng et al., 2021; Mozafari et al., 2020). Most of the literature on chatbot disclosure discusses the advantages and disadvantages of disclosing chatbot identities in a general context. The role of chatbot disclosure after service failures has yet to be explored. Therefore, this research is guided by three questions: 1) How does chatbot disclosure influence customers' perceived justice in the context of service recovery? 2) How does the perceived justice of a chatbot interaction during service recovery influence customer forgiveness and behavioural outcomes? 3) How does the severity of service failure moderate the effect of chatbot disclosure on customer forgiveness? Figure 1 presents the research framework and hypotheses.

Figure 1. Conceptual model



Methodology

This research will apply a 2x2 (chatbot disclosure vs. chatbot non-disclosure) x (high failure severity vs. low failure severity) between-subject scenario-based experiment in an online questionnaire setting. A sample of 250 US-based adults (18 years and older) will be recruited from MTurk. Participants will be randomly assigned to one of the four experimental conditions. After reading a service failure scenario, they will watch a video of a customer interacting with an online service agent and envision themselves in the role of the customer. Afterwards, participants will answer a questionnaire.

Discussion

It is envisioned that this study will make several important contributions to theory and practice. First, we identify the role of chatbot disclosure as service recovery agents. Prior research has found conflicting arguments about the importance of disclosure, which has created a dilemma for service organizations. Second, this study will add understanding of how perceived justice mediates the relationship between chatbot disclosure and customer forgiveness. Justice and forgiveness share complex relationships. This research will therefore contribute to the existing literature on the relationship between perceived justice and customer forgiveness. Third, this study will provide new insights regarding the moderating effect of service failure severity on the relationship between chatbot disclosure and customer forgiveness. Given the growing implementation of chatbots in frontline service encounters, this research will offer guidelines on if, and why, organizations should disclose or not disclose the identity (human vs. non-human) of the service recovery agent.

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Reshaping the Hospitality Industry by Technologies 4.0: The perspectives of top managers

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Type of manuscript: Extended abstract

Keywords: industry 4.0; emerging technology; technology adoption; smart hospitality.

Since Industry 4.0 was launched, every industry has gradually reshaped and transformed, and the hospitality industry was also inevitable. Buhalis and Leung (2018) mentioned that hospitality, a service-intensive industry, also needs Industry 4.0 technologies to form a new business operation model- smart hospitality that allows the stakeholders to interconnect and interoperate for better efficiency and effectiveness. There is a wide spectrum of views regarding the emerging technologies accompanied by Industry 4.0. Schwab (2016) mentioned the emerging technology of Industry 4.0, which covers wide-ranging categories such as AI, advanced robotics, internet of things (IoT), sensors, autonomous vehicles, 3D printing, nanotechnology, biotechnology, materials science, energy storage and quantum computing. Other 4.0 technologies, including simulation, horizontal and vertical system integration, cybersecurity, the cloud, augmented reality, big data and analytics, cyber-physical systems, blockchain, automation, computer-aided design and manufacturing, management information systems were also mentioned in the previous studies (Hsu, & Tseng, 2022; Sharma, Sehrawat, Daim, & Shaygan, 2021). Those technologies can form a corporate with smart service that can not only increase the operational efficiency, add value into business, and improve customer service experiences, and increase competitive advantages (Kabadayi et al., 2019).
However, there was rarely evidence to indicate the importance level and the possibility of adoption of Industry 4.0 technologies for the hospitality industry in the previous hospitality research that can help the practitioner improve their business sustainably (Frank et. al., 2019). Therefore, this study aims to explore the items of implementing Industry 4.0 technologies reshaping the hospitality industry for fixing the research gap and providing guidelines for practitioners to form smart hospitality.

Methodology

The research adopted literature review and Fuzzy Delphi Method (FDM) to extract the result. In the beginning, the authors conducted a comprehensive literature review on Industry 4.0 and its implications in the hospitality relevant field. After data collection, content analysis and research quality control methods were recruited to analyse the data and ensure trustworthiness (Graneheim & Lundman, 2004). After analysing and organizing the results from the literature review, a draft of Industry 4.0 technologies was extracted, and all of them had twelve items, including system integration: horizontal and vertical integration, cloud computing, Internet of Things (IoT), big data analytics, artificial intelligence (AI), automation and robots, extended reality (XR), additive manufacturing, simulation, cybersecurity, cyber-physical systems, and blockchain
Next, the author adopted FDM that serves as an efficient method to collect experts' opinions and consensus to confirme and validate the criteria (Murray, Pipino, and van Gigch, 1985).

Also, the purposive sampling was adopted, and the experts contained eighteen top managers who had more than 10 years of experience in the hospitality industry were invited to contribute their opinions. The FDM questionnaire was designed as a 10-level scale that asked about the technologies' importance level (from least important to most important) and possibility for adoption (from lowest possibility to highest possibility).

Conclusion

This study uncovered the importance level and the adoption possibility of 4.0 technologies for reshaping the hospitality industry through top managers' views and the outcome is shown in Table 1. The hospitality practitioners should implement the Industry 4.0 technologies uncovered in this research to reshape their business and take the steps to provide smart service.

Table 1. The FDM outcome

Technology	De-fuzzy Value	
	Importance	Possibility to adopt
System integration: Horizontal and Vertical integration	8.80	9.61
Cloud Computing	7.68	7.68
IoT	7.62	8.24
Big Data Analytics	7.97	7.67
AI	7.59	7.40
Automation and Robots	7.61	7.05
XR	7.39	7.23
Addictive Manufacturing	5.12	5.63
Simulation	6.51	6.25
Cyber-security	8.80	9.23
Cyber-physical systems	7.43	7.15
Blockchain	5.59	5.62

This article only uncovered the importance level and the adoption possibility of technologies 4.0 that can reshape the hospitality industry. However, the demands and tasks of a hospitality corporate and the implementation details should be further explored and constructed based on theories such as Task-technology fit theory for providing a more solid academic contribution. Moreover, the relationships between each technology can be further explored to provide a more straightforward path or more efficient understanding for hospitality practitioners to reduce costs and improve their ability to become "smart." This study only surveys the hospitality industry; however, many units in a smart hospitality ecosystem are wafting for further exploration because the "smart" investigation of different sectors or stakeholders is necessary and crucial for creating a complete network.

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Perception of avatar attitudes in Virtual Reality

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Virtual Reality (VR) has considerable potential in psychology and business when human behavior is under scrutiny. It's, therefore, no wonder that marketing research is so active in VR (Loureiro et al., 2019, Boyd and Koles, 2019, Beck et al., 2019, Bonetti et al., 2018).
Our project focuses on improving a very common business activity: speaking in public. It is well known that repeated training in front of an audience can help to improve speaking performances (Wallach et al., 2009). We, therefore, want to create a realistic, challenging, and interactive (as defined in Flavián et al., 2019) audience through AI-powered avatars. In this environment, the audience must be faithfully represented and correctly perceived and the VR environment itself must be truly immersive, Chollet et al. tried to understand in their work (2017) how participants perceive virtual audiences based on the nonverbal behavior of their members, also named avatars in this digital context. They explored which non-verbal behaviors are relevant to be perceived by the speaker as expressing high or low arousal and positive or negative attitude in terms of arousal and valence. However, their experiment was conducted on a 2D flat screen through the web and not in a fully VR (3D) setting. Furthermore, some work exists on how to improve the presence and immersion (Hyun and O'Keefe, 2012, and Hudson et al., 2019) and on how to stimulate additional emotions (Flavián et al., 2021, Collange and Guegan, 2020 but also Gabory and Chollet, 2020, and Mostajeran et al., 2020 in the public speaking context). However, to the best of our knowledge, a few studies (e.g. Amin et al. 2016) have compared the immersion between high-end and low-end headsets. Moreover, the presence and the immersion are real concerns when dealing with avatars and robots (Letheren et al., 2021 and Belanche, 2021a and b). However, too little had been done considering the quality of graphism used to represent the avatars.
Our research aims to fill in the identified gaps.

Our first goal is to build a library of animated avatars representing the most common attitudes and emotions of an audience as faithfully as possible. We use Chollet and Scherer's methodology (2017) to combine different body postures, facial expressions, and head movements such as to define various sets of potentially representative attitudes. We then measure how a speaker perceives them in VR through the concepts of valence (attractiveness and averseness) and arousal (level of alertness). Finally, based on these measures, the final step is to sort the different animations into categories corresponding to typical reactions to speeches of different qualities. In practice, we surveyed 125 adults in VR. They together rated the emotional valence and arousal of 40 animated sequences. Our second related question investigates whether fully rigged 3D photo-realistic models can significantly improve participants' perception of the avatar's arousal and valence or their confidence levels interpretation of the audience. To answer this question, four cartoon and four photo-realistic avatar models were designed in our lab. Each participant evaluated ten sequences out of the forty, featuring a cartoon model and ten sequences featuring a photo-realistic avatar. Finally, our last question investigates whether high-end or low-end headsets, like cardboards, impact the quality of immersion (four items of the Gatineau presence questionnaire) and the quality of the results. We expect better results with high-end headsets. However, if the difference in this context is limited, low-end headsets being extremely cheap, it would allow mass usage.

Regarding our first question, our study shows the associated valence and arousal for each parameter (posture and hands, facial expression, and head movements). Our results are coherent with Chollet's findings (2017), but in our case, for a 3D VR setting. Furthermore, among the combinations of behavior selected, we now have a library of avatar attitudes associated with some levels of valence and arousal. Moreover, we observe that some gestures dominate others and that links exist between valence and arousal. Thanks to these results, we know which animation to choose to represent a specific sentiment for the audience. Considering our second question, there is a positive impact of using photo-realistic avatars. While keeping the participants' judgment of valence and arousal unchanged, photo-realistic avatars improve their judgment's confidence level. Our results are coherent with Seymour et al.'s results (2021) about trustworthiness and affinity with human-realistic avatars. We expected that the assessment of the valence and the level of arousal would be changed, but this can probably be explained by a limited level of interactions in the setup. Regarding our last question, participants evaluated the level of arousal as higher when they used the high-end headset. Furthermore, the quality of immersion (the feeling of presence, the level of realism, and the spatial awareness) is improved when using a high-end headset instead of a low-end headset. Our results are coherent with Orús et al. (2021).

This research focused on investigating how people perceive a virtual audience delivered by VR technology and selecting attitudes to represent a set of audience reactions faithfully. We now have a library of avatar attitudes associated with some levels of valence and arousal.
This research is part of a three-step project to create a VR environment for public speaking training where the speaker will train himself in front of a realistic and challenging audience. We have already created different virtual rooms where participants will hold a presentation in front of a virtual audience. We have also started to work on automatic methods based on statistical, machine learning, and natural language processing methods to implement real-time biofeedback of the audience to the speaker's presentation. Even if the focus in this project is on speaking skills, the VR environment created can have many other applications to develop different business skills.
The project itself is part of a long-term project. We want to create a collaborative platform called *Eduverse* (a Metaverse for Education), where immersed users will train in totally controlled VR environments in front of two types of avatars: other participants (trainees, experts, teachers…) and Artificial Intelligence (AI) powered avatars (Butt, 2021).

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Analysis of seller`s persuasive styles impact on audience participation in a multi-brand live-streaming shopping event

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Live-streamed shopping transmit real-time audio and video information that allows online users to contemporaneously watch or share experiences, including buying or selling products (Thorburn, 2014), and it provides rich information to support the viewer´s decision-making process (Wongkitrungrueng *et al.,* 2020). In these environments, viewers can also engage in direct interactions with the anchor (i.e., the information sharer) and other viewers (Hamari & Sjo ̈blom, 2017). During each live-streamed shopping event, viewers can see the total number of viewers, hear interactive speeches, and engage in promotional activities (Xu *et al.,* 2021). Recently, we observed an increasingly rise of streaming functions on e-commerce shopping platforms such as Alibaba (Taobao) and Amazon (Cai *et al.,* 2018), and brands in different sectors like Burberry and Starbucks, are including streaming shopping in their marketing strategies (Wongkitrungrueng & Assarut, 2018).

Nonetheless, research of live streaming commerce is still at an early phase. Existing research examined the perspective of the audience, studying how host streamers may influence the viewers emotions and consequently purchasing decisions (Chen & Lin, 2018), or how co-viewers comments and recommendations provide informational, social, or emotional cues on consumer`s decision making processes (Hu *et al.,* 2017; Xu *et al*., 2020). Additionally, studies examined viewer's engagement in live-streaming commerce using S-O-R framework, relationship bonds or IT affordance theories (Wongkitrungrueng & Assarut, 2018; Sun *et al*., 2019; Hu & Chaudhry, 2020). However, to date, very limited empirical research has examined the seller`s perspective, when designing and planning their selling and product communication strategies in live-streaming shopping platforms. Previous studies relied mostly on quantitative approaches using self-reported questionnaires, to investigate customer decision-making process and purchasing responses. Accordingly, more accurate research related to actual seller´s perspective is needed.

Live streaming commerce can take place in three types of channels (Wongkitrungrueng & Assarut, 2018): (1) live streaming platforms incorporating commercial activities (e.g. Liveme) or platforms that offer services of livestreaming shopping, personal video shopper or shoppable videos to brands and influencers (e.g. Onlive.site); (2) e-commerce sites, marketplaces (e.g. Taobao), or mobile apps that integrate live streaming features (e.g. Talkshoplive, Shopshops), and (3) social networking sites (SNSs) that add live streaming features to facilitate selling (e.g. Facebook Live, Instagram Live).

This study focused on the first type of channel, in which sellers can create an event, in combination with other brands, to provide an environment with shopping and entertainment benefits. The main objective of this research is to understand how each brand participating in a multi-event of live streaming shopping, uses and implements different persuasive styles when communicating hedonic, utilitarian, or social values of their products or services. To achieve this overall objective, the following research questions are placed:

- What are the main similarities and differences between the brands, on the use of persuasive styles to communicate their product value in a stream-live shopping event?
- What type of product value brands communicated using a persuasive style, attained more viewers active participation?
- How the different types of stimuli used by each brand help them to gain higher consumer engagement during the ecommerce live event?

The study research context is an event carried out in Spain, during the month of February 2022, with the participation of ten brands of different sectors. During the live event transmitted by an online platform of livestreaming service, the brands used their anchors to perform shows, lasting 20 minutes for each brand, led by a stream host. The brands talked about their histories, values, products, provided selling incentives, interactive gaming and so forth. The live-stream shopping event was recorded using a screencast record software and had a length duration of four hours. The event recording includes number of viewers connected per hour, comments at the live chat, and viewers interactions with the brand´s anchors throughout the event. Based on a literature review, we developed a coding frame (Gaskell, 2000) to conduct the content analysis (Dimitrova *et al*., 2002; Wick & Harriger, 2018). The coding frame description is presented in Table 1.

Table 1. Description of the coding frame.

Categories	Main group	Subcategories	Descriptors
Host persuasive style (Luo et al., 2021)	Host/co-host appeals	Credibility	Mention to expertise, host personal experience in using the product; product description: colour, size, design, service, basic information and advantages and disadvantages.
		Rewards	Mentions to rewards: spiritual reward (value for money); and material reward (limited time seckill: the product is sold at a very low price in the live streaming room). The host distributes coupons and other benefits rewards to the audience.
		Emotions	Emotional stock: anchor utters “quick grab” and other emotion-stimulating phrases to the audience; real-time feedback on the stock of the product. Appealing to the hard work of the brand, requests or thanks sent by the host to the audience, etc.
		Logic	The host’s extreme description words such as “first”, “most”, “unique”, “super”, “amazing” “OMG” on commodities.
Product value type (shopping value) (Babin et al., 1994; Rintamaki et al., 2006)	Utilitarian	Authenticity	Seller´s face and expressions, background of the transmission (e.g., clothes, display) in a natural way, with no prior edition.
		Responsiveness	Questions consumers might place during the event; answers given by host or co-hosts.
		Visualization	Seller’s mentions of product usage, demonstrating how it works, explaining the consumers how it smells, textures, trying it on…
	Hedonic	Playfulness	Live Flash sales with discounts; content exploring behind the scenes aspects; live games and activities.
	Symbolic	Social identification	Comments viewers can make on the product, on the seller, providing real time feedback about their identification and sharing experience.
Stimuli to viewers Ha and Lam 2017; Liao et al., 2022	Types of stimuli	Streamer attractiveness	Comments related to streamer talent, style, personality, appearance.
		Parasocial interaction	Comments from streamer and viewers that give a sense of togetherness, and sense of friendship.
		Information quality	Comments related to product, experience, brand reliability (from viewers and from streamer), product trustiness.
Consumer engagement (Sashi, 2012; Van Doorn et al., 2010; Viglia et al., 2018).	Forms of engagement	Engagement behaviour	Comments on sellers’ content; comments on other viewers comments; emoji reactions to content of the live stream.
		Popularity	The number of concurrent customers of the live streaming room.

To ensure intercoder reliability (O´Connor & Joffe, 2020), two authors watched one hour of the video recording and independently coded the data to agree on the final coding frame (Campbell et al. 2013). The data video recording was uploaded to Atlas.ti v.9 to perform the content analysis. Results are discussed using the screenshots of the video content analysis, and quotations (audio and text chat) to support data analysis visualization. Current scientific research mostly focused on livestreaming shopping environments in China. So, it calls for expanded studies to consider different cultural backgrounds and methodological approaches.

This study answered this gap, as it is the first research to analyze this topic in the Spanish market. In addition, it expands the understanding of how brands communicate brand value and promote consumer engagement in these new emergent social and ecommerce environments. This study limits its analysis to the live interaction of ten brands in a streaming shopping event in Spain from the seller's perspective, however limited, it can provide a comparison of different brands in the same selling environment. It may contribute by expanding the literature of customer experience and brand engagement in ecommerce emerging platforms.

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Privacy-Personalization Paradox in Adoption of Facial Recognition Technology at Business Events

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Keywords: facial recognition; privacy-personalization paradox; technology adoption; perceived health risk.

Introduction

The utilization of facial recognition systems (FRS) at business events may have a significant impact on the event industry from the perspectives of decreasing the check-in time, controlling costs by reducing the number of check-in stations and temporary staff required (Event Manager Blog, 2018), as well as increasing security control at venues (Krueger, 2019). In the post-pandemic reality, customers may expect more non-contact technologies in hospitality services (Gursoy & Chi, 2020) to minimize their health risk, thus making the employment of contactless FRSs even more relevant. Also, FRS powered by artificial intelligence allows the personalization of the activities and services at events (Event Manager Blog, 2018; Krueger, 2019). Even though personalization may be an attractive service for business event attendees, they may not use FRS because of their privacy protection concerns (Chellappa & Sin, 2005). Despite practical importance, no empirical research has investigated adoption of FRSs at business events. Thus, this study aims to explore the privacy-personalization paradox in the context of FRS adoption by business event attendees. This study is designed to achieve its goal by investigating antecedents, such as performance expectancy, effort expectancy, perceived personalization, privacy concerns, perceived health risk, and trust in the system, that drive user intention to use this technology.

Methods

An online questionnaire was created for the purpose of this study. The questionnaire included a scenario that asked study participants to imagine using FRS at business events. The measurement items of the constructs were adapted from prior literature (e.g., Guo et al., 2016; Morosan, 2011; Morosan & DeFranko, 2016) to fit the context of using FRSs at business events.

The population of this study is adults 18 years old and older who reside in the US and have attended a business event within the last 24 months. The self-administrated questionnaire was distributed via MTurk. A total of 199 usable responses were used for further analysis. Confirmatory factor analysis was used to assess the measurement model, and partial least squares structural equation modeling (PLS-SEM) was conducted to test the hypothesized relationships and investigate the moderating effect of perceived health risk on other relationships in the model.

Findings and discussion

The study results showed that effort expectancy does not significantly affect the intention to use an FRS at business events. However, effort expectancy has a positive effect on performance expectancy, which, in turn, has a positive effect on the intention to use FRS. These findings suggest that business attendees intend to use the system if it is useful, efficient, and can easily and quickly grant access to the event facilities and services.

Further, perceived personalization does not have a statistically significant effect on the intention to use an FRSs at business events. However, the study found a positive effect of personalization on trust in the systems and a positive effect of trust on attendees' intention to use an FRSs at business events. These findings demonstrate that the promise of personalization, without attendees' trust in the system, will not drive user adoption of FRS at business events.

Also, the results of the study suggest that privacy concerns and perceived health risk do not have direct effects on trust and on the intention to use an FRS. These results are different from previous literature on this topic (e.g., Morosan, 2016; Pai et al., 2018) due to this study's unique context of FRSs at business events. However, according to Sarstedt et al. (2020), studies that use PLS-SEM rarely consider nonlinear effects. This study contributes to the literature by exploring the nonlinear nature of the relations between the model's constructs. The study reveals moderating effect of perceived health risk on the relationship between privacy concerns and trust, privacy concerns and intention to use the systems. The results suggest that trust in FRS and intention to use this technology at events differs for individuals with low and high health risks as privacy concerns pass a certain level.

Conclusions

This study contributes to an emerging research domain that evolves at the intersection of the fields of biometric technology and meeting and event management. FRS presents unique challenges for event planners, such as overcoming attendees' privacy concerns and promoting personalization and convenience resulting from biometric technology adoption. Despite practical significance, however, no study, to our knowledge, considered predicting acceptance of FRS in the context of business events. This study, therefore, proposed a new model of customer adoption of facial recognition and tested it in the field of meeting and event management.

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Implications of new technologies on consumer engagement

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Keywords: Internet of Things (IoT); Consumer Engagement; Consumer Behavior; New Technologies; Consumer Retention.

Purpose

New technologies will continue to create added values to companies that adapt, as it gives a competitive advantage that significantly influences consumer behavior (Rangaswamy et al., 2020). The customer's willingness to patronize the services of companies with the internet of things (IoT hereafter) enabled services through electronic channels gives the customer the 'control' over the business relationship with the company (Johnson, 2007). The concept of IoT has attracted a lot of attention, largely attributed to its importance due to its considerable internalization in our daily lives (Libai et al., 2020). Consumer engagement (CE hereafter), on the other hand, has equally gained some attention in recent times due to the dynamism in the academic, retail, business (Pansari and Kumar 2017) and practitioners' landscape (Dessart et al., 2017). With the advent of IoT, there has been a significant shift from human-to-human, human-to-machine, or machine-to-machine interactions (Bulmer et al., 2018).

Academic practitioners in recent times have highlighted several outlooks on the concept of IoT especially as it relates to new technologies, virtual reality, augmented reality, internet of things, artificial intelligence, robotics, drones, and autonomous driving (Pillai et al., 2020; Novak and Hoffman, 2019; Kamble et al., 2019). The (r)evolution in the retail space has been very intense due to its dynamic nature and further accelerated thanks to the recent global pandemic (Kotb and Adel, 2020). Hence, Nguyen and Simkin, (2017)'s clamor for further empirical reviews to examine the implications of IoT for an improved CE. While some researchers identified that the best consumer experience can be generated through the combination of human and technology-based services (Parasuraman et al., 2005; Reinders et al., 2008, 2015), Hoyer et al. (2020) and Rust (2020) further affirms the position of previous researchers in identifying this gap from an empirical standpoint.

The purpose of this paper is to propose an empirical model that can inform studies on the implications of new technologies on CE across different touchpoints in the retail landscape. In other words, will there be an increase in the level of consumer engagement because of machine-to-machine or human-to-machine relationships in retail marketing?

Previous research on IoT and CE have addressed a) the virtual customer environment, which encourages firms to enable innovation and value creation (Nambisan and Baron 2007); b) Kumar et al., (2019) adopted the S-D Logic of Hellebeek et al., (2016) to investigate CE in a service context by focusing on emerging markets; c) Gao and Bai, (2014) understood the significant of first attracting and then retaining IoT customers, established some factors that influenced consumer acceptance of IoT using the technology acceptance model (TAM) as a theoretical base. Other studies also focused on the direction of IoT and connectedness of consumer in a technology enabled world (Ng & Wakenshaw, 2017). Taking into consideration the importance of understanding the impact of IoT and new technologies in retail channels (Dhruv et al., 2017), it is pivotal to understand the influencing factors through a comprehensive empirical study and propose important managerial implications on how retailers and practitioners can further utilize IoT as an important value offering to consumers. This paper adopts a more rational approach by adapting the relationship investment model (RI) by Rusbult (1980).

Conceptual Model

Relationship investment model (RI) (Rusbult, 1980) suggests that the long-term persistence of an individual in a relationship is mediated by the commitment attached to it. The model was originally developed in social psychology to understand the human interpersonal relationships (Breivik and Thorbjornsen, 2008; Huang, Cheng, and Farn, 2007; Sung and Campbell, 2009). It has also been regarded as one of the most prominent and influential theories that explains commitment in relationships (Tran et al., 2019).

RI model is based on the principles of interdependence theory which is a viable framework for understanding the dynamics of dyadic interaction (Kelley et al., 2003; Kelley and Thibaut, 1978; Rusbult and Buunk, 1993; Rusbult and Van Lange, 2003; Thibaut and Kelley, 1959). The model has been used to describe the dispositional and contextual factors leading to specific patterns of interdependence (Kelley et al., 2003). The interdependence theory has been expansively used to explain how and why relationships are aided (Ogolsky, 2016). As an extension of the interdependence theory, RI model affirms that commitment is impacted by the outcome values of the current relationship and alternative, as well as the investment size (Rusbult, 1980; Rusbult et al., 1998).

RI model admits that commitment is a mediating factor that impacts satisfaction, quality of alternatives and investment size on relationship persistence (Rusbult, 1983; Rusbult, Martz, and Agnew, 1998). Previous studies revealed satisfaction, quality of alternatives and investment size as independent variables that predicts commitment as the dependent variables (Sung and Campbell, 2009; Sung and Choi, 2010; Rusbult, 1983). It has been established that an individual's commitment to a relationship increases to the extent that he or she is satisfied with the relationship, has unattractive alternatives, and has invested significantly in the relationship (Breivik and Thorbjornsen, 2008; Huang, et al., 2007; Rusbult, 1983; Sung and Choi, 2010). Invariably, satisfaction and investment have a positive effect on commitment while the quality of alternative has the opposite effect (Zainol et al., 2017).

Despite the considerable applicability and validity attributed to TAM (Alenezi, Abdul Karim and Vello, 2010), we need new theoretical foundations that could further explain this phenomenal from different perspectives, focusing on engagement and social aspect of consumer-brand relationship while adopting new technologies. We propose a conceptual framework and hypotheses to develop the study and observe the interrelationships between machine-to-machine and human-to-human relationship. (see Figure 1).

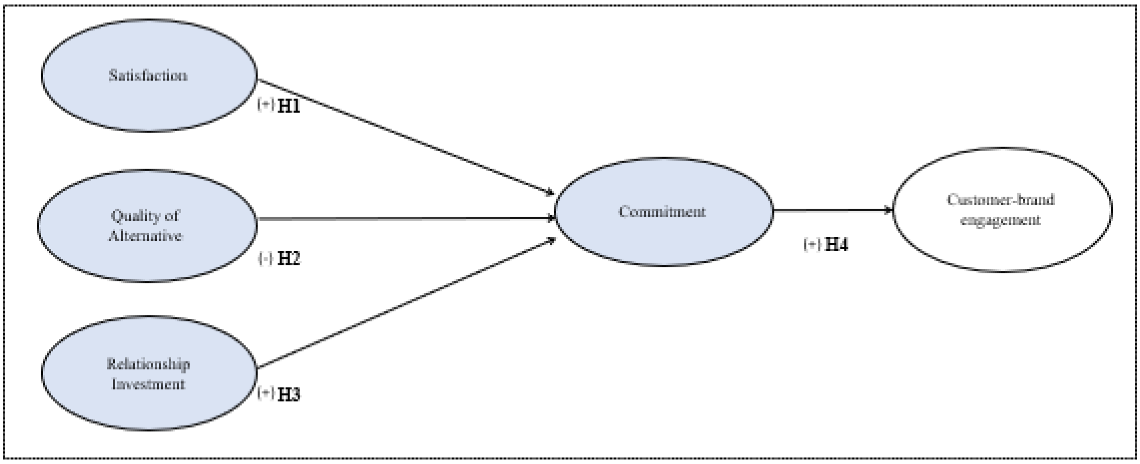

Fig. 1: The proposed relationships of this study

Satisfaction and CE

Satisfaction is regarded as the positive relationship derived between reward and cost (Tran et al., 2019). It is said to occur when the degree of reward obtained in a relationship outweighs the cost (Rusbult, 1980; Rusbult and Buunk, 1993; Rusbult et al., 1998). It describes the fulfilment and displeasure experienced by a person when compared to similar experiences. A satisfied customer reflects the excitement and typical desire of high customer engagement and trust (Gummerus et al., 2019; Brodie et al., 2013).
H1: Satisfaction with the use of IoT positively affects brand engagement.

Quality of alternative and CE

Impett et al. (2001) opined that quality of alternatives is an individual's subjective assessment of the rewards and costs that could be achieved outside the existing relationship (Impett et al., 2001; Rusbult et al., 1998). Quality of alternative can also be the judgement of the individual as regards the attractiveness of available alternatives (Rusbult and Buunk, 1993). We propose the below hypothesis:
H2: The quality of alternatives to the use of IoT is negatively associated with CE

Investment size and CE

Investment size can be regarded as the magnitude of resources invested into building a relationship (Sung and Campbell, 2009). Haron and Ismail, (2013) classified investment size into two types namely: 1) extrinsic investment which is where extraneous resources become inextricably connected to the relationship (e.g. memories, mutual friendship etc). 2) intrinsic investment these are resources directly invested into the relationship (e.g., time, emotional efforts, self-disclosures) (Rusbult, 1980a, 1983). This research examines investment from CE and IoT point of view.
H3: Perceived investment size associated with the implementation of IoT has a positive relationship towards CE

Commitment and CE

Commitment has been regarded to as the desire to persist in a relationship from a long-term perspective due to feelings of psychological attachment (Breivik and Thorbjørnsen, 2008). Gundlach, Achrol, and Mentzer (1995) remarked that commitment is an important element in maintaining a successful relationship between customer and brands (Morgan and Hunt, 1994). This research is interested in reviewing if consumers will despite long commitment in established relationship, opt for a more machine-to-machine relationships in view of the advent of IoT.

H4: Commitment to use IoT technologies is positively associated with CE

Implications

Despite the profound digital transformation, CE is undoubtedly still highly relevant in the retail space. Conceptualizing a model that proposes an accurate understanding of the impact of new technology on CE will further enable academics and practitioners to recognize to what extent consumers will prefer human-to-human vs machine-to-machine engagement. The rise in new technologies accelerates the need to understand CE, perspectives, and reactions.

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Effects of Perceived Risks on Innovation of Tourism Industry: The Case of Contactless Airline and Hotel Services

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Type of manuscript: Extended abstract

Keywords: innovation; perceived risk; theory of planned behavior.

In March 2020, COVID-19 was declared a global pandemic. The entire world closed all its borders and thus, national lockdowns were implemented (Chemli *et al.*, 2020). As a result, fewer tourists were travelling, particularly during the peak of the first wave of COVID-19 virus in the second half of 2020. As the borders were closed, most firms in the tourism and hospitality sector, which was the industry that suffered the most from the pandemic, were forced to close as well (Sigala, 2020).

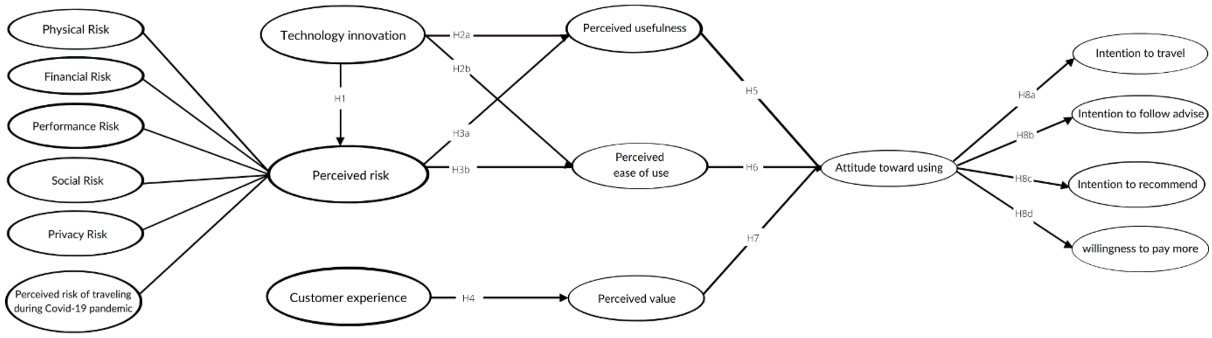
Due to the closure of a significant number of businesses that were gravely affected by the lack of tourists (Garrido-Moreno *et al*, 2021), used it as an opportunity to new possibilities for creativity and innovation (Sharma *et al.,* 2021). For businesses to thrive through a pandemic, they needed to find a creative way to attract more visitors. To succeed, it is suggested that these firms need to rethink how to address consumers' concerns and perceived risks, by implementing innovative features to respond to consumer´s issues regarding social distancing, hygiene, and safety (Fao, 2021). As the world recovers from the pandemic's economic impact, most travel and hospitality firms are turning to contactless airline and hotel services (Rahimizhian and Irani, 2020), to reduce health risks of COVID-19.
This innovation focuses on electronic and interactive services, to eliminate the need for face-to-face interaction with employees which could pose a health concern owing to airborne infections.

This includes voice control, motion detection, and mobile command (Garrido-Moreno *et al.,* 2021), which allow guests to control hotel amenities without interacting with hotel workers. Airline self-service kiosks situated at the airport have a built-in camera, for facial recognition and to easily scan the passengers' travel documents (Serrano *et al*., 2020). Auto temperature measurements, that are available for easy check-in to determine if the customer is not sick and suitable to travel. And thermal sensors, (Serrano *et al.,* 2020) a non-contact sensors that can measure short or long-distance infrared temperature, that are commonly used in airports.

This research will investigate how consumers react to innovative technology using the Theory of planned behaviour (TPB) (Azjen, 1985). The TPB is influenced by perceived risk, attitude towards using and perceived behavioural control.

After analyzing the factors associated with perceived risks and innovation, a theoretical model (fig.1) is developed to demonstrate the relationship between innovation technology, based on perceived risks, how consumers behave and adapt through technology on which the Technology Acceptance Model (TAM) (Davis, 1989) will be used, subsequently affecting satisfaction, intention to travel, and ultimately, willingness to pay an additional cost for innovation.

Figure 1 Theoretical model and hypotheses.



The items in the survey were slightly modified to adapt to the topic of contactless innovation in the tourism industry. All items are measured by a 5-point Likert scale ranging from "very unlikely" to "very likely.". The items for innovation were adapted from Ali *et al.* (2022) study. The perceived risk of travelling during COVID-19 pandemic is based on Sanchez-Cañizares *et. al.* (2021) study. Social risks were adapted from Yuan *et al.* (2021) articles. For performance and privacy risk, items were used from Yi *et al.* (2020) research. As for physical risk, items from Yang *et al*. (2017) were adapted. The items for customer experience from Hao *et al.* (2021) were used. For perceived usefulness and perceived ease of use, the scale from Cho *et al.* (2020) study is adapted. For perceived value, items from Han *et al.* (2017) are utilized. Attitude towards use is adapted from Sukendro *et al.* (2020) research. The scale developed by Sanchez-Cañizares *et al.* (2021) is adapted to measure intention to travel and willingness to pay. And lastly, for intention to recommend, items were adapted from Casalo *et al.* 2020.
This study intends to analyse the risks currently perceived by residents of Spain and the Philippines, and how these factors affect innovation in the tourism industry. Online survey that are based on the proposed model, will be distributed through social media with a disclaimer that only those who have travelled from 2020-present regionally and/or internationally can participate. The data collected will test the hypothesis using the Partial Least Squares (PLS) method. The suggested model will be tested using structural equation modelling (PLS-SEM), which allows for the addition of second-order constructs without causing the model to suffer from identification issues.

The managerial contributions of this research will be useful for hotels and airlines, and subsequently for the tourism industry. The findings will reveal how travellers react to technology that addresses their perceived risks and how this influences their willingness to pay for the expense of innovation. This will provide useful insights into how incorporating innovation technology will benefit both consumers and tourism firms.
This research will have academic implications on tourism and hospitality industry. This study aims to justify that the solution to meet the target consumer´s needs is through the use of contactless airline and hotel services.
The analysis of this model will determine the perception of consumers and their adaptability towards technological innovation, in the case of contactless hotel and airline services. The limitation of this study is that the investigation will be carried out in Spain and the Philippines including its survey respondents. A quota sampling method will be used to test the proposed model. Furthermore, future scholars should test the proposed model and be conducted in a different cultural setting, where consumers' perceptions and attitude towards using contactless technology differ.

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Virtual reality and other video types in destination marketing: Which one is more effective in attracting travelers?

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Type of manuscript: Extended abstract

Keywords: virtual reality, video types, tourism promotion.

Introduction

Virtual reality (VR) technology presents numerous opportunities not only for entertainment and gaming but also for marketing, sales, and employee training in different industries, including hospitality and tourism (Guttentag, 2010; Li-Xin, 2016; Tromp, 2017; Wagler & Hanus, 2018). However, companies that are interested in benefiting from VR have to invest in the creation of VR videos that come with a high price tag. Therefore, it is crucial for hospitality and tourism businesses to understand customer readiness to use VR tools and the effectiveness of VR as a marketing tool.
Hence, there seems to be a trade-off for the hospitality companies between jumping on the VR bandwagon and trying to improve sales and marketing by using this new technology, a sizable investment that should be made to create VR-ready content, and customer acceptance of VR technology. Given the opportunities and costs of VR technology and the availability of other media tools for the promotion of hospitality and tourism products, the purpose of this study is two-fold:

(1) Evaluate the effectiveness of VR, 360-degree, and regular videos in stimulating customer choice of hospitality and tourism products.
(2) Understand the factors influencing customer acceptance of VR, 360-degree, and regular videos for selecting and purchasing the hospitality and tourism products.

To address the first purpose, this research follows the media richness theory (Daft & Lengel, 1983; 1986) to explain the expected differences created by various video formats. To address the second purpose, this study relies on the technology acceptance model (TAM; Davis, 1989; Disztinger *et al.*, 2017; Li & Chen, 2019) and the flow theory (Csikszentmihalyi, 1990/1991) to predict behavioral intentions to visit a destination (BIVD) and to use a video type (BIUV) for tourism information search based on perceived ease of use, perceived usefulness, flow, self-location, and perceived possible actions.

Methods

This study used an experimental design where participants were randomly assigned to one of the three video types: VR, 360-degree, or regular. To account for potential destination effects, the study selected videos of several destinations: Bhutan, Moscow (Russia), Dubai (UAE), and Venice (Italy). The population of this study is adults 18 years old and older residing in the United States who traveled during the last 12 months. Participants for the VR condition were recruited in the lobbies of two branded hotels and online using the Qualtrics panel for two conditions with 360-degree and regular videos. All participants were asked to report their initial interest in visiting each of the destinations included in the study (pre-test), an intention to visit the destination after watching a video (post-test), their general travel behavior, responses to all core variables included in the study, and demographic information.

Findings and discussion

The study recruited a total sample of 291 respondents. The study participants reported different initial interest levels in visiting the selected destinations across all experimental conditions (in descending order): Venice, Dubai, Moscow, and Bhutan. However, after watching any type of video, no statistically significant differences were discovered in the interest in visiting different destinations. Therefore, the videos showed the ability to increase the interest in visiting a destination, however, such an effect has a different magnitude for different places.

To address the second purpose of the study, an SEM group comparison was used. The full structural model showed perceived usefulness, self-location, and perceived possible actions as statistically significant predictors of flow. The behavioral intentions to visit a destination were predicted by perceived usefulness, flow, and perceived possible actions. However, the behavioral intentions to use a specific video type for tourism information search was found to be an outcome of perceived ease of use, perceived usefulness, flow, and perceived possible actions.

Conclusions

This study compared the effectiveness of VR, 360-degree, and regular videos in promoting a destination. The results indicated that all video types were effective in increasing customer intentions to visit destinations and helped researchers reach an equal level of interest in visiting all destinations in the post-test. Therefore, destination marketing organizations may start with any type of promotional video when working with a limited budget.

These findings also suggest that a video that stimulates an interest in going to a destination should provide a meaningful viewing experience (to be perceived as useful), create the experience of flow when watching a video, and provide an opportunity to interact with the video (e.g., turn around, choose the path or attractions viewed, etc.).

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Barriers to full-adoption of digital payment methods: the mediating role of barrier-breakers

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Type of manuscript: Extended abstract (Old work-in-progress)

Keywords: full-adoption; barriers; barrier-breakers.

Introduction

It took 75 years for the adoption of telephone services to reach 50 million users, while the adoption of Internet services took just 4 years to reach the same number of users (Hannemyr, 2003). This illustrates the increasing rate of change linked to the ongoing development. The adoption of digital financial services, however, has been occurring at a slower rate than expected, even though the Covid-19 pandemic has played a significant role in pushing it forward (Flavián *et al*., 2020). Nevertheless, digitally driven societal change has encouraged bank customers to increasingly use digital payment methods (DPMs), which has resulted in a stage close to the full-adoption of DPMs (i.e. a cashless society) in some countries.

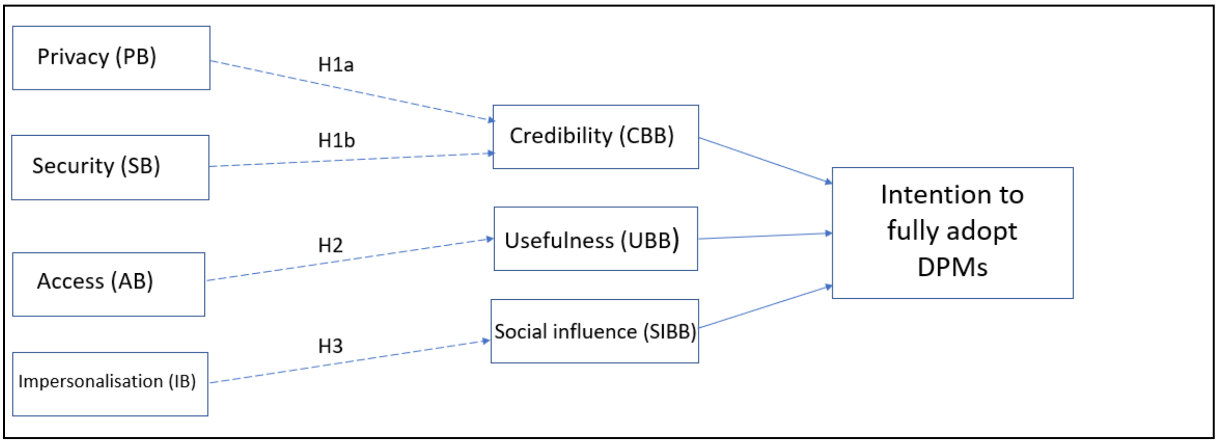
However, various groups of citizens still resist the full-adoption of common DPMs representing bank cards, Internet banking and mobile banking (Sveriges Riksbank, 2019), which eventually may leave them excluded from the payment system. Dimitrova *et al*. (2022) reported on a group of bank customers they called 'adopters-resisters' (ARs), who have adopted DPMs but still hesitate to increase their use of this technology.

The adoption of any technology are hindered by barriers (Moriuchi, 2021). In the DPM context, privacy, security and access barriers (PB, SB and AB) affect the perceived functionality (Shankar *et al*., 2020). The rapid transition from human-to-human to human-to-machine interaction has also highlighted the importance of social-psychological barriers such as impersonalisation (IB) (Dimitrova & Öhman, 2021).

In response to existing barriers, the positive influence of various barrier-breakers – credibility (CBB) (Gupta *et al*., 2019), usefulness (UBB) (Rajaobelina *et al*., 2021) and social influence (SIBB) (Moriuchi, 2021) – can help to increase the use of DPMs. Westaby's (2005) behavioural reasoning theory (BRT) suggests that it is possible to combine barriers and barrier-breakers under a single framework. In addition, the psychological theory of cognitive dissonance (Festinger, 1962) has been related to the negative influence of barriers on ARs (Oentoro, 2021). For example, cognitive dissonance occurs when a customer knows that online payments could be unsecured and tracked, but still chooses to pay online due to its convenience.

The purpose of this study is to examine the mediation effect of a number of barrier-breakers on the relationship between barriers and ARs' intention to fully adopt DPMs. Based on a BRT model, built on Gupta and Aroras' (2017) framework, and the psychological theory of cognitive dissonance, the research model and hypotheses are presented in Figure 1.

Figure 1. Research model



H1a: The CBB mediates and reduces the negative effect of the PB on ARs' intention to fully adopt DPMs.
H1b: The CBB mediates and reduces the negative effect of the SB on ARs' intention to fully adopt DPMs.
H2: The UBB mediates and reduces the negative effect of the AB on ARs' intention to fully adopt DPMs.
H3: The SIBB mediates and reduces the negative effect of the IB on ARs' intention to fully adopt DPMs.

Methodology

Data was collected via an online questionnaire sent to a Swedish group of bank customers known as 'cash rebellion', who represent the ARs in this study. The questionnaire was distributed via a social media platform to reach the active followers (estimated to be 1600). A response rate of 24.2% was reached, based on the 388 completed responses. The main section consisted of Likert scale questions, graded from 'Agree' (1) to 'Not agree' (4) to prevent respondents from just selecting the mid-point (cf. Nadler *et al.*, 2015).
Fornell and Larcker's (1981) approach were applied for measuring the square roots of the average variance extracted (AVE) for every factor, respective discriminant validity (DV) and composite reliability (CR). For five of the seven constructs, the AVE was above the threshold of 0.50. In addition to Cronbach's α, the CR values of above 0.859 (for barriers) and 0.788 (for barrier-breakers) confirmed the internal consistency. A variance inflation factor (VIF) was measured for a multicollinearity test. To test the hypotheses, serial mediation analyses were conducted via the software extension PROCESS macro (cf. Hayes, 2018).

Results and conclusion

The total effect relationship for PB has the coefficient b = -0.0727 (p = 0.000); after the mediator CBB, the coefficient decreases (b = -0.0107, SE = 0.0044; 95% CI from -0.0200 to -0.0029), supporting H1a. Also the SB coefficient (b = -0.0426 (p = 0.000)) decreases after the mediator CBB (b = -0.0119, SE = 0.0049; 95% CI from -0.0221 to -0.0028). Therefore, H1b is supported. The total effect relationship for AB has the coefficient b = -0.0628 (p = 0.000); after the mediator UBB, the coefficient decreases (b = -0.0121, SE = 0.0047; 95% CI from -0.0218 to -0.0039), meaning that H2 is supported. The fourth mediation analysis indicates that the SIBB does not mediate the relationship between the IB and the intention to fully adopt DPMs, since the model is not significant (p = 0.3566) and zero is between the CI. The total effect relationship has the coefficient b = -0.0779; after the mediator SIBB, the coefficient remains approximately the same causing the following indirect relationship (b = -

0.0004, *SE* = 0.0026; 95% CI from -0.0059 to 0.0047). Consequently, H3 is rejected.
The results show that the privacy, security and access barriers can be reduced by increasing the credibility and usefulness barrier-breakers, respectively. The impersonalisation barrier was found to be unaffected by the social influence barrier-breaker in regard to ARs' intention to fully adopt DPMs. In other words, communication with and advice from friends, family and co-workers could not reduce the negative effect of the lack of human-to-human service providing sympathy and empathy, which is in line with the work of Belanche *et al*. (2021). A possible explanation is that the group of ARs perceive the IB to be so decisive that it cannot be balanced by social influence.

Originality
This study contributes to the literature on technology resistance. A BRT model was empirically measured, and the credibility and usefulness barrier-breakers were found important in achieving a possible cashless society. At the same time, impersonalisation seems to be a barrier to overcome. Although the results indicate the difficulty to completely remove all barriers, new regulations for DPMs can be implemented to address the most important ones. For example, mobile applications are still locally limited (Ng *et al*., 2021) and depend on each merchant's choices. Another novelty of the paper is the relation of adopters-resisters to cognitive dissonance theory since the coexistence of adoption and resistance (cf. Ram, 1987) may cause an internal conflict and a mental discomfort which may hinder the DPM full-adoption process.

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Together or Alone: Should Service Robots and Frontline Employees Cooperate at the POS?

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Type of manuscript: Extended abstract

Keywords: service robot; frontline employee; social presence; retail; field study; POS conversion funnel.

The purpose of this study is to empirically investigate how shoppers behave when interacting with an employee-robot team (vs. both actors in isolation), along the metrics of the POS conversion funnel. The study comprises an unobtrusive field study, involving 40 hours of video observations. The footage was evenly spread over four conditions: (1) a control condition (i.e., no stimulus), (2) a frontline employee, (3) a humanoid service robot, and (4) an employee-robot team. Passersby were systematically coded and their interactions were registered. The study found that a service robot is the better option to generate attention and stop passersby, but in this condition the least amount of passersby actually visited the store. The frontline employee was found to be the most effective in converting passersby into actual buyers, but passersby seemed to generally avoid the employee. The robot-employee team performed the best in terms of convincing passersby to look at the store, but not in terms of conversion rate. Theoretically, we advance the understanding of shopper behavior towards an employee-robot team. Actual shopper behavior is measured, and categorized along the consecutive stages of the POS conversion funnel.

Introduction

The service encounter used to be a people's game, but frontline employees are ever more being augmented or substituted by technologies (Belanche et al., 2020). One of those emerging technologies are service robots (Wirtz et al., 2018). Van Doorn et al. (2017) provide a dichotomization of automated social presence (ASP, or "the extent to which technology makes the customer feel the presence of another social entity", p. 743) vs. human social presence (HSP, or "the sense of being with another"; Biocca et al. 2003, p. 456). In this regard, the service encounter can be categorized by low levels of both ASP/HSP (e.g., traditional self-service terminals), low HSP/high ASP (e.g., humanoid service robots), low ASP/high HSP (e.g., Skype calls) or high levels of both ASP/HSP (e.g., service robots helping nurses in elderly care). Few studies have examined customer behavior towards a service encounter where employees and services robots *work together* (e.g., Yoganathan et al. 2021). Most studies are scenario-based, and gauge for intentions instead of actual customer behavior.

Research objective and hypotheses

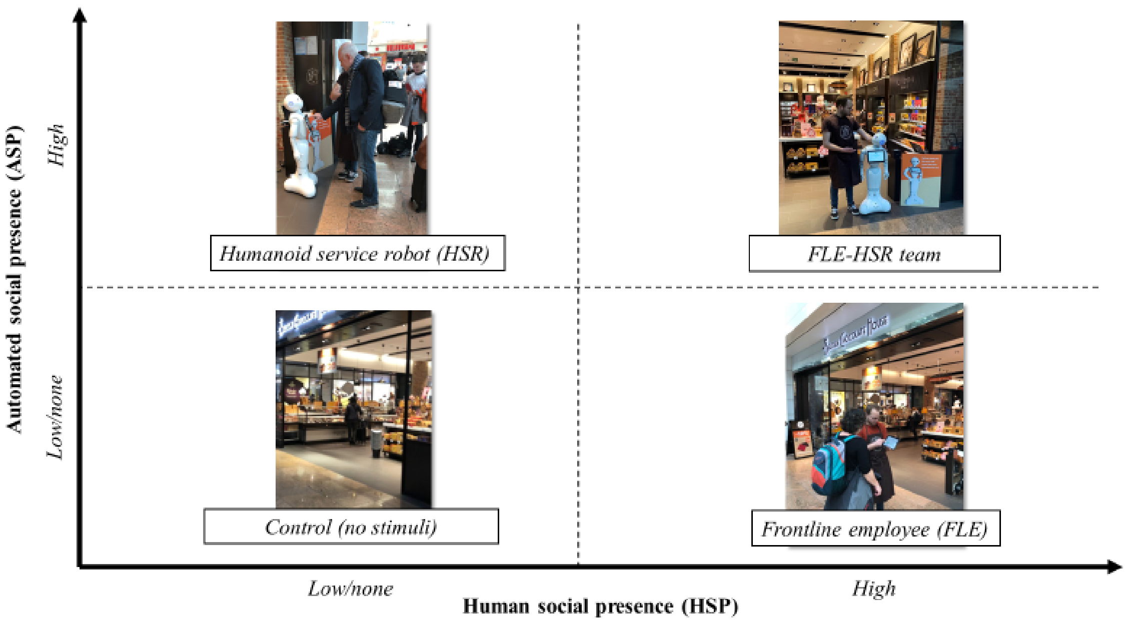
We compare the conversion power of an FLE, an HSR, and an FLE-HSR team along four sequential stages in the POS conversion funnel (Brengman et al. 2021):

(1) *Stopping power* – stopping passersby and engage them into an interaction
(2) *Engaging power* – interaction times and looking at the store
(3) *Attraction power* – entering the store
(4) *Selling power* – transactions and amount spent

Methodology

A 2x2 between-subjects experimental field study comprising unobtrusive observations was conducted at a Belgian airport chocolate store (Figure 1). Three surveillance cameras monitored passersby's behavior. A total of 89,243 passersby was captured in 40 hours footage ($N_{CONTROL}$ = 26,451; N_{FLE} = 22,701; N_{HSR} = 17,784, N_{TEAM} = 22,307). In total, 393 interactions were registered (N_{FLE} = 42; N_{HSR} = 239, N_{TEAM} = 112).

Figure 1. Experimental design of the field study



Analyses and results

Stopping power

The HSR was able to attract the highest amount of passersby to an interaction (1.34%), followed by the TEAM (0.50%), and lastly the FLE (0.19%), Pearson $\chi^2(2, 62792)$ = 223.854, $p < .001$.

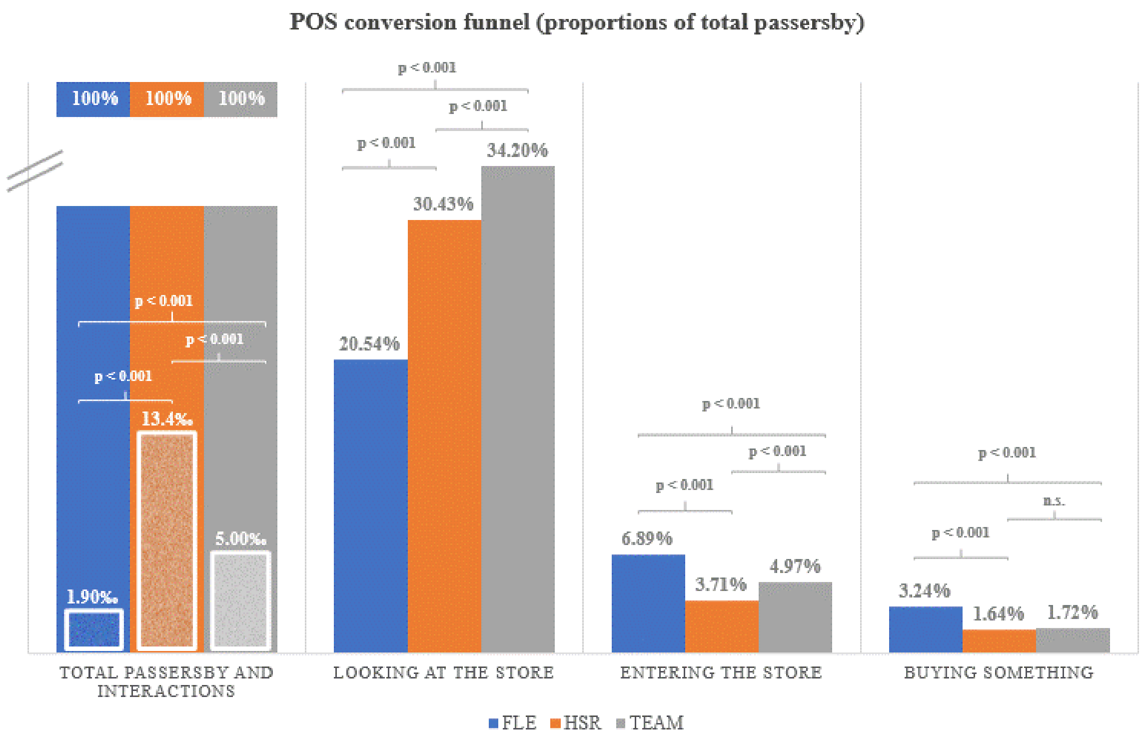
Engaging power

An ANOVA indicated a significant difference in interaction times between the three conditions, F(2,393) = 12.822, $p < .001$. The mean interaction time did not differ between the FLE and HSR conditions. Both FLE and HSR conditions did significantly differ from the TEAM condition.

The TEAM elicited the highest amount of passersby looking at the store (34.20%), followed by the HSR (30.43%), and lastly the FLE (20.54%), $\chi^2(3, 89243)$ = 1421.706, $p < .001$.

Attraction power
A larger proportion of passersby entered the store when the FLE was present (6.89%), followed by the TEAM (4.97%), and lastly the HSR (3.71%), $\chi^2(3, 89243) = 212.497$, $p < .001$.
4.4. Selling power
The proportion of passersby buying something in the store differed significantly across the four conditions, $\chi^2(3, 89243)$ 167.309, $p < .001$. The FLE (3.24%) scored higher than the HSR (1.64%; $\chi^2[1, 40485] = 103.537$, $p < .001$) and TEAM (1.72%; $\chi^2(1, 45008) = 106.700$, $p < .001$) conditions. The HSR and TEAM did not significantly differ.
The average amount spent per transaction did not significantly differ between the control, HSR, and TEAM conditions.

Figure 2. POS conversion funnel (proportions of total passersby). Note: # passersby = 100% (N_{FLE} = 22,701; N_{HSR} = 17,784; N_{TEAM} = 22,307); # interactions is shown on top of the total passersby bar (‰)



Discussion
Stopping power. Eliciting less social pressure (Song et al., 2021), the HSR can convince most passersby to engage in an interaction and it excels in attracting *groups*.
Engaging power. While fewer passersby started an interaction with the TEAM vs. with the HSR, more passersby looked at the store when the TEAM was present. Passersby seem to avoid interacting with the FLE, looking away from the him, and from the storefront.
Attraction power. The highest number of passersby actually entered the store when the FLE was present. The HSR seems to be perceived of as a 'gimmick' and 'attention grabber' but couldn't match the human FLE as conversation builder.
Selling power. The FLE performed best in terms of selling power. The TEAM yielded inferior results to the control condition.
Our study advises managers to mind their specific conversion goals upon deciding whether or not to invest in service robots. A service robot is useful to create a "buzz effect" (i.e., attention towards the store, e.g. upon store opening), but human FLEs are better to convert

passersby into buyers.

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Humans and/or robots? Tourists' preferences towards the humans-robots mix in the service delivery system

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Type of manuscript: Extended abstract

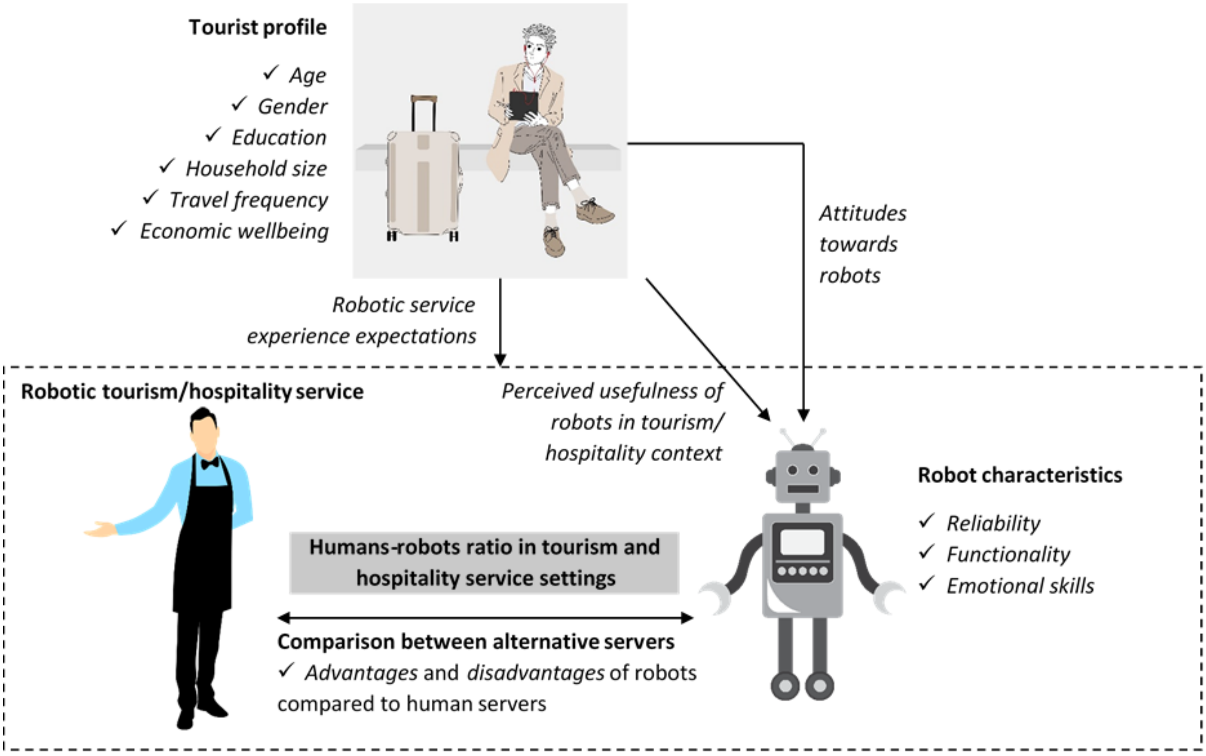
Keywords: humans-robots ratio; service delivery system; tourism.

This paper tries to answer the question: *How much automation in tourism and hospitality is too much automation*? It investigates tourists' preferences toward the humans-robots ratio in the service delivery systems of tourism and hospitality companies and the factors that shape them. The topic is important because the use of robots in the service delivery systems of tourism and hospitality companies impacts the perceived service quality (Chiang & Trimi, 2020) and tourists' experience (Tuomi, Tussyadiah, & Stienmetz, 2021). Thus, knowing tourists' preferences towards the humans-robots mix would allow companies to use the optimal number of robots in their service delivery systems and avoid the 'too much automation' problem. This is especially important in hospitality where the intimate and interactive relationship between service providers and consumers (Kandampully & Duddy, 2001) and the politeness and empathy in the service delivery process (Marković et al., 2013) are vital for the tourists' experience.

Based on the review of the literature (e.g. Chuah & Yu, 2021; Ivanov, Webster & Garenko, 2018; Reich & Eyssel, 2013; Tung & Au, 2018; Tussyadiah, Zach & Wang, 2017; Webster & Ivanov, 2021; Wirtz et al., 2018; Zhong et al., 2022, among other sources) the authors developed 15 hypotheses presented in Table 1. In general, the hypotheses state that tourists' preferences towards a higher share of robots in the service delivery systems of tourism and hospitality companies will be:

- *positively* related to robots' characteristics (their reliability, functionality, emotional skills), the perceived advantages of robots as servers compared to humans, the robotic experience expectations of tourists, robots' usefulness and tourists' attitudes towards robots;
- *negatively* related to the perceived disadvantages of robots as servers compared to humans;
- shaped by the demographic characteristics of respondents.

Figure 1. Drivers of the humans-robots ratio in the service delivery systems of tourism and hospitality companies



This research presents part of the findings from a global survey on robots in tourism. The sample includes 1537 respondents from nearly 100 countries. Data were collected during the period March 2018-October 2019. Factor and regression analyses were implemented. The findings are presented in Table 1. The results show that a higher preferred share of robots is positively associated with the perceived emotional skills of robots, their perceived usefulness in the tourism/hospitality context, perceived robotic service expectations, attitudes towards robots in general, and the male gender. On the other side, it is negatively associated with the perceived disadvantages of robots compared to human servers and the household size of respondents.

Table 1. Summary of hypotheses outcomes

Hypothesis	Outcome
H1: Perceived service robot reliability is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Not supported
H2: Perceived service robot functionality is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Not supported
H3: Perceived emotional skills of service robots are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported
H4: Perceived service robot advantages compared to human employees	Not

are positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	supported
H5: Perceived service robot disadvantages compared to human employees are negatively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported
H6: Tourists' robotic service experience expectations are positively related to their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported
H7: Perceived service robot usefulness in the tourism/hospitality context is positively related to tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported
H8: Tourists' attitude towards robots is positively related to their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported
H9.1: Gender shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported
H9.2: Age shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Not supported
H9.3: Household size shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Mixed results
H9.4: Education shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Not supported
H9.5: Economic wellbeing shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Not supported
H9.6: Travel frequency shapes tourists' preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Not supported
H10: Different clusters of tourists exist based on their preferences towards the share of robots in the service delivery systems of tourism and hospitality companies.	Supported

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When is artificial intelligence "too intelligent"? A critical thresholds approach in retail service

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Type of manuscript: Extended abstract

Keywords: AI; critical thresholds; retail service; consumers' reaction; emotions; cognitive absorption; control.

Despite the benefits of artificial intelligence (AI) in marketing, service, and retail (Davenport et al., 2020; Balakrishnan and Dwivedi, 2021; Bertacchini et al., 2017; Huang & Rust 2021a, b), an increasing research stream is focusing on the potential negative effects of AI (Pitardi et al., 2022; Lobschat et al., 2021; Xiao & Kumar, 2021).

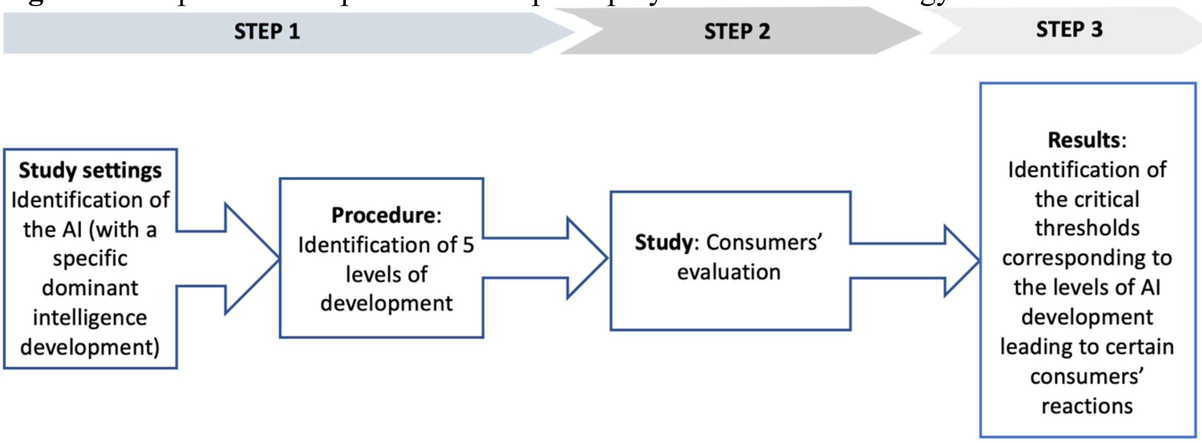
Thus, there is a need of deeper understanding of the level of AI developments that still ensure a level of benefits for consumers, to limit future "risky" developments that would be counterproductive for service providers, retailers, and consumers. Drawing upon the critical thresholds approach used in physics to describe the mechanism that induces a dramatic status change (Duan et al., 2014), this research aims at figuring out the critical level of developments of AI for retail service that lead to specific positive/negative consumers' reations. In other words, the critical thresholds consists of the levels or values beyond which a change in the behaviour of a certain complex network occurs. Accordingly, the critical thresholds approach has been used to predict cascading failure in network grids (Li et al., 2014), the diffusion of epidemic outbreaks (Huang et al. 2009), and the habitat loss for certain species (Swift & Hannon, 2010).

Moreover, past studies already demonstrated that AI interactions with consumers would generate both positive and negative reactions (Pantano & Scarpi, 2022). Similarly, different AI types generate different emotions in the consumers interacting with them (Pantano & Scarpi, 2022). Also, AI could range from being completely under the user's control to completely independent. We add here that AI can be at different development stages (i.e., more or less "intelligent"), which might affect how consumers react to it.

In this research, we consider only the logic-mathematical intelligence from Pantano and Scarpi (2022) classification. It consists of the machine's ability to solve analytical problems requiring logical thinking (Huang & Rust, 2018). Since the first application in a computer, the complexity of the calculus able to be solved increased with the time. Thanks to this intelligence, machine can also make autonomous decisions based on the results of the calculus and adapt their behaivour accordingly (Wirtz et al., 2018). For instance, systems for selecting the best driving route are equipped with this kind of intelligence type, due to their ability to evaluate the traffic in real time and suggest better routes to reduce the cost and time of the journey (i.e., BMV Connected Drive service). Thus, this intelligence is similar to the human ones able to analyze situations and problems logically and find possible solutions accordingly.

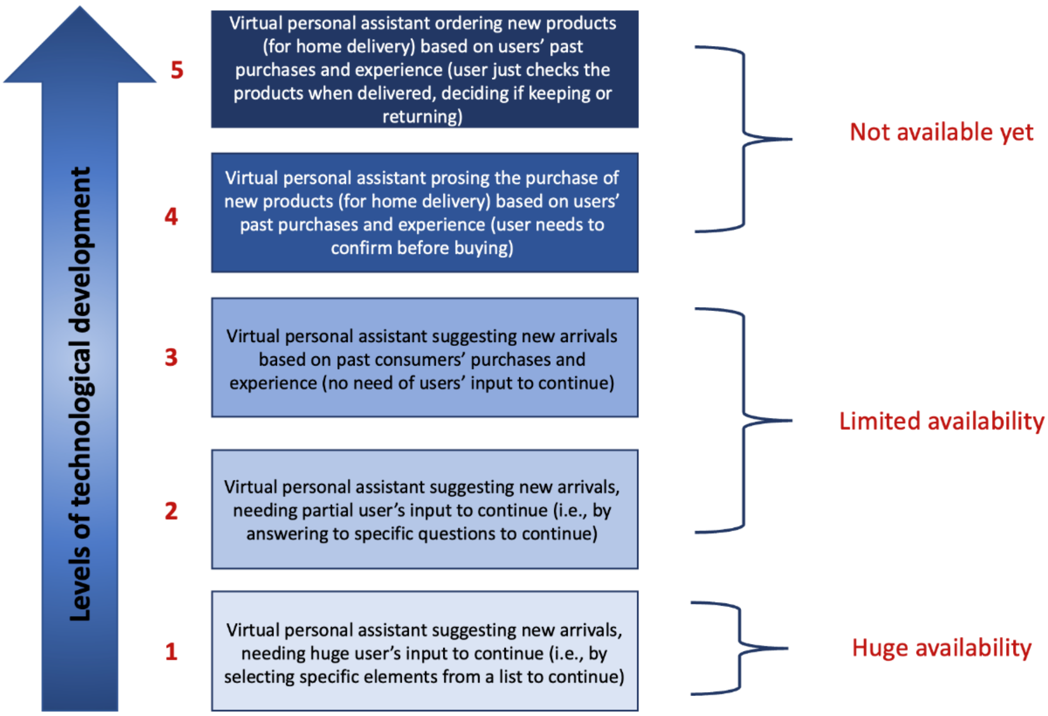
This research is based on a 3 step approach (Figure 1): i) identification of the AI and five (possible) different levels of development; ii) consumers' evaluation; and iii) identification of the critical thresholds corresponding to the levels of AI development leading to certain consumers' reactions.

Figure 1. Graphical description of the steps employed in the methodology.



This study considers an AI embedded with the logic-mathematical intelligence type (like virtual personal assisntants), where AI's development level is manipulated to range from 1 (very low logic-mathematical intelligence) to 5 (very high logic-mathematical intelligence) (Figure 2).

Figure 2. Technology with five different levels of development (critical thresholds).



We involve 300 individuals interacting with the AI at different development levels. Thus, we measure consumers' reactions in terms of positive and negative emotions (Klonsky et al., 2019), satisfaction (Lim et al., 2019), technology continuation intention (Balakrishnan and Dwivedi 2021), emotional attachment to the retailer (Sánchez-Fernández & Jiménez-Castillo, 2021), and cognitive absorption. The latter comprises temporal dissociation, focused immersion, enjoyment, control, and curiosity (Balakrishnan & Dwivedi, 2021).

Our research contributes by (i) identifying three critical thresholds of AI in retail service, showing the effects on emotions, attachment, satisfaction, continuance intention, and cognitive absorption; (ii) showing if and when an AI can become "too" intelligent; (iii) bringing the literature on critical thresholds, which is well-established in physics, into the domain of service research by showing an application for thresholds identification in service; and (iv) showing the extent to which a specific AI solicits a specific range and intensity of human emotions.

Finally, we believe that service managers could use these findings as a guideline to develop more efficient AI and avoid AI implementation backfiring on their consumers. Specifically, our outcomes would help retailers deciding whethere or not apply the certain AI, since each thresholds represent the level beyod which consumers react negatively to the interaction with the AI.

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Anthropomorphic Service Robot Design: The Impact of Linguistic Human Cues on Customer Reactions

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Purpose
Customers are increasingly confronted with service robots. Unlike machines such as self-scans and ATMs, service robots are typically anthropomorphized (i.e., being experienced by customers as being more “humanlike” than “machinelike”) because of their design. Indeed, existing research showed that customers are more likely to imbue human characteristics to robots when their embodiment is more humanoid compared to the mechanic. Despite its importance, service robot research has yet not focused on the anthropomorphic design caused by linguistic human cues. This is surprising since machines such as service robots also need to communicate with customers to provide the service, such that verbal communication features (e.g., tone, speed, pitch and excitement) become prevalent. Like the service robot’s appearance (i.e., hardware), the speech of the service robot (i.e., software) can be designed to be more humanlike versus machinelike. In addition, the service robot literature to date has merely relied on population-averaged research methods (such as SEM or regression models), thereby ignoring that different routes may lead to the same favorable destination (here, customer experiences). To overcome this limitation, complexity and configuration theory in tandem with new methods such as Fuzzy-set Qualitative Comparative Analysis (fsQCA) have been recently proposed in the management literature as “a novel methodological approach to unveil the complexity behind the adoption of service robots”. By bridging the service robots, communication, complexity and configuration literature, the current research aims to unravel the complexity of the relationship between the service robot’s linguistic human cues and customers’ service robot experience.

Design
This study makes use of the Fuzzy-set Qualitative Comparative Analysis (fsQCA) technique to detect contrarian cases, and various routes that can lead to favorable service robot experience, thereby allowing alternative routes that deviate from population-averaged findings, which are investigated by means of Partial Least Squares Structural Equation Modeling (PLS-SEM). The results of PLS-SEM as a benchmark show that if managers only rely on the population-averaged results may lead to some inappropriate decisions. In total 360 subjects participated in our studies, which focuses on the hospitality industry (here, check-in and restaurant at the airport).

Findings
Our pretest confirms that it is both viable (here, by using a voice simulator) and realistic (i.e., scenario realism) to manipulate the linguistic cues of a service robot, in which a more

anthropomorphized linguistic design is associated with a more extraverted service robot personality overall – in line with the communications literature.

Our fsQCA's results provide further evidence that alternative routes of service robot design x customer personality x service encounter type x anthropomorphism level can lead to favorable customer outcomes, which means that no single best solution exists, but that there are multiple and equally important casual configurations to lead to the favorable service robot experiences. In addition, our fsQCA findings also reveal that perceived anthropomorphism is the necessary but insufficient condition that leads to the favorable service robot experiences. In addition, we find evidence of a heterophily effect between the service robot's linguistic cues (that are a proxy for the service robot's personality according the communication literature) and the customer's personality, and also a complementary effect between the service robot's linguistic cues and different service settings (here, hedonic versus utilitarian service setting) is shown to be crucial.

The PLS-SEM results, that serve as a benchmark in this study, further unveil that a more extroverted service robot is associated with more warmth, competence, and overall experience, but also more discomfort. These relationships are mediated via the perceived anthropomorphism of the service robot. In addition, our results show that contextual effects matter, since overall a heterophily effect (i.e., when the service robot and the customer have opposite personality traits with regard to extraversion/introversion) and hedonic (vs. utilitarian) service encounters result in better customer outcomes.

Implications

The personality of a customer or a human service provider is difficult to manipulate; in the contract, the personality trait of service robots can be easily manipulated by design as it relates to the anthropomorphic linguistic cues. Our findings help managers to better understand which linguistic cues lead to the best outcomes, thereby taking individual and situational contextual heterogeneity into consideration, and relying on complexity and configuration theory.

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Consumer experience with voice-based artificial intelligence: exploring voice love and its acoustic origins

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Introduction
Ever felt stimulated by a voice on the phone, or fallen in love with a radio personality's voice? We ask whether voice assistants could be the next conduit for consumer pleasure? Consumers are increasingly interacting with voice-based artificial intelligence such as voice assistants (e.g., Amazon's Alexa). Prior research has shown that artificial intelligence technologies may foster intimate bonds with their users, including sentiments of pleasure and love (Levy, 2007; Yaklarasimlar, 2018). In the specific case of voice-based artificial intelligence the interaction is purely vocal. Prior research in psychology has shown that the vocal characteristics of a speaker can induce powerful affect, such as pleasure and attraction, in listeners. However, this remains to be proven in the field of voice-based artificial intelligence (VBAI). This paper therefore investigates the vocal characteristics of AI voices to understand their effect on consumers and how they generate affect. We first conduct a multidisciplinary literature review on the experiences of consumers with VBAI as well as on voice perception and then employ a mixed method using psychoacoustic analysis to examine the vocal characteristics of leading voice assistants. Voice assistant users will then be interviewed after which we expose consumers to the voice of their usual voice assistant and of others to explore voice perception in more depth.

Context and theoretical background
VBAI is a form of conversational AI, the ability of a system to hold humanlike conversations, Puntoni et al., 2021) including the ability to respond orally in human language via a synthesizer. The most common forms of VBAI accessible to consumers are voice-based conversational agents (mostly online) and voice assistants embedded in computers or smart objects such as smart phones or speakers.
Prior research on VBAI has mostly built on the Technology Acceptance Model to explain consumer experience. For instance, technology acceptance depends on functional factors (perceived usefulness and ease of use; Davis, 1989) as well as hedonic factors (enjoyment) and social factors (social presence induced by the technology; Venkatesh et al., 2012). A more recent stream of research shows how emotional factors such as consumer desire and enchantment also play an important role in technology acceptance (Belk, Weijo, and Kozinets, 2020). AI can be an object of desire for consumers (Belk, 2022) and induce feelings of engagement, loyalty, trust (Pitardi and Marriott, 2021), as well as love (Hernandez-Ortega and Ferreira, 2021; Moriuchi, 2019; Ramadan, Farah, and El Essrawi, 2021). With VBAI, voice is the sole source of affect, such as pleasure and love, as problematized in the film "Her" (Jones, 2013). However, the vocal dimension of the influence of VBAI on consumer pleasure remains unstudied.

Scholars have investigated the sensory dimension of AI experiences (Flavián, Ibáñez-Sánchez, and Orús, 2021) and, as far as the vocal dimension is concerned, several authors have analyzed the impact of naturalness of the voice on technology acceptance (Chérif and Lemoine, 2019). Prior research in psychology indicates that the most important factors in voice perception and influence on listeners are acoustic in origin: voice pitch (perceived highness, low vs. high) and timbre (perceived brightness, dull vs. bright, Baumann and Belin, 2010; Von Bismarck, 1974). For instance, voice pitch and timbre affect arousal and pleasure (Laukka, Juslin, and Bresin, 2005), gender identification, attraction (Puts et al., 2011) as well as attitude and behavior towards the speaker (Zoghaib, 2017; 2019).

Method

In order to examine the influence of the vocal characteristics of voice assistants, we undertake the following three-step approach: voice analysis, in-depth interviews, and voice perception analysis. First, in-depth interviews are best suited to understand the complexity of affective processes at play between consumers and non-human objects (post-human affect). Therefore, our principal method relies on in-depth interviews with VBAI users to understand the psychological mechanisms underlying the influence of the voice of VBAI on consumer affect. Voice assistants being the most utilized VBAI among consumers (Adobe, 2019), our sample includes users of the three leading voice assistants (Alexa, Google Assistant, and Siri).

Moreover, according to psychoacoustic research, it is necessary to analyze the acoustic characteristics of a sound beforehand and then analyze its reception to fully grasp the process of acoustic perception. Therefore, before interviewing voice assistants' users, it is necessary to know which vocal characteristics are at play. Since the vocal characteristics of leading voice assistants have yet to be studied, we will analyze the vocal characteristics of voice assistants used by our sample of respondents using a standard psychoacoustic voice analysis. Finally, following the interview process, we analyze the reception of users by exposing consumers to the voice of their usual voice assistant and of others to explore the role played by the vocal characteristics of voice assistants on consumer affect.

In particular, psychoacoustic voice analysis encompasses the study of overall pitch, timbre brightness, pitch evolution, and speech tone of a voice as well as the study of the perception by listeners (Wang et al., 2021). In our study, two acousticians will first analyze and compare a sample of seven voices, including both the three feminine default voices of Alexa, Google Assistant, and Siri and the three default masculine voices attached to these devices. Following this we also examine the gender-neutral voice of Q, to enable an understanding of the role of voice gendering. Each voice will be recorded iterating the same question, ("Hi, what can I do for you?"). Spectrograms and acoustic measures will then be calculated via acoustic software (Melodyne). The cases of divergence between the two experts will be resolved through discussion.

Conclusion

Prior research has shown that consumers can experience pleasure and love while interacting with VBAI (Hernandez-Ortega and Ferreira, 2021) and develop strong relationships, especially people with various disabilities (e.g., visual or mobility impairment, Ramadan, Farah, and El Essrawi, 2021). The novelty of this study lies in its investigation of the acoustic origins of such emotional and social responses Thanks to the cross-fertilization of prior research on Human-Computer Interaction as well as on psychoacoustics, this paper suggests a new mechanism, linked to voice perception, explaining emotional, social responses and the construction of post-human affect (Ishiguro, 2021) with regards to VBAI. This analysis also has important managerial implications for practitioners using voice assistants and selecting voices because these vocal characteristics are the only parameter practitioners can really configure to incite consumer pleasure.

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