LIÈGE université Gembloux Agro-Bio Tech

LABORATORY OF GASTRONOMIC SCIENCES

SMART GASTRONOMY LAB

Innovative Sensor-Enabled Tray for Understanding Consumer Eating Behavior

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Context

Nowadays, a thorough understanding of consumer behavior is essential for the development of new products, effective marketing strategies and hospitality/catering models. Innovation in the field of sensory analysis and digital technologies offers new perspectives for deeply understanding consumers' eating habits and behaviors. Furthermore, the interest of connected tools lies in their ability to be deployed on a large scale, to be used in various environments other than traditional sensory analysis rooms, and to collect a wide range of pertinent data.

Experiment

This study focuses on the use of a connected tray equipped with a weight sensor to track the evolution of a meal over time. This pilot study with 60 participants in a restaurant environment during the 2022 KIKK Festival, was conducted by consuming the same dish "Scallops in sauce with vegetables" on the smart tray.

The data collected through the smart tray underwent mathematical processing to follow variables such as the number of bites, applied force, meal duration, and quantity consumed. The objective of this study is, on the one hand, to compare data from all consumers and, on the other hand, to attempt and characterize the types of eating behaviors. Out of the 60 data sets collected, 39 were usable for analysis.

Presentation Video
Scan Me !

Outcomes

Individual Characterisation

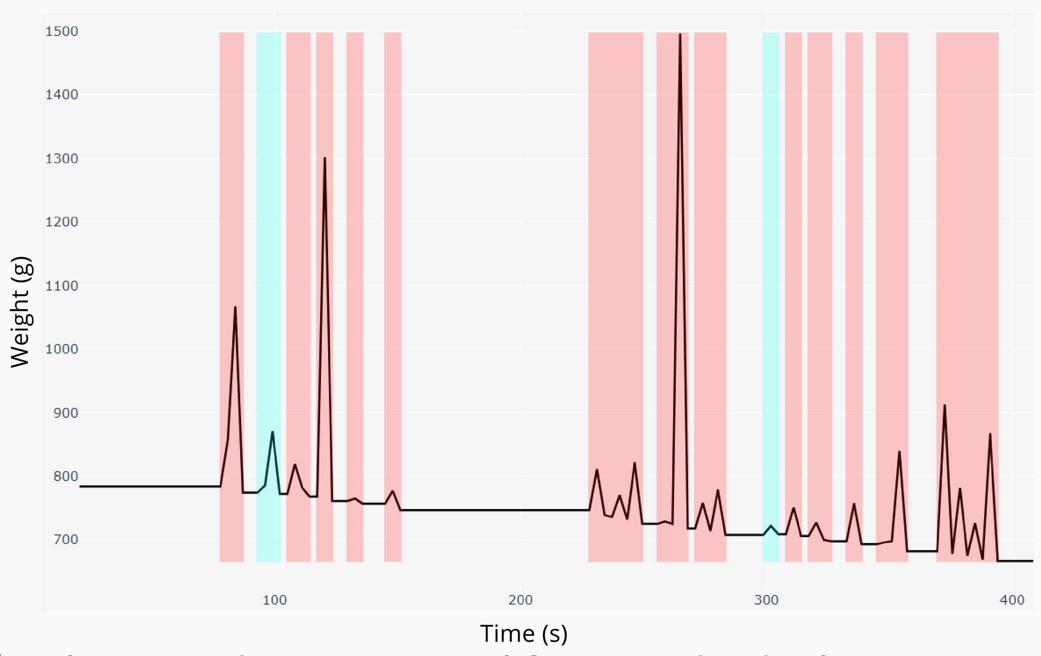


Plate Weight Over a Meal for an Individual

Total Meal Duration (s)	Total Activity Duration (s)	Weight consumed (g)	Bites
316,1	162,5	117	13

Main Individual Consumption Metrics

	Bite Weight (g)	Time Interval Between Each Bite (s)	No Activity Duration (s)	Activity Duration (s)	Work* (N.s)
Min	3,0	3,1	3,0	3,1	20,1
Max	22,0	76,9	129,2	24,6	178,6
Mean	8,9	14,6	24,7	9,6	71,9
Median	8,0	6,2	6,2	9,1	64,0
Standard deviation	5,2	20,7	36,9	5,8	43,6

Individual Consumption Metrics

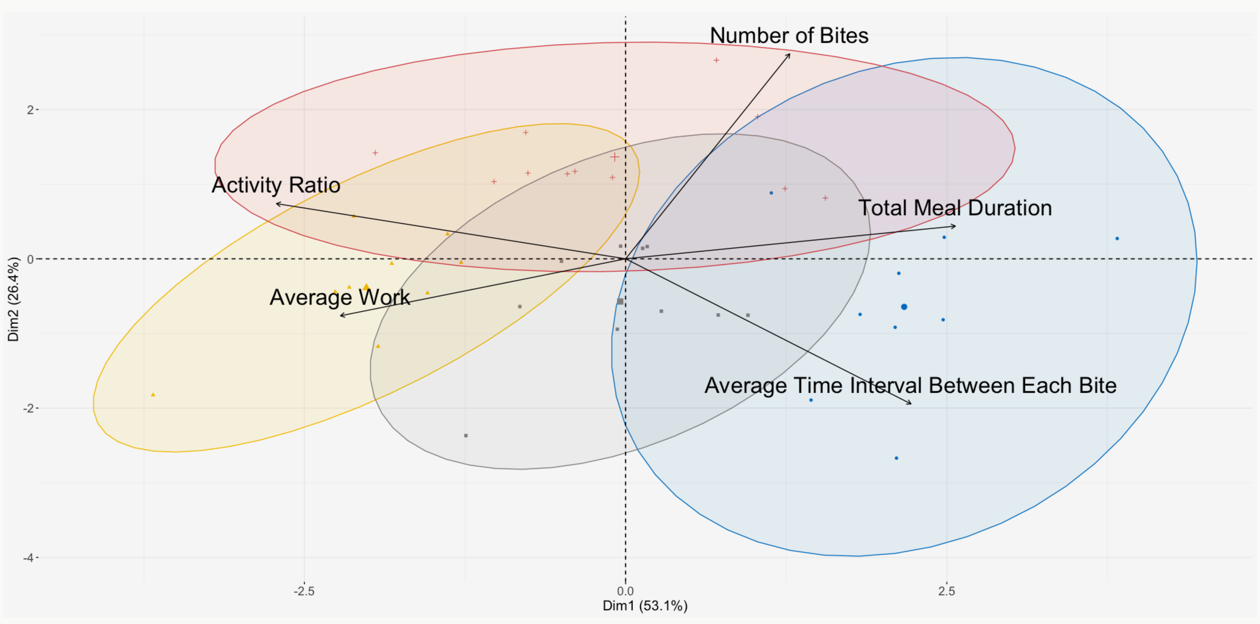
* Work : Area under activity period (N.s)

Activity period followed by a bite

Activity period not followed by a bite

Meal Characterisation

Method: Standardised PCA followed by Hierarchical Clustering on PCA coordinates



PCA Biplot with Colorization According to Groups from Hierarchical Clustering with 95% Confidence Ellipses

	Total Meal Duration (s)	Activity* Ratio (%)	Number of bites	Average Time Interval Between Each Bite (s)	Average* Work (N.s)
Min	203,8	23	6	7,2	24,1
Max	837,1	79,7	24	50,6	151,8
Mean	399,6	51,1	14,3	18,7	77,5
Median	374,1	51,4	14	16,1	76,2
Standard deviation	132,7	14,1	3,9	9,3	22,2

Summary of Meal Metrics on the 39 Individuals

* $\text{Activity Ratio} = \dfrac{\text{Total Activity Duration}}{\text{Total Meal Duration}}$ (%)

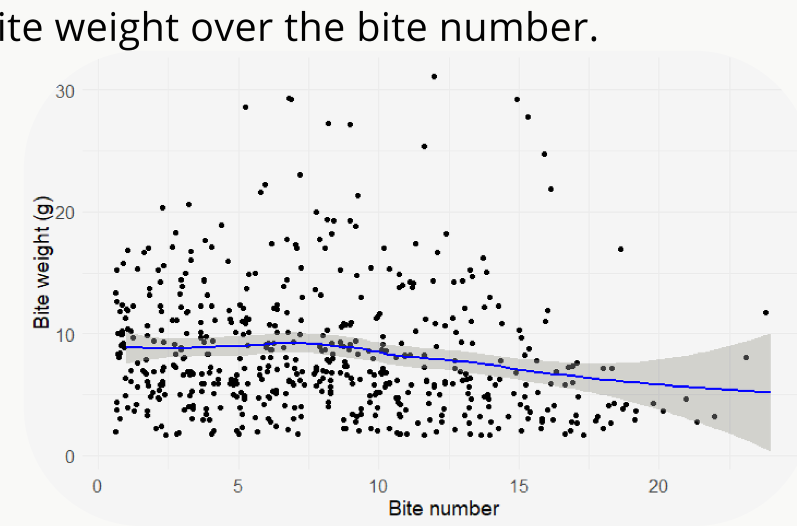
* Average Work: Average area under activity period (N.s)

Cluster	Caracterisation
1	Have longer meal durations
2	More active and do more bites
3	Exert more effort or intensity during eating
4	Balanced and moderate eating behavior

Cluster interpretation

Perspectives

- Currently, the tray can estimate the consumed weight and the number of bites with an accuracy of over 97% following a laboratory experiment. The accuracy of the algorithm will be tested in real-life conditions and on other variables.
- Conduct a detailed study of the effects of meals or populations on the variables. Indeed, the observed trends may vary from one meal or population to another. Example below with the bite weight over the bite number.



Bite weight over the bite number, across all meals, fitted with LOESS regression

- The algorithm correction should prevent various biases such as the placement of utensils on the plate.
- From these encouraging results, the tray can be used in other contexts, particularly in hospitals, as a tool to monitor patient food intake.
- Ongoing work on action and utensil recognition through artificial intelligence is currently under development in order to optimise and automated more the data interpretation.

References

Mattfeld, R. S., Muth, E. R., & Hoover, A. (2017). Measuring the Consumption of Individual Solid and Liquid Bites Using a Table-Embedded Scale During Unrestricted Eating. IEEE Journal of Biomedical and Health Informatics, 21(6), 1711–1718. https://doi.org/10.1109/JBHI.2016.2632621

Mertes, G., Ding, L., Chen, W., Hallez, H., Jia, J., & Vanrumste, B. (2020). Measuring and Localizing Individual Bites Using a Sensor Augmented Plate During Unrestricted Eating for the Aging Population. IEEE Journal of Biomedical and Health Informatics, 24(5), 1509–1518. https://doi.org/10.1109/JBHI.2019.2932011

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