Prospects in the field of learning and individual differences: Examining the past to forecast the future using bibliometrics

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Introduction

For over 200 years, researchers, practitioners, and policymakers have pursued investigating individual variation in behavior and relevant latent psychological constructs (Revelle et al., 2011; Sackett et al., 2017). The pursuit to understand individual differences was turbulent (Revelle et al., 2011; Sackett et al., 2017) and, throughout its history, shaped by two aims: the first scientific, to uncover how dimensions of individual variation interact with one another in order to advance scientific theory and measurement, and the second applied, to forecast individual learning in educational and professional contexts (Lubinski, 1996; Revelle et al., 2011; Sackett et al., 2017). Due to these aims, individual differences were often investigated in the context of learning, likewise eagerly studied for over a century (Charles, 1976; Illeris, 2018). Based on the past and the present developments in the field, we forecast future directions in the field of learning and individual differences. After briefly recounting the two centuries of research, we cast a close look at the last century, using bibliometric analysis (e.g., Apiola et al., 2023), to chart out the trends in the field and speculate on its future course.

Individual differences

Individual differences involve relatively stable dispositions, such as ability (e.g., Carroll, 1993; Galton, 1892; Spearman, 1904a; Horn & Cattell, 1966; Eysenck, 1952), personality (Allport, 1937; Eysenck, 1967; McCrae & Costa, 1997; 1999; Kluckhohn & Murray, 1948), motivation (Atkinson, 1957), interests (Holland, 1959; 1996) and values (Feather, 1995; Rohan, 2000), additionally underpinning individual variation in variability and volatility of states and emotions, along with demographic characteristics and a host of contextual factors embedded in learning environments. Individual dispositions, while (somewhat) stable over time, change across development and may be malleable, albeit to a varying extent, through training and intervention (Riding, 2005; Shuell, 1986). Identifying and assessing such dispositions is critical to discovering how individuals learn and to predicting their learning in the educational or vocational context (e.g., Snow, 1989; Schmidt et al., 1992). Understanding the contribution of individual differences to learning is, however, challenging because they interact with other variables such as gender (Ruffing et al., 2015; Severiens & Dam, 1994) or home background (Darling & Steinberg, 1993).

The last four decades witnessed considerable progress in the identification and assessment of myriad variables that contribute to learning (Jonassen & Grabowski, 1993) with regard to gender (Ruffing et al., 2015; Severiens & Dam, 1994), personality (Hessen & Kuncel, 2022), cognitive abilities (Cowan, 2014; Mackintosh, 1998; Ruffing et al., 2015), motivation (Dörnyei & Ushioda, 2021; Pintrich, 2003), interest (Ainley et al., 2002; Schiefele, 2001), and home environment (Darling & Steinberg, 1993; Daucourt et al., 2021; Torppa et al., 2022). Entering the current millennium supposedly coincided with a new era in the history of individual differences research, the era of theoretical and methodological refinement (Revelle et al., 2011; Sackett et al., 2017). Assessing whether we have indeed been living in the era of such refinement demands turning toward the previous eras and debates that shaped the current state of research on learning and individual differences.

A brief history of differential research

The scientific interest in individual differences originally emerged in 19th-century Europe and focused on statistical methods (Galton, 1888; Spearman, 1904b) and the hereditary basis of ability (Galton; 1892). The scientific focus on ability, introducing intelligence tests and the concept of the general factor of ability, coincided with the interest in ability and emotional testing at the service of the US military (Driskell & Olmstead, 1989; Revelle et al., 2011). Therefore, from early on, differential research served political and social demands (Revelle et al., 2011) and, as we will elaborate later in the editorial, still serves such demands today even though applications have (fortunately) become much more diverse over the last decades.

Soon before the Second World War, the interest in the measurement and the predictive value of ability extended towards personality (Revelle et al., 2011). In the United States, differential psychologists became involved in the selection and training of the Army Air Force, the Office of Strategic Services (the future Central Intelligence Agency; OSS Assessment Staff, 1948), and the first US astronauts (Wiggins, 1973). Meanwhile, on the scientific side of the field, the theoretical models of personality (Allport, 1937; Kluckhohn & Murray, 1948), temperament (Guilford & Zimmerman, 1949), thinking (Guilford, 1959), cognitive ability (Horn & Cattell, 1966), learning theory (Eysenck, 1952) and achievement motivation (Atkinson, 1957) were developed. This coincided with an explosion of personality inventories, which eventually led to skepticism toward the measurement of personality (Mischel, 1968) and, in general, the role of noncognitive variables in observed (Mischel, 1968) and predicted (Guion & Gottier, 1965) performance. However, the interest in individual differences resurged in the 1990s, with the development of meta-analysis, which allowed for pooling research findings across empirical studies (Sackett et al., 2017). This marked a significant development of the field, as meta-analyses allowed for pooling evidence across multiple empirical studies, constraining the impact of sampling errors and other statistical artifacts on the results. This development was soon followed by an introduction of Bayesian statistics (Lippa & Connelly, 1990) and general linear modelling to the field (Muthén & Curran, 1997), followed by decades-long reevaluation of classic statistical concepts such as Cronbach’s alpha (Schmidt et al., 2003) and effect size (Gignac & Szodorai, 2016). Further, in the 1990s, the five-factor (Big 5) model of personality emerged as a uniform conceptual framework for personality traits and was extensively reviewed (McCrae & Costa, 1997; 1999). The sub-field focused on ability witnessed another major theoretical advancement, as the models of general cognitive ability were integrated into a single model, introducing a unifying theoretical framework to reassess previous datasets on human cognitive abilities with modern statistical methods, such as confirmatory factor analyses (McGrew, 2009). Soon, the unifying theoretical framework allowed for reframing the g-factor as a product of multiple domain-general (executive) and domain-specific processes (Kovacs & Conway, 2016), laying ground for integrating research on general cognitive abilities and executive functions (Buczylowska et al., 2020), clarifying the contribution of age, environment, and educational background to cognitive performance across the life span (Kaufman et al., 2016) and elucidating the so-called Flynn effect, in which manifest performance on intelligence tests improves from generation to generation (Flynn & Blair, 2013; McGrew, 2010). Establishing such integrative theoretical frameworks for bridging the past and the present research, in this case on cognitive abilities, contributed to the theoretical and methodological refinement of the field that began in the early 2000s (Revelle et al., 2011; Sackett et al., 2017). Of note, the revival and refinement of such research should be marked by an increase in the output citing relevant keywords and an increase in the interest in theoretical models and statistical methods in our bibliometric analyses.

Differential, developmental, and educational research

Recounting the history of the field through the lens of chronology may mask major theoretical shifts in response to concurrent shifts in social-philosophical orientations and tensions with other fields of psychology. For instance, in the early days of the field, differential psychologists had a rather elitist approach to individual differences in ability, as some individuals had it, and others did not (Shuell, 1986). This approach changed fundamentally after the Second World War, when both social philosophy and psychology acknowledged that learning was an active, constructive process and a more egalitarian conception of individual differences was assumed by differential psychologists (Resnick, 1976; Shuell, 1986). The hitherto interest in individual “talent” or “ability” and other difficult-to-modify factors shifted to learning experiences of the individuals in the 1960s and 1970s, which, in turn, led to the interest in instruction and learning tasks (Shuell, 1976). This coincided with a cognitive revolution in psychology and education (Wittrock, 1978), which prompted researchers to focus on mental processes mediating the observed performance rather than on performance itself (White, 1981). Thanks to these changes, findings from differential and experimental psychology began to jointly inform learning research, for instance, elucidating individual, situational and task-specific factors behind student’s motivation (Eccles & Wigfield, 2020), forging the connection between learning differences and executive functions (Meltzer, 2018), and offering effective techniques to improve students’ learning (Dunlosky et al., 2013). Beforehand, experimental psychologists would typically disregard individual differences or view them as a nuisance that hindered the understanding of the fundamental principles of learning (Shuell, 1986), leading to tensions with differential psychologists (e.g., Weinert et al., 1989). The compatibility of the theoretical orientation of differential psychology with developmental psychology was likewise questioned (Fischer & Silvern, 1985; Scarr, 1992). To investigate both typical human development and individual variation in developmental psychology, new theoretical frameworks were introduced in the 1990s and the 2000s, namely, the evolutionary approach (Geary & Bjorklund, 2000; Tooby & Cosmides, 1990; 1992; Scarr, 1992) and the bioecological approach (Bronfenbenner, 2005). The evolutionary approach focused on the biological and the cultural influences on learning, showing how instruction may modify primary abilities such as speaking into secondary academic competencies such as reading (Geary & Xu, 2022), and investigating the link between uncertainty and procrastination (e.g., Chen & Chang, 2016). The bioecological approach, on the other hand, focused on the child's learning environment, supporting, for instance, research on gender values and differences in academic achievement (Eriksson et al., 2020) and fostering educational equity for diverse families (Herbstrith, 2021). In a nutshell, in the last decades, differential psychologists have, in a way, joined forces with experimental and developmental psychologists and this trend may be evidenced by an increase in research on learning and individual differences across these disciplines. Promoting such connections has certainly been central to the mission of *Learning and Individual Differences* as an academic outlet in the last decades. With the emphasis not only on the stability but also the malleability of individual differences, the journal has advocated for a better understanding of individual learning and its facilitation through training and intervention.

Recent socioeconomic trends

Throughout its history, differential psychology remained closely related to the political and social demands, as it facilitated assessment and selection for vocational, military, and educational purposes (Lubinski, 1996; Revelle et al., 2011; Sackett et al., 2017). While competency assessments still frequently guide professional recruitment (e.g., Becker et al., 2011), the global society has faced an unprecedented challenge, that of social digitalization (e.g., OECD, 2019). From the humble beginnings of the world wide web in 1989, the digital network has been considerably expanded, altering the way in which we learn, work, interact with others, and participate in the democratic society. Learning has become life-long and is no longer bound only to the classroom context (e.g., OECD, 2021). Strongly hierarchized workplaces were replaced with flatter work structures and delegation of responsibility to individuals and teams, which led to a demand on higher adaptability and skill levels from the individual employee (OECD, 1999; OECD/Statistics Canada, 2000). Open access to information and the possibility to actively participate in the global community, literally at one's fingertips, forced individual citizens to assume responsibility for their own navigation in dynamic information landscapes (Bobrowicz et al., 2022). As participation in society and the labor market demanded new skills and attitudes, standardized large-scale assessments began to increasingly focus on cross-curricular competencies such as problem solving (e.g., OECD, 2005). Cross-curricular competencies build on traditional learning domains such as reading, writing, or mathematics to support the individual in active participation in the society as well as a satisfying individual and social life (e.g., Reeff, 1999). This focus may be reflected in the bibliometric analysis on learning and individual differences, as recent years may have witnessed an increase in the output on cross-curricular competencies such as problem solving in addition to more traditional domains.

The standardized large-scale approach to assessment, regardless of the target competencies, was repeatedly contested by educational psychologists (e.g., Andrews et al., 2014; Meyer & Zahedi, 2014). In fact, an individualized approach to educational instruction and assessment, stemming from differential psychology, has remained a core topic in individual differences research since the 1980s (Riding, 2005; Weinert et al., 1989), which may likewise be reflected in the bibliometric analysis. Finally, another major societal trend, namely, the focus on merit-based and achievement-based recruitment (e.g., OECD, 2020), may lead to an inflation of output focusing on academic performance and academic achievement, as these outcomes supposedly secure one's life success in a meritocratic society (Markovits, 2019).

To sum up, recent developments suggest that the field of learning and individual differences is in the state of theoretical and methodological refinement with vivid developments and controversies that are evidence of an active research area with discussions evolving around theoretical models, empirical approaches, and statistical methods. These publications may have increasingly endorsed aspects from other fields of psychology, namely, experimental, and developmental psychology. Finally, given the close relationship between the research on learning and individual differences and the contemporary political and social demands, the present demands on cross-curricular competencies, individualized instruction, and assessment as well as academic performance/achievement may be reflected in an increase of the output on these topics.

In order to chart out the most recent trends in the field and test whether they are consistent with the above-mentioned narratives, we employed bibliometric analysis (e.g., Apiola et al., 2023). Bibliometric studies utilize article meta-data to offer an overarching bird's-eye view of literature. Bibliometrics encompasses a vast array of methods that enable researchers to map research fields, chart the temporal trends and understand the social structure and the collaboration among authors or countries. Recent developments have incorporated several natural language processing (NLP) and machine learning techniques that make use of the article textual data (abstracts) to offer an in-depth analysis of research themes and important topics. In this article, we make use of bibliometric methods augmented with topic modeling (an NLP technique) to offer a holistic view of the field over the past decades and propose an agenda for the future (Roberts et al. 2013; Apiola et al. 2023).

Methods

In order to search for all relevant literature on learning and individual differences, we relied on the Dimensions database (Digital Science, 2018), as it offers a wider coverage and higher quality metadata than traditional databases (e.g., Scopus or Web of Science), enables full-text search, and has a dedicated category for educational research. Given that there are no standard keywords that capture all articles related to individual differences, we limited our search to articles that mentioned the term “individual differences” in the abstract or title and to articles that were published in a venue with a focus on *individual differences.* This decision enables us to capture all papers that explicitly state that their research addresses individual differences as a theme. To limit the noise in our literature search, we searched only the *Education* category in the database to exclude articles from other fields; of note, the Education category includes all education and learning related sciences (psychology, linguistics, art, social sciences, information sciences). In other words, it is not exclusive to education venues but rather excludes articles irrelevant to the topic of this analysis. The search resulted in 4,445 articles. We also included all articles published in specialized venues (conference or journal) that have the term “individual differences” in their title such as "Learning and Individual Differences", which resulted in 2,246 articles. Such venues were included in their entirety for several reasons: their articles are highly related to the topic and of high quality given the specificity and focus and the peer-review by the highly specialized community. Also, researchers publishing in these venues are likely to omit the keywords in the actual abstract or meta-data given the venue name. The total number of articles from the search and dedicated venues was 6,556 after removing duplicates.

General Statistics

The analysis began with the descriptive statistics of the whole dataset in terms of paper types, authors, author collaboration, as well as total and average citations (López-Pernas et al., 2023). The R package *bibliometrix*, an open-source tool for dealing with bibliometric data (Aria & Cuccurullo 2017), was used, given its compatibility with the most common databases and its comprehensive set of rigorous functions for cleaning, disambiguation, preparation, and analysis of bibliometric data.

Knowledge dissemination

In order to chart out the evolution of the field, journals publishing the highest number of articles on learning and individual differences were identified and classified by the overall number of the relevant articles and the average number of citations per article.

Keywords and Research Topics identified with STM

The main themes were explored through keyword and topic analysis. Two labels were introduced to analyze the results: *keyword,* to refer to a term or a common word or phrase extracted from articles' title, abstract or author keywords, and *topic,* to refer to a "cluster" of terms that were grouped together using topic modelling. The *UDpipe* R package (Straka & Straková, 2017) was used to clean and prepare the articles' textual data (abstracts and keywords) through tokenization (dividing the text into words), part-of-speech (POS) tagging (classifying words according to the part of speech they occupy e.g., adjective, noun, verb), and lemmatization (reducing words to their dictionary form).

First, the individual words or noun phrases that appeared most frequently in the pre-processed text (tokenized, POS-tagged, and lemmatized; excluding stop words such as prepositions and conjunctions), were extracted using the *UDpipe* package. This package used regular expressions to identify phrases with a certain sequence of POS tags; in the present case, simple noun phrases. Combinations of words offered a more nuanced analysis than single words, allowing the identification of repeated patterns in the text.

Second, we performed structured topic modeling (STM) to identify the main topics. STM is an unsupervised machine learning method that can detect distinct themes in textual data (Roberts et al. 2013) and can successfully extract themes from educational research (e.g., Apiola et al. 2023). STM groups related words into coherent topics, revealing the connections between different concepts and facilitating a deeper understanding of the underlying patterns in the textual data. To achieve this, STM uses a variational Expectation-Maximization algorithm as well as Latent Dirichlet Allocation algorithm. The R package *stm* (Roberts et al., 2019) was used to conduct the STM, and, since the number of topics was not known a priori, several models with 5 to 60 topics were estimated. To choose the optimal model, fit indices (semantic coherence and exclusivity) and a consensus of two researchers (S.L.-P. & M.S.) were employed. Semantic coherence allowed identifying the most frequent keywords, and exclusivity facilitated separation of distinct keywords. Whereas the combination of the two indices allowed narrowing down the possible topics, they could not guarantee the "true" number of topics. Therefore, careful examination was performed by two researchers (S.L.-P. & M.S.) who reached a consensus on 33 topics, based on internal coherence and closeness of keywords, lack of overlap with other topics and lack of internal dissonance among the keywords. Thereafter, the selected topics were categorized into coherent topics and tabulated. To understand the temporal evolution, a plot of each topic and the topic category were created using the topic frequency over the past 20 years.

Knowledge foundations

To understand the theoretical underpinnings of the field, the most frequently cited papers were tabulated. Further, a network of co-citations was built by classifying same-paper references as "co-cited". Seventy-five most-connected articles (by number of co-occurrence with other references) were used to create the network. Since papers contain a varying number of references, a fractional counting weighting was used so that papers with large numbers of citations would not have an amplified weight. The resulting network was plotted using the Fruchterman Reingold force-directed algorithm and similar color was assigned to similar papers based on manual classification of their categories.

Results

Descriptive statistics

The dataset included 6,556 articles published over the span of more than a century ranging from 1910 to 2022. However, articles were on average 15 years old (*SD* = 17), i.e., most articles (4,603) were published in the last 15 years. The average number of citations per article was 25.8, far higher than in education technology (14.4), computing education (7.8) or computational thinking (6.8) (Apiola et al. 2023; Valtonen et al. 2022; Saqr et al. 2021).

Contributors

Authors affiliated with institutions from ninety-one countries contributed to the body of knowledge about learning and individual differences (Figure S1) but, in fact, the main corpus of research came from a few select countries, with only a single article from 19 countries, and less than five articles from 41 countries.

Authors affiliated to institutions from the top 10 contributing countries generated around 65% of all articles in the dataset. Most such countries were developed and Western. The authors affiliated to the US institutions topped the list with almost 30% of all articles, and the authors affiliated to institutions in China, the only non-Western country in the top 10, contributed around 5% of all articles. The other top contributing countries were European, jointly producing around 29% of all the articles. Countries from the Global South, notably Turkey, Taiwan, Indonesia, and Iran, appeared further down on the list.

Knowledge dissemination

The dataset comprised 1,562 venues spanning over a century of research (Table S1). A total of 1,016 venues (65%) in our dataset published a single article, 1414 (91%) venues published five articles or less, and the remaining 5,142 articles (78%) were published by 148 (9%)

venues. *Learning and Individual Differences* topped the list of the venues with 34% of all published articles, 41% of all the citations and an average of 30.8 citations per article. Note, however, that the metrics for *Learning and Individual Differences* may have been somewhat inflated, compared to other journals, as the search included all articles published in *Learning and Individual Differences*, and only relevant articles from the other outlets. *Learning and Individual Differences* has been active the last 34 years, over which the number of yearly published articles increased from an average of 22 in the first half to an average of 126 in the second half.

Long before *Learning and Individual Differences*, individual differences were a purview of education psychology venues such as *Journal of Educational Psychology*, *The British Journal of Educational Psychology* and *Developmental Psychology* (first articles published in 1910, 1935, and 1971, respectively). Overall, psychology was represented by 104 venues, published 614 (9%) of all articles and had 20% of all citations in our dataset with an average of 17 citations per article. Venues with focus on children and development (e.g., *Child Development*, *Early Child Development and Care*, and *Journal for the Study of Education and Development*) totaled 107 journals, published 450 articles (7%), and had 10% of all the citations with an average of 17 citations per articles. Educational journals (e.g., *Computers & Education*, *Learning and Instruction* and *The Journal of Educational Research*) totaled 603 venues, published 1641 (25%) and had 18% of all citations and an average of 11.6 citations per article.

Keywords

The thirty most common phrase keywords between 1910 and 2022 were identified in the bibliometric analysis (Figure 1). The two top phrase keywords pertained to Educational Outcomes ("academic achievement" and "academic performance"; 1,152 occurrences combined), and the remaining keywords pertained to Individual Differences, Educational Domains, Statistics, and Age/Stage of Education. Taken together, keywords from Individual Differences were the most common and well-represented, including ten keywords ("intrinsic motivation", "test anxiety", "prior knowledge", "personality traits", "cognitive ability", "achievement goals", "phonological awareness", "cognitive style", "cognitive abilities", and "memory capacity") across 1,962 occurrences. The Educational Domains area involved five keywords ("foreign language", "reading comprehension", "English language", "mathematics achievement" and "word reading"; 1,233 occurrences) and the Statistics area was represented by four keywords ("structural equation", "structural equation modeling", "equation modeling", "factor analysis"; 827 occurrences). Finally, Age/Stage of Education comprised five keywords ("secondary school", "elementary school", "primary school", "middle school", "school children"; 1,259 occurrences). Four further keywords could not be classified into any of the areas, including "short term", "special education", "educational psychology", and "teacher education".

Research Topics identified with STM

To understand the development of the field, we plotted the frequency of topic occurrence over the last twenty years (Figure 2). Further, closely related topics were grouped into six categories: Performance, Methods, Literacies, Brain & Development, Learning Environment and Psychology & Behavior (for a detailed topic list see Table 1). Taken together, all categories, except for Performance and Psychology & Behavior, showed an ascending trend between 2000 and 2022.

A closer look at the concrete topics reveals a more fine-grained and, in some cases, a slightly different picture. First, within Performance, the topic of "Academic achievement" was the most frequent, rapidly ascending in early 2010s, noting the first drop between 2013 and 2015, peaking in 2016 and descending since. Second, Methods noted a rapid growth, with “Research methods” as the most frequent topic whose rising popularity has driven the general trend. Third, the category of Literacies was likewise rising, with “English language”, “Reading” and “Writing” rapidly rising in 2010s. The rise of “Science” was less pronounced and “Literacy skills” remained stagnant over time apart from a spike in 2013. Fourth, in Brain & Development, the use of the most frequent topics followed diverse trends. While “Development”, “Developmental issues”, and “Neurophysiology” noted a sustained rise in frequency, “Memory” and “Cognitive abilities” remained stagnant. Fifth, Learning Environment noted the most rapid rise of all categories, with “Education Technology” as the most frequent and the most increasingly popular topic between 2000 and 2022. The second most frequent topic, “Human-Computer Interaction” became increasingly popular across the 2000s and the 2010s, exploding in the early 2020s alongside “K-12”. The topic of “Teaching and teachers”, kept growing since the late 2000s, attracting an increasing interest in the 2010s. This increase was less pronounced for “Classrooms”, “Physical & special education” and “Higher education”. Finally, Psychology & Behavior grew rapidly in the first half of the 2010s, but then stabilized, probably due to the same pattern in the frequency of “Engagement” and “Self-efficacy”. The trends for the remaining topics remained rather stagnant.

Knowledge foundations

To examine the theoretical structure, the underlying scientific base, and the field’s theoretical background, knowledge foundations were analyzed. Figure 3 (the co-citation network) represents clusters of papers that were commonly cited together, and the connection between those papers, showing major and minor research themes in the field. All works in the network are marked with an asterisk in the reference list.

Ten clusters were identified, with five major and five minor research themes. Among the major and most-interconnected themes, the most prominent ones focused on Motivation, Achievement Goals and Statistical Methods (orange, light blue, and sea green, respectively). All these themes were connected to another major theme, i.e., Self Beliefs and Self-Competence (light green), but only Statistical Methods was robustly connected to Cognition (pink). The other themes focused on Reading (forest green), Second Language Learning (dark blue), Personality and Achievement (dark red), College Outcomes (bright red), and, finally, Learning Strategies (violet).

Motivation. This research theme was represented by the largest cluster (15 nodes; orange). The most co-cited works, from the 1980s, introduced Dweck's theory of motivation that charted out links between children's motivation, cognition, and behavior/achievement (Dweck, 1986; Dweck & Leggett, 1988). This theory emphasized individual goals in prospective performance and reaction to feedback, and had a strong applied angle, identifying adaptive motivational processes and addressing maladaptive ones. The interest in individual psychological needs and goals was reflected in another highly co-cited work, later giving rise to Deci's and Ryan's Self-Determination Theory of motivation (Deci & Ryan, 1985). This theory focused on goal-oriented and self-directed behavior, and lay foundation for later work on self-regulated learning, as reflected in its interconnection with the light green cluster in the co-citation network (i.e., the Self Beliefs and Self-Competence research theme; Figure 2; see also Atkinson, 1957; Rotter, 1966; Weiner et al., 1986).

The next two decades resulted in further works, both theoretical (Eccles et al., 2002; Fredricks et al., 2004; Jacobs et al., 2002; Pintrich et al., 1993; Pintrich 2000a/n39; Ryan & Deci, 2000a; Wigfield et al., 2000) and empirical (Jacobs et al., 2002; Pintrich et al., 1993; Pintrich 2000a), introducing the Expectancy-Value Theory of motivation (Eccles et al., 2002; Wigfield et al., 2000) as well as discussing performance-approach goals (Middleton &

Midgley, 1997; Midgley et al., 2001) and the concept of student engagement (Fredricks et al., 2004).

Achievement Goals. With 12 nodes, this research theme was second largest (light blue) and highly interconnected with Motivation, Statistical Methods, as well as Self Beliefs and Self-Competence, with a narrower focus on achievement goals. Elliot and colleagues' work was the most central, represented by over half of the nodes (7; Elliot & Dweck, 1988; Elliot, 1990; Elliot & Harackiewicz, 1996; Elliot & Church, 1997; Elliot et al., 1999; Elliot & McGregor, 2001; Elliot & Murayama, 2008). Elliot's Achievement Goal Theory began with empirical investigations of how learning and performance achievement goals underpin (mal)adaptive behaviors (Elliot & Dweck, 1988). Shortly afterwards, the theoretical framework became integrated with the construct of achievement-avoidance motivation (Elliot & Harackiewicz, 1996; Elliot, 1999; Elliot et al., 1999; Elliot & McGregor, 2001; Harackiewicz et al., 2002), and further empirical work mapped out the relationships between the achievement goals, their antecedents, mediators, and consequences (Elliot & Church, 1997; Elliot et al., 1999; Elliot & McGregor, 2001; Harackiewicz et al., 2002; see also Ames 1992; Ames & Archer, 1988). In the late 2000s, the achievement goal theory and assessment were fine-tuned and meta-analyzed (Elliot & Murayama, 2008; Hulleman et al., 2010).

Statistical Methods. This theme, represented by 8 nodes (sea green), was heavily co-cited with both Motivation and Achievement Goals. The umbrella-theme of Statistical Methods comprised conceptual developments (Cronbach, 1957; 1975), power analysis (Cohen, 1988), the distinction between mediator and moderator variables (Baron & Kenny, 1986; Bentler et al., 1986) and evaluation of model fit (Bentler 1990; Hue et al., 1999; Cheung et al., 2002; Chen, 2007). Hu and colleagues' (1999) and Cheung and colleagues' (2002) works on goodness-of-fit were the most co-cited in this Research Theme.

Self Beliefs and Self-Competence. With fewer citations than Statistical Methods and two additional nodes (10; light green), this theme was heavily interconnected with Motivation, Achievement Goals and Statistical Methods. The frequent co-citation with Motivation is not surprising, given that works by Pintrich (1990), Pintrich and colleagues (2000), Deci and Ryan (2000), and Ryan and Deci (2000b) were interconnected in both research themes. The theoretical/review works focused on Self-Determination Theory of Motivation (Deci et al., 2000; Ryan & Deci, 2000b) and the connection between goal orientation and self-regulated learning (Pintrich, 2000b). Pintrich and colleagues (1990) tested correlations between both motivational orientation and self-regulated learning (SRL), but also self-efficacy, learning strategies, and academic performance in the classroom. Zimmerman and colleagues (1990; 2000) investigated the correlation of SRL and self-efficacy (1990), the cyclical processes in SRL, and the role of social agents in optimizing these processes (2000). Alongside SRL, self-efficacy was the second prominent sub-theme with Bandura's (1977) and Pajares' (1996) works (see also Marsh et al., 2005; Pekrun, 2006).

Cognition. Comprising 11 nodes, this theme was slightly larger than Self Beliefs and Self-Competence size-wise but was far less interconnected with Motivation and Achievement Goals. The works on Cognition focused on intelligence/cognitive ability (Blackwell et al., 2007; Carroll, 1993; Deary et al., 2007; Neisser et al., 1996), working memory and executive functions (Baddeley et al., 1974; Daneman & Carpenter, 1980; Mayer, 2001; Miyake et al., 2000), spatial abilities (Linn & Petersen, 1985; Vandenberg & Kuse, 1978), and cognitive styles (Riding et al., 1991). Note that only Blackwell and colleagues' work on implicit theories of intelligence and mathematics achievement attracted significant attention from researchers interested in Motivation, Achievement Goals, Statistical Methods, as well as Self Beliefs and Self-Competence.

Remaining Research Themes. Five additional Research Themes were identified, namely, Reading (Gough et al., 1986; Hoover & Gough, 1990), Second Language Learning (Horwitz et al., 1986; Dörnyei & Ryan, 2015), Personality and Achievement (O'Connor & Paunonen, 2007; Poropat, 2009), College Outcomes (Richardson et al., 2012; Robbins et al., 2004), and, finally, Learning Strategies (Marton, 1976; Pask, 1976).

The most cited works

The ten most cited works in the field comprised eight theoretical, and two empirical works, spanning cognitive, developmental, and educational psychology. The highest number of citations was attracted by empirical work on motivation, self-regulated learning, and academic performance (Pintrich & DeGroot, 1990), gathering 4000 citations. The next two places went to literature reviews on teachers and teaching (Veenman, 1984) and interactive models of reading (Stanovich, 1980). The remaining spots in terms of mere numbers of citations were occupied by seminal works on the development of reading (Cunningham & Stanovich, 1997), lifespan resilience (Rutter, 2006), the dual coding theory and the support of learning via both visual and auditory modalities (Clark & Paivio, 1991), the fuzzy-trace theory differentiating between gist and verbatim representations (Reyna & Brainerd, 1995), a meta-theory of problem solving (Jonassen, 2010), and a theory of development accounting for both the individual and the context factors (Sameroff, 2010).

Discussion

The Past and the Present

The field of learning and individual differences has steadily developed over the last decades, and, despite continuous exchange with experimental and developmental psychology, has been most closely connected to educational psychology. This is not surprising, given that the search focused on learning and individual differences in relation to education. The most impactful work in the field focused on motivation, achievement goals, and statistical methods as compared to cognition or development, which play a role but a somewhat less pronounced one. Perhaps not surprisingly, given that the search was constrained to English and the general underrepresentation of the Global South in academic publishing (Mori, 2022), the Global North was overrepresented in the field.

Well-grounded theoretically and methodologically, the field has been rather immune to hype and fashion, with few clear research trends while exhibiting a steady rise in overall output. Despite the surging interest in Massive Open Online Courses (MOOCs), learning analytics and educational data mining in educational technology research (Valtonen et al., 2022), these topics are, thus far, hardly represented in the field of learning and individual differences. Strong theoretical and methodological background is certainly advantageous, as it encourages the researchers to intensively pursue selected, well-established research avenues, but this orientation, characteristic for academically oriented fields, may somewhat hamper the adaptation of the field to the societal demand that take place in a dynamic environment. For instance, despite a long-standing demand on tailoring the environment to the learner's needs, only after the COVID-19 pandemic, the field has noted a rise of interest in learning environments and educational technology. Furthermore, contrary to our expectations, traditional competencies such as reading or writing were far more represented than cross-curricular competencies, such as problem solving. On the other hand, as expected, the field seems to have adapted to the society-wide focus on merit-based and achievement-based recruitment, given that "academic achievement" and "academic performance" emerged as the most common keywords in our analysis. Overall, the field may have adapted well to these societal demands that were explicitly articulated by states and international organizations but less so to other trends emerging in the society, off the policymakers' radar.

In line with our expectations, the field entered an era of methodological refinement in the 1990s, but the theoretical refinement was rather limited to the achievement goal theory (Elliot & Harackiewicz, 1996; Elliot, 1999; Elliot et al., 1999; Elliot & McGregor, 2001; Elliot & Murayama, 2008; Harackiewicz et al., 2002; Hulleman et al., 2010). Meta-analyses were key to such methodological refinement throughout the last three decades, and statistical methods in general were at the heart of the field, having been frequently co-cited with virtually all major research themes. Yet, the theoretical refinement seemed constrained to motivation and achievement, with few advancements (if any) in self beliefs, self-competence, and cognition.

The bibliometric analysis highlighted Self-Regulated Learning (SRL) as an overarching research subject, spanning across motivation, achievement goals, methods, and, to a far lesser extent, cognition. That SRL has become an important research subject is not surprising, given the increasing individual responsibility for lifelong learning. However, it is surprising that research on (meta)cognitive components of SRL or SRL development was either relatively infrequent or failed to attract as much attention as that on motivation. Although a rising trend is not evident in the bibliometric analysis, we anticipate that this will change in the coming decade.

Prospects for the Future

In the present Editorial, we aim to forecast the future directions in learning and individual differences. While the bibliometric analysis offers a better picture of the field's development so far, forecasting the future course must rely on the community's joint expertise and hitherto activity in the field.

The field will likely honor its academic traditions, retaining its focus on traditional literacies and educational psychology. However, given the growing importance of cross-curricular competencies and their acknowledgment by policymakers, the relevant research may become highly impactful in the next two decades. Given that international organizations recently advocated for student agency, and co-agency of peers, parents, teachers, and communities in learning, the research focus may expand from the individual and the learning environment towards family, community, and social factors that underpin learning (OECD, 2023). Furthermore, the emphasis on educational outcomes may shift towards well-being, triggering a change of educational philosophies promoted in the field. In other words, "learning to achieve" may shift towards "learning to secure the current and the future well-being", sparking impactful collaborations between psychological, sociological, and health research. Furthermore, we would hope that the field will become more open to societal demands raised by other stakeholders, including parents, teachers and, most of all, learners. As inclusive, individualized approaches to instruction and assessment are gaining more traction among education stakeholders (e.g., Cerna et al., 2021), we would expect that research on tailoring learning environments to individual needs of learners and teachers will gain impact, too.

That 2000s-2020s witnessed an era of the methodological refinement of the field became clear in the bibliometric analysis, but the theoretical refinement was far narrower. We prognosticate that the coming years will witness an era of theoretical refinement and reorganization. We expect that cross-disciplinary research will become increasingly impactful, clarifying relationships between motivation and (meta)cognition in relation to educational performance and learner's wellbeing across development. Broad, comprehensive, and cross-disciplinary theories will surge, triggering the theoretical reorganization of the field because such theories will likely address a well-defined subject (for instance, SRL or learning analytics) viewed from diverse perspectives across psychology and other social and health sciences. In line with this prognosis, we expect that SRL will attract more attention in terms of theory, developmental trajectories, and relationship to such constructs as executive functions, decision making, beliefs, values, and emotion regulation throughout the lifespan. We also believe that person-specific and idiographic methods that aim at studying inter-individual processes will become increasingly adopted, leading to more precise understanding of individual differences and possibly better support for individual learner's needs (Saqr, 2023).

Social digitalization is here to stay, unless the demand on keeping the servers cool and running becomes unsustainable. Digital environments for education and work often rely on learner's self-regulation, conflict resolution, and collaboration with others, and so we expect that these themes will be increasingly impactful in the next two decades. With the public availability of generative AI agents, and, therefore, their accessibility for learners, the next few years will likely witness a rise in research on learner's use of generative AI, including collaboration with such agents.

While social digitalization increases individual access to education and work, it also facilitates academic publishing and open access to research output world-wide. With an ongoing discussion on inequalities in access to publishing and research, and the commitment of major publishing houses to address such inequalities, the Global South may become more represented in the field. This would, however, demand bottom-up, international initiatives in the academic community aimed at a tighter research collaboration between the Global North and the Global South. Finally, it is also possible that social digitalization will fail to include the underprivileged, and that the field will overlook learning and individual differences in this population. We hope, however, that this will not be the case, and that the contribution of the disadvantage due to migration, language, ethnicity, culture, socioeconomic status, sexual orientation to individual differences in learning will become a key research theme with palpable real-world improvements in the years to come.

To sum up, the field of learning and individual differences will likely maintain its strong academic orientation, with a continued refinement of theory and methods, and will strive for cross-disciplinary research on relevant topics, such as SRL. Given the field's historical civic engagement and interest in contemporary social challenges, we further hope that this strong academic orientation will be paired with applied research, investment in learner's wellbeing and attention to broader socioeconomic factors that contribute to the field of learning and individual differences.

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Figure 1

Most common phrase keywords (left), most common single words (right)

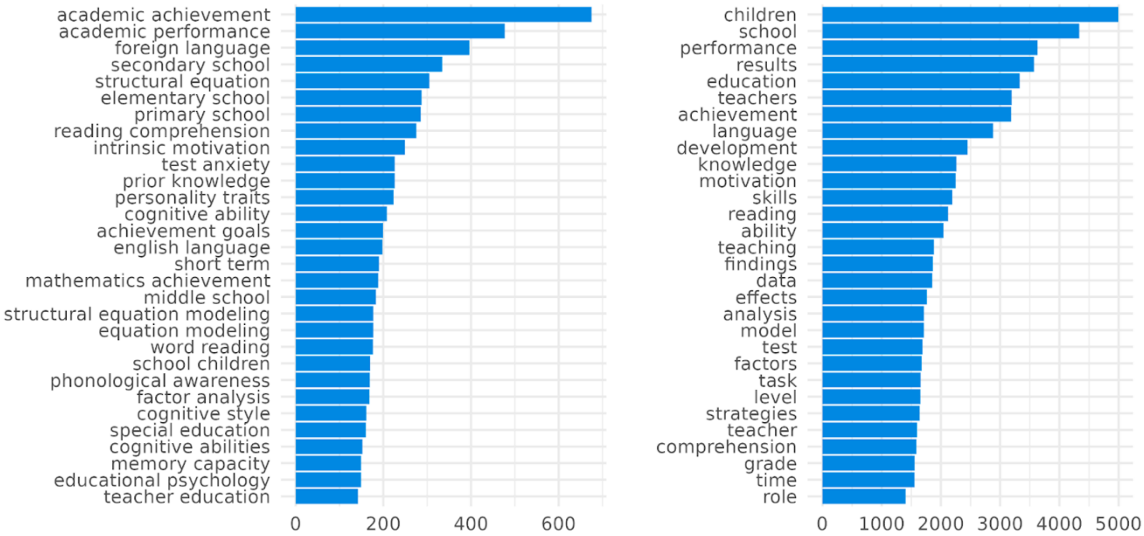

Figure 2

Trends for categories (first graph in each row) and topics (subsequent graphs in each row) (total number of articles per year)

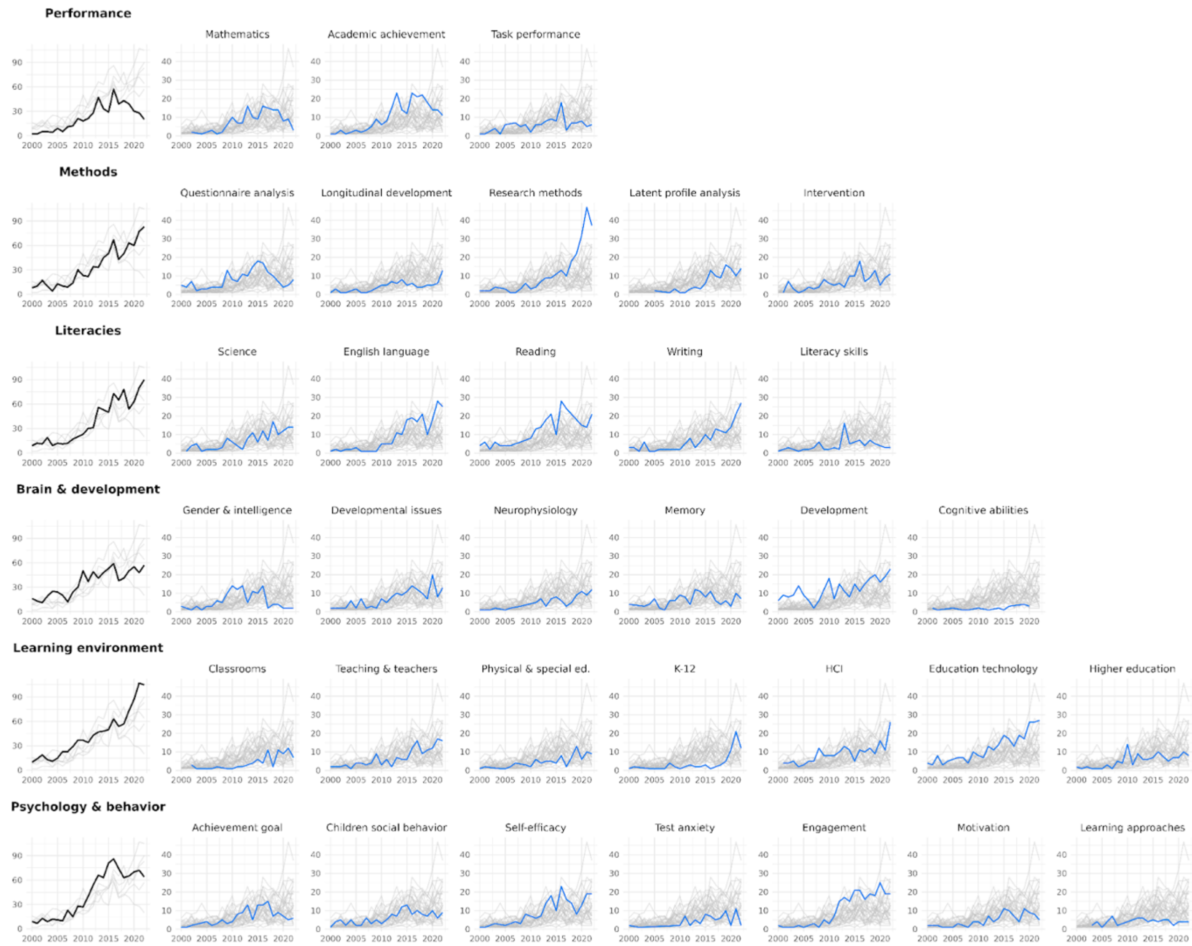

Figure 3

Co-citation network. Nodes represent cited references. Edges are proportional to the number of times two nodes have been cited in the same article. All works in the network are marked with an asterisk in the reference list.

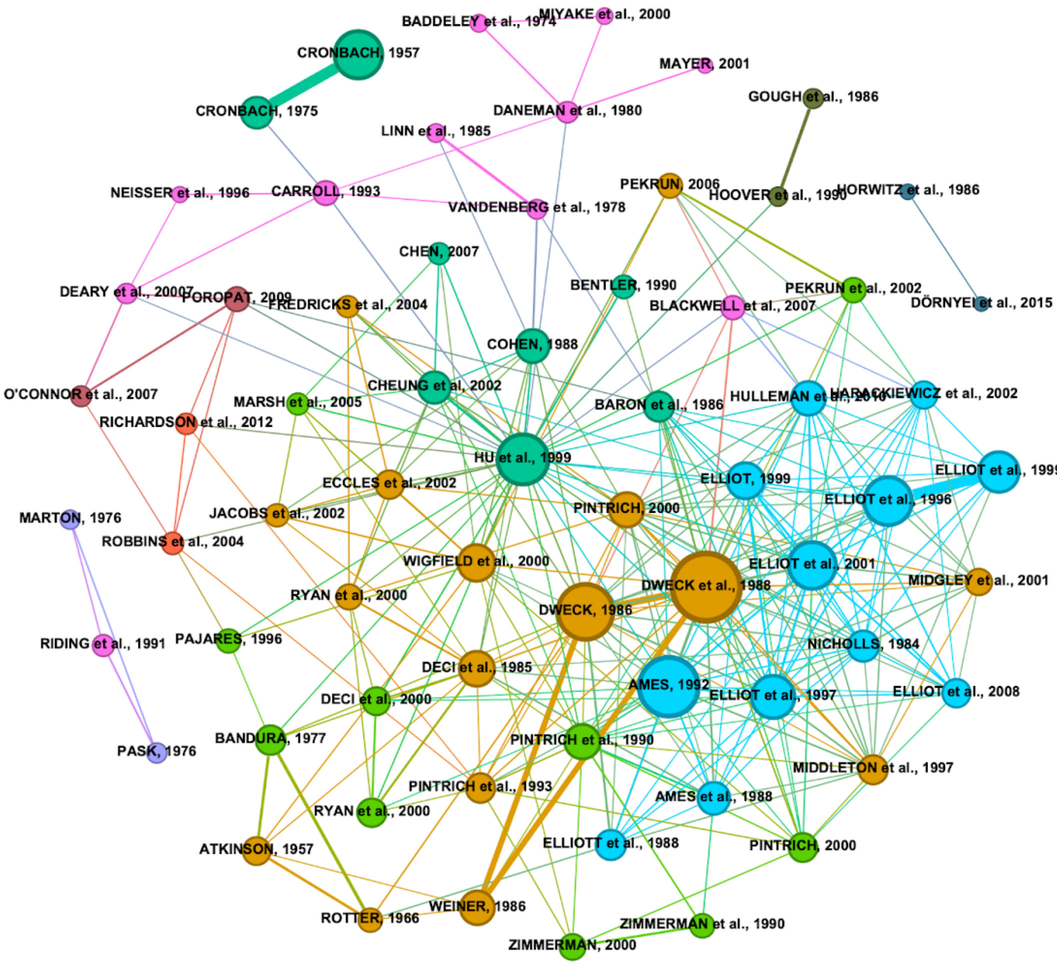

Table 1

Topics grouped into categories and most common terms of each topic

Category	Topic	N	Terms
Performance	Mathematics	161	math, grade, performance, girl, arithmetic, boy, predict, ability, homework, numerical
	Academic achievement	251	achievement, academic, effect, concept, grade, science, level, educational, model, sample
	Task performance	161	task, performance, reasoning, tasks, solve, difficulty, reason, result, participant, speed
Methods	Questionnaire analysis	233	factor, measure, test, scale, model, item, assessment, construct, analysis, score
	Longitudinal development	116	time, change, growth, longitudinal, development, increase, level, initial, rate, data
	Research methods	283	method, data, teaching, result, analysis, activity, methods, base, process, evaluation
	Latent profile analysis	121	profile, low, pattern, identify, analysis, latent, person, cluster, profiles, average
	Intervention	223	effect, test, intervention, training, control, condition, performance, score, experimental, improve
Literacies	Science	190	knowledge, text, prior, science, information, metacognitive, question, game, scientific, multiple
	English language	227	language, english, foreign, efl, proficiency, vocabulary, acquisition, linguistic, aptitude, factor
	Reading	341	read, comprehension, word, grade, reader, vocabulary, awareness, fluency, phonological, measure
	Writing	174	write, feedback, online, assessment, writing, collaborative, engagement, quality, video, interaction
	Literacy skills	100	skill, literacy, development, genetic, spelling, letter, speech, numeracy, acquisition, influence
Brain & development	Gender & intelligence	154	intelligence, gender, spatial, age, female, mental, male, ability, sex, adult
	Developmental issues	212	child, attention, age, gift, disorder, kindergarten, executive, deficit, development, adhd
	Neurophysiology	129	response, error, brain, day, tdc, effect, infant, stimulation, activity, neural
	Memory	156	memory, visual, verbal, capacity, recall, multimedia, term, load, effect, span
	Development	448	development, theory, issue, discuss, perspective, educational, understanding, theoretical, include, concept
	Cognitive abilities	37	cognitive, ability, process, influence, characteristic, instructional, processing, design, role, affect
Learning environment	Classrooms	152	classroom, instruction, lesson, instructional, pupil, activity, curriculum, program, grade, provide
	Teaching & teachers	181	teacher, teaching, practice, professional, development, educator, experience, education, pre-service, pedagogical
	Physical & special ed.	174	education, educational, physical, special, psychology, life, development, curriculum, journal, book
	K-12	94	school, primary, secondary, relationship, elementary, middle, pupil, social, influence, identity
	HCI	236	model, system, base, design, environment, computer, creativity, creative, adaptive, music

	Education technology	311	technology, education, challenge, experience, support, practice, inclusive, diversity, educational, opportunity
	Higher education	141	college, university, career, cultural, country, culture, medical, major, american, program
Psychology & behavior	Achievement goal	168	strategy, goal, performance, regulation, orientation, mastery, approach, achievement, regulate, avoidance
	Children social behavior	184	social, behaviour, parent, child, peer, family, play, activity, parental, interaction
	Self-efficacy	217	efficacy, personality, belief, perceive, attitude, trait, relationship, predict, satisfaction, role
	Test anxiety	86	anxiety, test, confidence, experience, sport, performance, affective, report, trait, exercise
	Engagement	239	academic, emotion, engagement, performance, emotional, control, predict, negative, university, positive
	Motivation	118	motivation, motivational, intrinsic, autonomy, support, examine, extrinsic, persistence, autonomous, mindset
	Learning approaches	100	style, type, preference, approach, relationship, deep, approaches, significant, prefer, inventory

Appendix

Figure S1

Countries whose institutions published research output on learning and individual differences

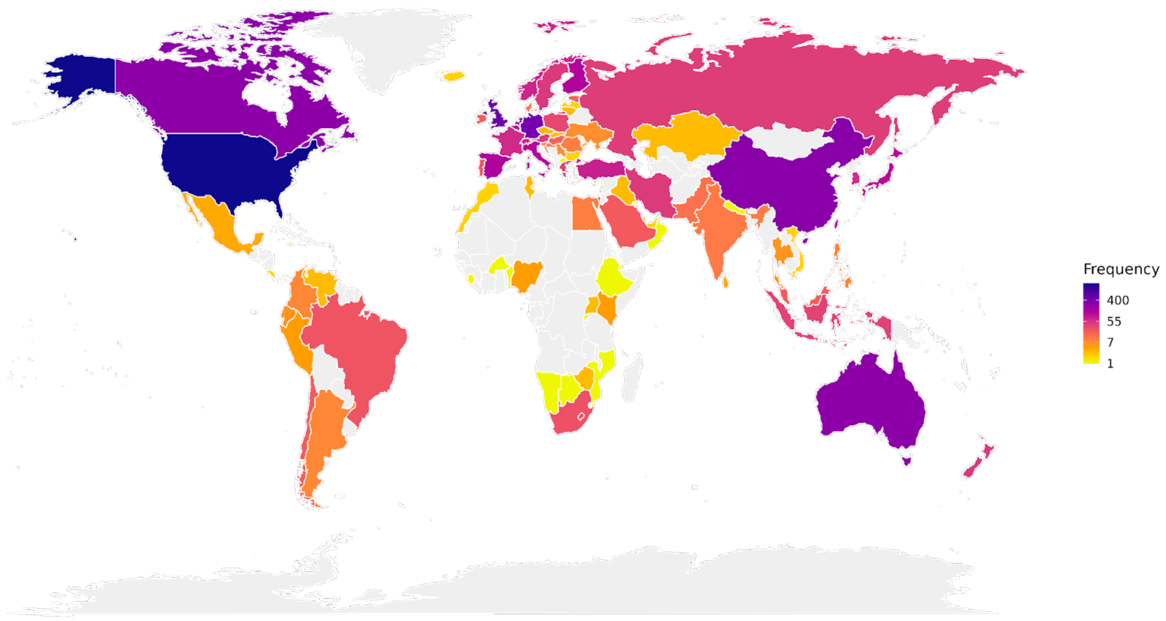

Table S1

Most relevant venues publishing research on learning and individual differences. The search involved all articles published in Learning and Individual Differences and, in the other outlets, it was limited to mentions of "individual differences" in the abstract or title. Note that this may have led to an overrepresentation of Learning and Individual Differences

Source	Tot. Art	Tot. Cit.	Cit./Art.	Earliest	Latest
Learning and Individual Differences	2244	69015	30.76	1989	2023
Journal of Educational Psychology	121	12589	104.04	1910	2022
Child Development	61	6017	98.64	1965	2021
PsyArxiv	53	37	0.70	2017	2023
British Journal of Educational Psychology	48	1083	22.56	1935	2022
Developmental Psychology	45	5570	123.78	1971	2023
Contemporary Educational Psychology	42	1942	46.24	1978	2023
Readinga and Writing	41	1203	29.34	1989	2023
Computers & Education	40	1815	45.38	1985	2022
Teachers College Record the Voice of Scholarship in Education	39	228	5.85	1925	2021
Educational Psychology	38	1328	34.95	1983	2022
Early Child Development and Care	33	236	7.15	1986	2020
Journal Of Learning Disabilities	29	841	29.00	1972	2021
System	28	570	20.36	1992	2022
British Journal of Educational Technology	27	1412	52.30	1994	2022
Frontiers In Education	27	118	4.37	2017	2023
Modern Language Journal	27	1250	46.30	1916	2021
Educational and Psychological Measurement	26	652	25.08	1942	2022
The Journal of Educational Research	26	698	26.85	1920	2018
European Journal of Psychology of Education	24	378	15.75	1988	2023