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A Systematic Review of Idiographic Research in Education: Trends, Gaps and Future Directions

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Abstract

The past decade's data surge has spurred interest in precision education, aiming to tailor educational interventions to individual learners based on robust evidence. Precision education is powered by the increasing availability of educational data and advancements in computational analytics, promising personalised learning experiences that can enhance learning outcomes and promote equity. However, traditional methods, which rely on group-level nomothetic approaches, have faced significant challenges in generalisability, as they often fail to capture individual learning processes and diverse contexts in which learning occurs. We argue that these limitations necessitate a shift towards idiographic approaches that focus on person-specific insights through longitudinal data collection from a single individual learner. The idiographic methodology also holds the potential to promote inclusion as it enables deep, fine-grained and learner-centric personalisation. This paper systematically reviews the existing application of idiographic approaches in educational research to address the gap in understanding how these methods have been used and their potential for future research. This review included 34 peer-reviewed articles that employed idiographic methods, revealing that idiographic approaches have been traditionally used to incorporate contextual factors and psychological dispositions unique to each learner. While idiographic research remains relatively scarce in education, the findings illustrate a growing trend that idiographic research is enriched by the increasingly available data and advanced computational techniques. Additionally, the findings highlight the need for future research to consider longitudinal within-person temporal processes, extend idiographic methodologies to K-12 education, and develop person-centred theories within educational psychology. These methods could also address inclusion by focusing on underrepresented populations such as learners with disabilities. In conclusion, idiographic approaches offer a promising complement to nomothetic approaches, providing personalisation that can enhance precision education and inclusion. Future research should explore the potential of idiographic methods to advance inclusive, personalised learning environments in the digital age.

Keywords: e-learning; data; idiographic; person-specific; within-person; learning analytics; scoping review; systematic literature review.

Introduction

The last few decades have seen an exponential increase in the amount of data generated, sparking the idea that these vast datasets could be used to enhance our lives through targeted, personalised solutions. In the realm of education the concept of precision education has gained traction and has been increasingly discussed in educational policy circles (Hart, 2016; Mertanen, Vainio and Brunila, 2022). Precision education involves research and practice aimed at tailoring prevention and intervention to individual learners based on available evidence, thereby allowing learning and learning environments to be personalised according to the needs of different learners (Cook, Kilgus and Burns, 2018; Qushem et al., 2021). The promise of precision education is fuelled by the growing availability of educational data as well as advancements in computational power and analytical methods. Learning analytics has been a burgeoning discipline, where researchers have developed tools and methods for personalising learning and learning environments (Baker and Siemens, 2014; Romero and Ventura, 2020). Personalising learning experience based on digital devices and analytical methods has the potential not only to enhance learning outcomes but also to promote inclusion and equity (Vincent-Lancrin, 2023).

However, personalisation based on big data and traditional methods—which rely on a group-level nomothetic approach—has faced major challenges related to poor generalisability (Wilson et al., 2017; Winne, 2017; Dawson et al., 2019; Yarkoni, 2020). That is, the effectiveness of group-level or institution-wide learning analytics in improving student performance is not generally guaranteed (Wilson et al., 2017). Also, successful personalisation on a certain sub-population of learners may fail to perform well for another sub-population (Yudelson et al., 2014; Gašević et al., 2016). Moreover, group-level approaches do not reflect individuals, failing to provide precise understanding and personalisation of learning processes (Wilson et al., 2017; Winne, 2017; Saqr, 2023, 2024). The evidence of these empirical studies necessitates a new approach to increase the impact of learning analytics in personalised, precision education.

To address this problem, a more holistic, system-wide approach utilising even larger-scale data has been advocated (Dawson et al., 2019; Shafiq et al., 2022). Nonetheless, this nomothetic paradigm may not entirely solve the issue, as it still fails to capture individual learning processes and the broader contextual factors (Wilson et al., 2017; Yarkoni, 2020; Mertala, 2021). Rather, it might involve undesired consequences such as biassed data-driven decision-making or personalisation by favouring the social groups most represented in their datasets. (Selwyn, 2019; Riazy, Simbeck and Schreck, 2023). In fact, a recent review highlights that learners with disabilities are still an underrepresented population in learning analytics research (Baek and Aguilar, 2023).

Nomothetic vs. Idiographic

The issue of poor generalisability stems from the inherent limitations of group-level nomothetic analysis, where data is collected from a sample of students to derive aggregate insights that represent the average learner. This approach is problematic for several reasons. First, the average learner does not exist in real life, as students are essentially different and unique. Second, the theoretical underpinning behind the group-based approach lends itself to the notion that capturing inter-individual variances from many people is equivalent to capturing intra-individual variance. In other words, collecting data from many people would amount to collecting data from an individual on many days; in both cases, we will capture the same variance. For inter-individual variance to be equal or represent intra-individual variance, ergodicity conditions must be met (Molenaar and Campbell, 2009). That is, individuals are homogeneous (so it will not matter whom we include in the study, they are similar anyway) and individuals do not change across time (so it will not matter when we measure, they are stable anyway). However, humans are neither identical nor stationary but rather exhibit remarkable heterogeneity and temporal variations across time. A substantial body of evidence contradicts the homogeneity and stationarity assumptions, undermining the central premise of group-level inferences (Howard and Hoffman, 2018).

To address the problem, the idiographic approach—the main aim of this review—has been studied and applied in behavioural sciences, particularly in psychology (Molenaar and Campbell, 2009; Piccirillo and Rodebaugh, 2019). This approach centres on person-specific insights, which are generated by collecting data from the same individual over time to devise person-specific precise information about that individual. As illustrated in Figure 1, on the group level (left side), data is collected at a certain time point from several people representing an example of group-level data. It should be noted that even if data are collected at multiple time points, this approach still creates a statistical model for the average learner. On the other hand, the right side of the figure displays data collected from the same person on several occasions, representing an idiographic approach. In other words, a statistical model is developed to represent that individual.

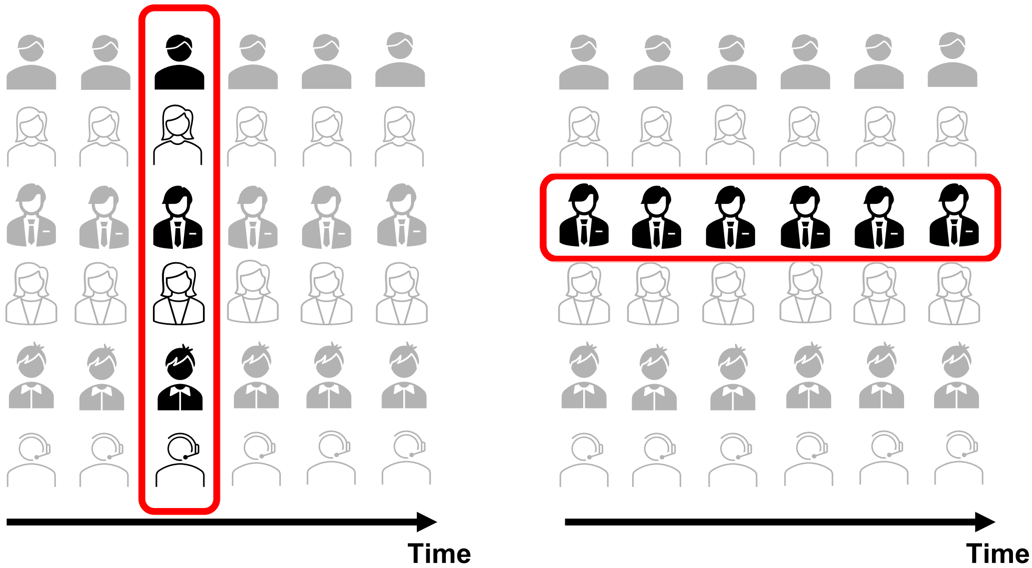

Figure 1: Group-level (left) vs. idiographic analysis (right)

To leverage this methodology in education, Saqr and López-Pernas (2021a) proposed idiographic learning analytics, defining it as “the development of insights about a single student based on the collection and analysis of the student’s own data.” Given that understanding a person entails several data points, idiographic learning analytics requires relatively considerable effort and, by design, lacks the generalisability of a group-level approach. In other words, there is a necessary trade-off between scope and specificity when considering both approaches. Idiographic methods can provide individualised, precise, and accurate insights but offer a narrow view of human behaviour. In contrast, group-level approaches can yield general, potentially more widely applicable insights, though their specificity is often limited and not guaranteed. Perhaps partly due to these challenges, idiographic research in learning analytics remains relatively underexplored.

Need for idiographic approaches

Although idiographic approaches more precisely reflect individual learners and thus facilitate more appropriately personalised learning experiences, this does not imply that the idiographic approach should necessarily be the primary methodology of learning analytics. Both the nomothetic and idiographic approaches have their place in research depending on the research question (Windelband, 1980; Murayama et al., 2017; Howard and Hoffman, 2018). Nomothetic approaches are preferred for theory testing or examining relationships within a population. For instance, in higher education nomothetic learning analytics has been effectively employed to improve student retention (Wong and Li, 2020; Shafiq et al., 2022). On the contrary, idiographic methods are suitable when individual differences are significant, or when sample data are highly biassed. They are also useful for personalising learning experiences for different student needs.

The rationale behind this argument can be found in the literature on personalised learning. The definition of personalised learning varies in the literature depending on the context (Walkington and Bernacki, 2020; Bernacki, Greene and Lobczowski, 2021). Essential distinctions between individualised and differentiated learning are outlined by the U.S. Department of Education (2010) as follows: individualised learning is paced according to the different needs of learners; differentiated learning is tailored to various learning preferences; and personalised learning encompasses both of these approaches but also adapts to the specific interests of different learners. In other words, while individualised and differentiated learning involve a shared learning goal for all students, personalised learning does not necessarily require a common goal. Thus, individualised and differentiated learning are instructor-oriented, whereas personalised learning is learner-centric. Since nomothetic methods implicitly assume a shared learning goal, idiographic learning analytics are better suited for learner-centric personalised learning.

Furthermore, idiographic approaches have the potential to enable varying levels of personalisation. Walkington and Bernacki (2014) characterise personalisation approaches by three components: depth, grain size and ownership. The depth of personalisation concerns the extent to which deep, meaningful connections are made between learning contents and learners’ interests or experiences; the grain size refers to whether they are tailored to a group of people or an individual; and the ownership addresses whether the personalisation is managed by an instructor or the learners themselves (Walkington and Bernacki, 2014). Since idiographic methods are able to capture to some extent the context in which learning occurs, they facilitate deep, fine-grained personalisation where learners take an active role in the process.

Finally, the idiographic approach has significant implications for inclusion in education. Although there have been efforts to integrate learning analytics into inclusive education (Martins et al., 2020; Costas-Jauregui et al., 2021; Baek and Aguilar, 2023), this area remains relatively underexplored (Baek and Aguilar, 2023; Vincent-Lancrin, 2023). Key challenges in designing learning analytics for students with special needs include privacy concerns (Lang, Woo and Sinclair, 2020) and the need for modified or personalised instructions (Lindner and Schwab, 2020). Idiographic learning analytics offers the potential solutions to these challenges. By designing an analytics system on learners' own digital devices, privacy concerns can be addressed, as data does not need to be shared with third parties (López-Pernas and Saqr, 2021). Furthermore, the idiographic approach supports the development of modified instructions, thereby advancing inclusion. Nonetheless, it is important to recognise that this does not imply or assume that inclusive education should be less collective or social. Rather, idiographic approaches should be seen as the complement of nomothetic approaches in supporting inclusive education.

Research questions

Despite the immense potential of idiographic methods, their adoption has been slow in behavioural sciences (Barlow and Nock, 2009). Particularly, to the best of our knowledge there has been no comprehensive study to date that examines the potential and possibilities of idiographic methods in educational research. In order to advance research on idiographic methods in education, including learning analytics, it is crucial to review existing research and to identify potential areas for future study. Therefore, our main research question of this study is:

Main Research Question: In what ways has idiographic methodology been used in education research?

To address this question, we systematically review past research that has applied idiographic approaches. Our main research question is further decomposed into the following five sub-questions, which guide the review process:

- **RQ1:** How has the idiographic approach been used in relation to nomothetic methods in educational research?
- **RQ2:** What subject matters have been studied with an idiographic approach?
- **RQ3**: What methods have been operationalized in idiographic studies in education?
- **RQ4:** What data sources have been used in idiographic educational research?
- **RQ5:** Which educational levels have been researched with idiographic methods?

This review aims to provide a comprehensive understanding of the application of idiographic methods in education research. By identifying potential areas for future study, we seek to contribute to the development of idiographic learning analytics methodologies and the broader discourse on personalised, precision education.

Method

Our study followed scoping review guidelines (Levac, Colquhoun and O'Brien, 2010). Scoping reviews are particularly useful for examining emerging fields, mapping the range of research activities, summarising findings, and identifying research gaps. Recognizing the lack of existing reviews, we planned our study to evaluate current idiographic research.

To investigate our research questions, several databases were used to search for relevant scientific papers with the terms "idiographic" or "person-specific" (as a synonym of idiographic) in the title, abstract or keywords of the articles. For Web of Science and Dimensions, we limited the search to the "Education" category. For Scopus, since such a category is not available, we included "education" as an additional search term. Lastly, no additional field-related constraints were added to the query in ERIC, since the database exclusively contains educational research. We further limited our search to peer-reviewed journal articles, conference papers or book chapters and did not set the range of publication years. A total of 712 records were retrieved from our search. After removing duplicates (n=232), 480 records remained. The remaining records were then filtered by reading the titles and abstracts. After the first screening step, 58 records remained, which were assessed for eligibility by reading the full text. Papers that incorporated person-specific data analysis were included and those that investigated topics not directly relevant to education (e.g., psychiatry) were excluded. Manuscripts written in languages other than English were also excluded. The final list of manuscripts included in the review contained 34 papers. This process of screening is summarised in Figure 2.

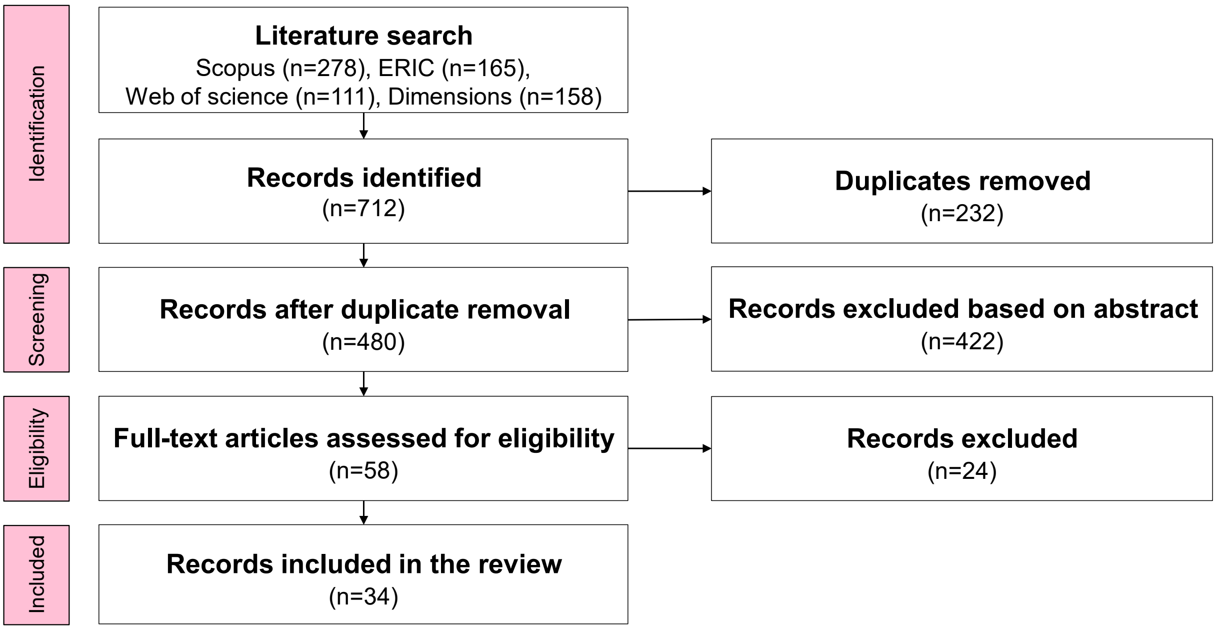

Figure 2: Summary of the review process

Results

Table A1 in the Appendix summarises the information extracted from the reviewed articles. The following subsections describe the results regarding our research questions.

RQ1: How have idiographic approaches been used in relation to nomothetic approaches?

Firstly, we analysed how the reviewed papers use idiographic approaches in relation to nomothetic ones. The findings show that only 9 out of the 34 included manuscripts had a fully “Idiographic” approach, where data analyses were conducted for one single person or one person at a time. Some 13 articles incorporated both idiographic and nomothetic methods (labelled as “**Combination**”). For example, O’leary (1971) conducted a short-memory test using vowel-consonant-vowel trigrams: the author collected data on how relevant the trigrams are to each participant and analysed how person-specific relevance was related to memorising trigrams for each participant (idiographic analysis); then the results were aggregated to derive group-level conclusions (nomothetic analysis). A total of 12 papers conducted both idiographic and nomothetic methods separately (labelled as “Comparison”). They often report inter-learner variations or pilot some novel idiographic methods in comparison to traditional nomothetic approaches. For instance, Bruno (1975) compared how well different models, including both nomothetic and idiographic, predict long-term educational effects.

In addition, we explored the reason why these fully idiographic studies employed idiographic methods. Table 1 summarises the purposes of utilising person-specific approaches in the articles labelled as idiographic. A careful examination reveals that six of these studies aim to incorporate the context in which learning occurs, while the other, more recent papers focus on temporal processes within individuals. This indicates that idiographic approaches have traditionally been used to reflect varying contexts between subjects, whereas recent research also applies these approaches to explore within-person temporal changes. Moreover, the latter development has likely been facilitated by the increasing availability of educational data through digital tools, as capturing temporal changes requires a substantial number of repeated measurements.

Reference	Why idiographic?	Category
(Cooksey, Freebody and Davidson, 1986)	To examine the accuracy of teacher expectation in the context of a specific classroom ecology.	Context
(Haensly and Lee, 2000)	To describe early signs of giftedness in young children from culturally diverse and economically disadvantaged backgrounds as examples in context.	Context
(Athanasou, 2013)	To determine what features of the context are likely to be relevant to the future interests of each person	Context
(Hurley and Murphy,	To incorporate social and cultural context and to reflect a	Context

Reference	Why idiographic?	Category
2015)	person's subjective experience.	
(Ordem, 2017)	To investigate the dynamic nature of motivation in accordance with a certain context.	Context
(Saqr and López-Pernas, 2021a)	To account for temporal processes that unfold within individuals.	Temporal
(Saqr and López-Pernas, 2021b)	To account for temporal processes that unfold within individuals.	Temporal
(Malmberg *et al.*, 2022)	To investigate how certain events proceed sequentially within individuals.	Temporal
(Paba, De Castro Daza and Roncancio, 2022)	To understand individuals' regulation of positionings on a topic in argumentative writing.	Context

Table 1. Purposes of using person-specific approaches in fully idiographic research

RQ2: What subject matters have been studied?

Next, we extracted research subjects that the reviewed articles focus on. Figure 3 shows a word cloud of the subjects. It should be noted that some of the papers cover multiple topics. The findings suggest that idiographic studies frequently pertain to aspects of educational psychology, such as motivation (Ordem, 2017), stress (Aalbers et al., 2023), self-regulated learning (SRL) (Saqr and López-Pernas, 2021a), or engagement (Saqr, López-Pernas, et al., 2023), rather than merely about academic performance or learning conceptual knowledge and skills. This might be because the psychological dispositions of learners vary significantly between individuals. Also, it would be a natural consequence of the fact that the concept of idiographic analysis has been discussed in psychology as mentioned in the introduction. Moreover, this result aligns with the previous findings (RQ1), as psychological characteristics are highly context-dependent.

Figure 3. A word cloud showing topics studied in the reviewed papers where the size of the topic is proportional to the frequency of appearance

RQ3: Methods

Figure 4 displays what methods were used in the reviewed studies. As in the previous subsection (RQ2), individual studies may employ multiple methods (e.g. qualitative analysis in combination with descriptive statistics). First, only three articles in the review solely relied on qualitative methods while the majority of the papers utilised quantitative analysis. Second, Figure 4 reveals a clear trend that papers published before 2020 predominantly used basic statistical methods, such as descriptive and inferential statistics. After 2020, there was a shift towards more advanced techniques, including sequence mining, psychological networks, and machine learning, as illustrated in Figure 4. This trend can be attributed to recent improvements in computational power and increased availability of educational data. However, overall, such advanced person-specific data analysis in those manuscripts mostly rely on methods developed within psychometrics (e.g. latent state-traits (LST) model). A starting point of future research on idiographic methods in education would be, thus, to leverage existing psychometric techniques, in line with this trend.

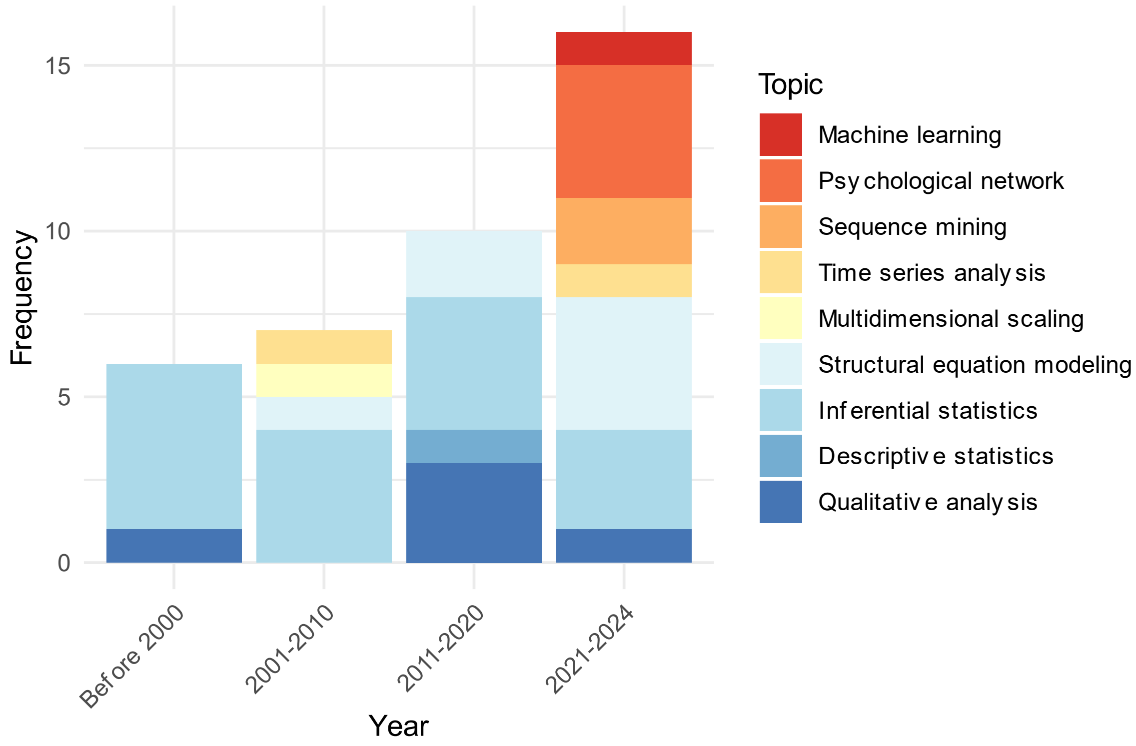

Figure 4. Methods used in the reviewed literature

RQ4: Data sources

Figure 5 illustrates the data sources used in the reviewed papers. The most common source of data in the existing research employing idiographic methods is surveys or questionnaires, used by over half of the reviewed studies (19). Test scores have also been frequently used, appearing in 11 articles. These results are consistent with the previous observations that psychological dispositions and academic performance are the primary topics in the reviewed articles. Surveys are often used to assess psychological dispositions, while test scores are typically used to evaluate academic performance. Additionally, recent studies have increasingly utilised digital log data from learning management systems (LMSs) or other learning tools for longitudinal research due to their ability to unobtrusively capture student behaviour. This trend mirrors the earlier shift toward advanced computational techniques, particularly after 2020 (RQ3).

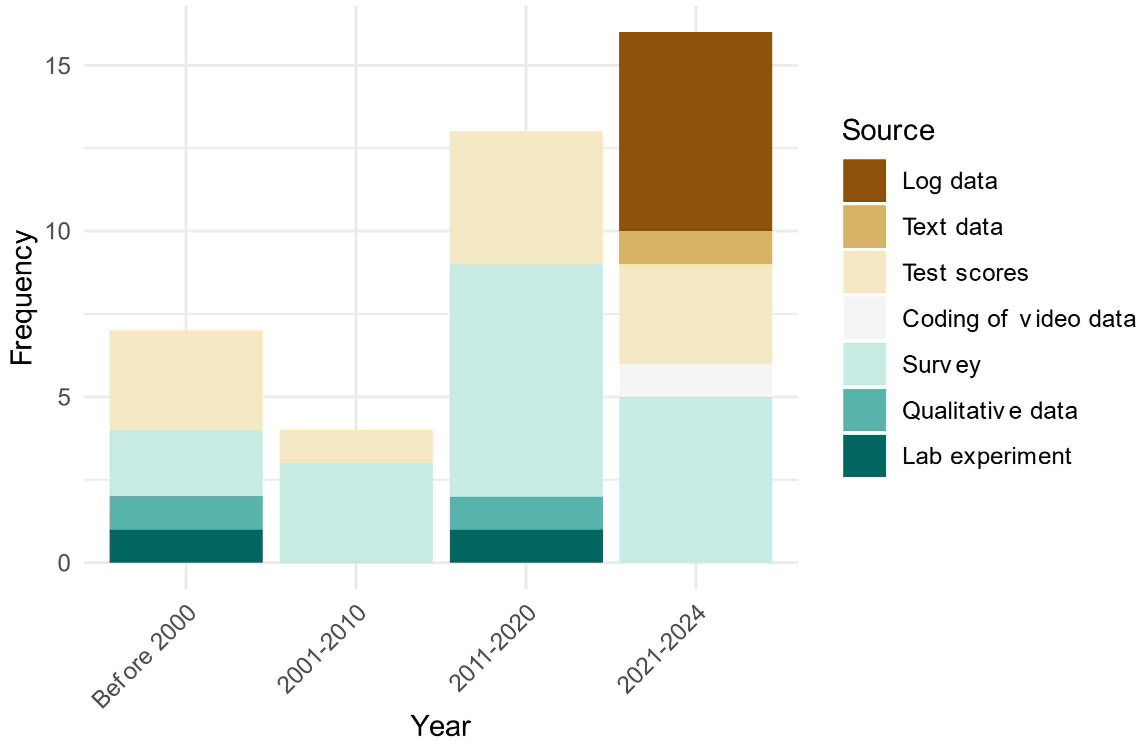

Figure 5. Data sources used in the reviewed literature

RQ5: Educational levels

Finally, we analysed educational stages at which the reviewed papers conducted their research. Out of the 34 included articles, 18 were in tertiary education, 15 were in K-12 (2 in early childhood, 7 in primary, 5 in secondary education and 1 spanning all K-12 educational levels), and 1 was on adult education (see Figure 6). Notably, more recent papers have increasingly concentrated on tertiary education (see Table A1 in the appendix). This shift likely reflects the growing availability of data, as the use of digital tools such as learning management systems (LMSs) is more prevalent in higher education institutions compared to K-12 education settings. Thus, this aligns with the previously observed trend in the data sources (RQ4).

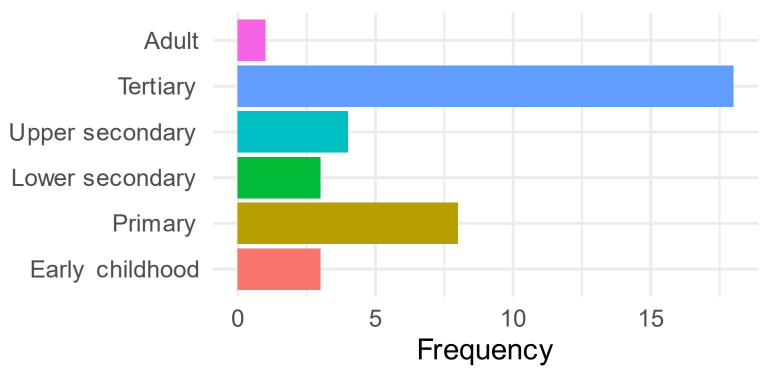

Figure 6. Educational stages studied in the reviewed literature

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Discussion

Answering the main research question

The distinction between idiographic and nomothetic methods in scientific methodology has been long recognized by psychologists (Molenaar and Campbell, 2009; Piccirillo and Rodebaugh, 2019). Yet, idiographic research remains relatively scarce in the field of education. Despite the limited number of reviewed articles, the findings of the scoping review provide an answer to our main research question from two perspectives: the methodological tradition and the emerging trend.

First, the findings show that idiographic methods have been traditionally used to incorporate the context where learning occurs (RQ1), and that educational psychology has been the main arena of idiographic research in education (RQ2). Individual learners have different social and cultural backgrounds, and the learning context is unique to each learner. On one hand, integrating the broader context of each learner into the investigation of learning or educational activities is challenging due to the myriad potential variables. On the other hand, findings obtained by capturing the contexts are less generalisable since the context of each learner is inherently idiosyncratic. Perhaps due to these difficulties, the use of idiographic methods has been limited in education research. The findings also illustrate this point, as most of the reviewed studies use idiographic methods either for testing them in comparison to or to combine them with nomothetic ones, not attempting to derive general insights solely through idiographic approaches (RQ1).

Second, the results reveal that there is a growing trend with an increasing number of studies, likely due to the rising availability of data (RQ4, RQ5) and advancements in computational techniques (RQ3). Digital log data in addition to traditional data collection such as surveys and test scores have been utilised after 2020 (RQ4). All reviewed research that employed log data was conducted in tertiary education settings (see Table A1). Also, advanced analytical techniques such as machine learning, psychological network analysis and sequence mining have been increasingly used after 2020, while earlier studies primarily employed basic statistical methods or qualitative methodology (RQ3). Furthermore, the use of log data and advanced analytical methods has facilitated the exploration of temporal processes within individuals (RQ1). These findings illustrate the emerging trend of computational methods in idiographic education research, underscoring the potential of idiographic learning analytics.

To summarise, idiographic approaches have primarily been used to explore psychological dispositions by integrating relevant contexts specific to each subject. In addition, the growing trend in idiographic education research highlights the possibilities and potentials of advanced analytical methods.

Implications for future research

The findings identify several potential areas for future study. First, as person-specific methodology has traditionally been used to capture the contexts in which learning occurs, a potential research question would be what learner-specific contexts should and could be considered for idiographic analysis. Modern idiographic education research, as observed, holds potential for exploring temporal learning processes within individuals (RQ1). Hence, future research would benefit from accounting for longitudinal temporal changes within individuals. Second, the findings show that idiographic research in K-12 education is notably scarce (RQ5). Increased research using person-specific methods in this area is needed. Third, given that educational psychology presents a promising arena of idiographic research (RQ2), person-specific perspectives should be integrated into the development of psychological theories relating to individual learning processes (e.g. self-regulated learning). Theoretical developments in this area are also crucial for advancing learning analytics (Wise and Shaffer, 2015).

Additionally, as discussed in the Introduction, idiographic methods are suitable for learner-centric personalised learning. This approach opens up new avenues of research in areas that have been underexplored, such as special education (Baek and Aguilar, 2023), giftedness (Haensly and Lee, 2000), doctoral education (Prieto et al., 2023) and adult education (Athanasou, 2013), where such personalised approaches are crucial. Idiographic research in these areas will shed light on learning analytics design for those sub-populations of learners who are underrepresented in contemporary learning analytics research, enhancing inclusion in the digitalisation of education.

Limitations

The design of this review entails several limitations. First, the search query used may not have captured all relevant research. Since “idiographic” is less common in educational literature compared to psychology, there may be other synonyms or related terms that describe similar methodologies. Additionally, the review was restricted to manuscripts written in English, which could have excluded relevant studies published in other languages. As a result, the findings may not fully represent the breadth of research in this area. Moreover, the review included a relatively small number of articles—34 in total—which might be insufficient for drawing comprehensive conclusions. Nevertheless, the clear trends and implications described above provide a valuable foundation for guiding future research on idiographic methods in education. Future research should aim to expand the scope of this review, including studies from psychological research, to help educational scientists and learning analytics researchers develop more refined methods for educational research and practice.

Conclusion

The field of precision education has grown with the increasing availability of educational data and advancements in computational methods. Learning analytics seeks to optimise and personalise learning and its environments but often faces challenges with generalisability and precision when using traditional group-level approaches. As a result, there have been efforts to scale up these approaches to improve their impact. Though less generalisable, Idiographic learning analytics offers a promising alternative by potentially enhancing personalised, precision education. However, idiographic methods have seen limited use in education research compared to other behavioural sciences like psychology.

To shed light on the possibilities of the idiographic methodology in education research, this scoping review explored idiographic research in the literature within the education domain.

The findings illustrate that while fully idiographic educational research remains rare, there is a significant potential for this approach, particularly in the context of digitalisation of education and modern analytical methods. Future research should focus on exploring temporal processes, extending idiographic methods to K-12 education, and developing person-centred theories within educational psychology. Also, since idiographic methods offer the capacity for deep, fine-grained personalisation by learners themselves, future research should be also directed to currently underrepresented populations, promoting inclusion.

While idiographic approaches offer significant potential, it should be noted that they are intended to complement, rather than replace, nomothetic approaches, depending on the specific context of research and practice. Fully harnessing the potential of idiographic methods could be pivotal in advancing precision education in the digital age, where personalisation and contextualisation are increasingly achievable. Integrating both methodologies may provide a more comprehensive understanding and more effective solutions in the evolving landscape of educational research and practice.

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Appendix

Year	Reference	Approach	Methods	Topic	Objectives	Data	Educ. stage	N
1971	(O’leary, 1971)	Combination	Inferential statistics	Short-term memory	Investigate the influence of relevance of learning materials to learning	Survey	Tertiary	96
1975	(Bruno, 1975)	Comparison	Inferential	Cognitive	Compare methods	Standard	Primary	1500

Year	Reference	Approach	Methods	Topic	Objectives	Data	Educ. stage	N
			statistics	growth	to predict students' long-term test scores from past scores	test scores		
1986	(Cooksey, Freebody and Davidson, 1986)	Idiographic	Inferential statistics	Reading skills	Predict children's end-of-year reading skill from teachers' expectations based on their current skills such as word knowledge.	Survey	Tertiary	20
1998	(Salonen, Lepola and Niemi, 1998)	Comparison	Inferential statistics	Reading skills	Predict the development of reading skill based on motivational orientations, coping strategies and language development	Survey, test scores	Early childhood	32
2000	(Haensly and Lee, 2000)	Idiographic	Qualitative analysis	Giftedness	Explore early signs of giftedness in children	Observational data	Early childhood	20
2000	(Hintze *et al.*, 2000)	Combination	Inferential statistics	Oral reading fluency	Demonstrate the practicality of generalisability theory with curriculum-based measurement of oral reading fluency	Test scores	Primary	240
2003	(Fitzgerald, White and Gruppen, 2003)	Combination	Inferential statistics	Performance	Evaluate medical students' ability to self-assess their performance	Survey	Tertiary	
2004	(Oosterwegel, Littleton and Light, 2004)	Combination	Inferential statistics	Engagement with computer-based tasks	Evaluate gender differences in children's computer attitudes, use, and enjoyment. Examine self-evaluation against ideal self, prototype, and gender stereotypes	Survey	Lower secondary	73
2010	(Schmidt, Perels and Schmitz, 2010)	Comparison	Inferential statistics, Time	SRL	Demonstrate the advantages and limitations of time	Survey	Primary	44

Year	Reference	Approach	Methods	Topic	Objectives	Data	Educ. stage	N
			series analysis		series analyses and hierarchical linear modelling for assessing longitudinal data			
2012	(Raudenbush, Reardon and Nomi, 2012)	Combination	Structural equation modelling	Academic performance	Propose a statistical analysis method that incorporates person-specific and site-specific variables to embrace between-person variances	Standard test scores	Lower secondary	12916
2013	(Athanasou, 2013)	Idiographic	Inferential statistics	Course selection	Investigate decision-making of course choice with respect to vocational interests	Survey	Tertiary	4
2015	(Hurley and Murphy, 2015)	Idiographic	Multidimensional scaling	Cognitive reasoning, engagement	Propose a new method of person-specific measurement for dynamic assessment interventions	Interview, test scores, observational data	Upper secondary	1
2016	(Van Norman and Parker, 2016)	Combination	Inferential statistics	Oral reading fluency	Identify discontinuous growth of oral reading and investigate patterns of such growth	Test scores	Primary	1600
2017	(Ordem, 2017)	Idiographic	Qualitative analysis	Motivation	Explore how different dimensions of motivation affect second language learning	Interview, diary	Adult	1
2018	(Merk *et al.*, 2018)	Combination	Structural equation modelling	Epistemic beliefs	The coexisting between-person distinctions and within-person fluctuations in epistemic beliefs related to specific topics	Survey	Tertiary	577
2019	(Respondek,	Comparison	Structural	Achievement	Examine the	Survey,	Tertiary	98

Year	Reference	Approach	Methods	Topic	Objectives	Data	Educ. stage	N
	Seufert and Nett, 2019)		equation modelling	emotions	relationship between achievement emotions and perceived academic performance	test scores		
2019	(Singh, 2019)	Combination	Qualitative analysis, Descriptive statistics	Engagement, transformative learning	Investigate the effects and results of anti-racist social work education, assessing the pedagogical significance and practical value of instructing social work students on anti-racism	Survey	Tertiary	36
2019	(Sleeman *et al.*, 2019)	Comparison	Inferential statistics	Self-control in learning maths	Investigate the effects of a novel self-regulated learning program to improve basic facts fluency	Survey, test scores	Primary	47
2020	(Cervone, Mercurio and Lilley, 2020)	Combination	Inferential statistics, Qualitative analysis	Self-efficacy	Investigate variations in students' self-efficacy appraisals across different contexts	Survey	Tertiary	72
2020	(Samuel and Burger, 2020)	Combination	Inferential statistics	Dropout intentions	Evaluate the predictive roles and interactions among major negative life events, self-efficacy and social support in upper secondary education dropout intentions and actual dropout	Survey	Upper secondary	4956
2021	(Ruble *et al.*, 2021)	Comparison	Inferential statistics	Academic performance in special education	Examine the correlation between parental and teacher self-report assessments of a child's progress in special education	Survey, test scores	K-12	89

Year	Reference	Approach	Methods	Topic	Objectives	Data	Educ. stage	N
					and an objective evaluation by an independent observer			
2021	(Saqr and López-Pernas, 2021b)	Idiographic	Psychological networks	SRL	Person-specific self-regulated learning	Survey	Tertiary	1
2021	(Saqr and López-Pernas, 2021a)	Idiographic	Psychological networks	SRL	Person-specific self-regulated learning	Survey	Tertiary	1
2022	(Brunn, Freise and Doebler, 2022)	Comparison	Structural equation modelling	Learning curve	Propose and experiment a method of smoothly modelling longitudinal computer testing data	Test scores	Primary	3500
2022	(Dong *et al.*, 2022)	Comparison	Inferential statistics, Structural equation modelling	Learning curve	Propose analysis methods to model how student attributes contribute to the between-person variance	Standard test scores	Primary	1305
2022	(Malmberg *et al.*, 2022)	Idiographic	Psychological network	Socially shared regulation of learning	Investigate social and individual regulation of learning that occur concurrently and sequentially in collaborative learning contexts	Coded video data	Upper secondary	12
2022	(Paba, De Castro Daza and Roncancio, 2022)	Idiographic	Qualitative analysis	Collaborative argumentative writing	Explore students' regulation of positioning on a controversial topic in remote teaching of collaborative writing	Log data of online writing activity	Tertiary	2
2022	(Peng, Lowie and Jager, 2022)	Comparison	Time series analysis	Linguistic complexity	Identify developmental patterns of second language writing skill on individual and group levels	Writing samples	Tertiary	9
2023	(Aalbers *et al.*, 2023)	Comparison	Machine learning	Momentary stress related	Investigate the role of smartphone use	Survey, log data	Tertiary	224

Year	Reference	Approach	Methods	Topic	Objectives	Data	Educ. stage	N
				to smartphone use	to predict students' stress on individual level and identify the between-person variance of these predictive models	from smartphone		
2023	(Henry, Thorsen and Uztosun, 2023)	Combination	Structural equation modelling	Self-concordance model	Explore the effects of self-concordant goals on engagement and resilience in second language learning	Survey	Tertiary	41
2023	(Saqr, López-Pernas, *et al.*, 2023)	Combination	Sequence mining	Engagement and achievement	Study the relationship between engagement and achievement across a whole tertiary education program	LMS data	Tertiary	106
2023	(Saqr, Lopez-Pernas, *et al.*, 2023)	Combination	Sequence mining	Learning strategies	Explore students' learning strategies over a full program on between- and within-student levels	LMS data	Tertiary	106
2023	(Saqr, 2023)	Comparison	Inferential statistics	Academic performance	Compare within-person variance to group level one in longitudinal academic performance	LMS data	Tertiary	286
2024	(Saqr, 2024)	Comparison	Psychological networks	Engagement and achievement	Study the relationship between engagement and achievement across a whole tertiary education program.	LMS data	Tertiary	238

Table A1. Extracted information from the reviewed literature