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Associations of Research Questions, Analytical Techniques, and Learning Insight in Temporal Educational Research: A Systematic Mapping Study

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Abstract

Learning has a temporal characteristic in nature, which means that it occurs over the passage of time. The research on the temporal aspects of learning faces several challenges, one of which is utilizing appropriate analytical techniques to exploit the temporal data. There is no coherent guide to selecting certain temporal techniques to lead to results that truthfully uncover underlying phenomena. To fill this gap, this systematic mapping study contributes to understanding the type of questions and approaches in works in the area of temporal educational research. This study aims to analyze different components of published research and explores the current trends in educational studies that explicitly consider the temporal aspect. Using the thematic coding method, we identified trends in three components, including asked research questions, utilized methodological techniques, and inferred insight about learning. The distribution of codes regarding asked research questions showed that the highest number of studies focused on method development or proposing a methodological framework. We discussed that methodological development, with the underlying theory, led to identifying learning indicators that can provide the ability to identify individual students with respect to the learning concepts of interest. In terms of utilized techniques, there was a strong trend in visualization analysis and process mining. This study found that to discover insight into learning, it is important to utilize techniques that are interpretable to characterize temporal patterns.

Notes for Practice

- We reviewed 176 papers to capture trends in asked research questions, utilized techniques, and inferred insight about learning in temporal studies published between 2017 and 2022.
- We identified two categories of insight about learning, including user-centric and instructor-centric.
- To capture the temporal nature of online behaviours, process mining, clustering, and visualization techniques were the most prevalent techniques to identify learning indicators.
- Studies that aimed to develop a method or propose a new algorithm for prediction modelling were less likely to lead to learning insights.

Keywords

Learning analytics, systematic mapping, temporal analytics

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1. Introduction

The rapid advancement and extensive adoption of technology in education media have generated a copious amount of data that can provide the knowledge needed to improve learning and education (Bienkowski et al., 2014). To fulfill this promise, the field of learning analytics (LA) formed to expand our understanding of learning and how to improve it (Gašević et al., 2015). According to Zimmerman (1990), learning is the acquisition of knowledge that influences the thinking and behaviour of individuals. As for the learning phenomenon itself, it is critical to understand the innate relation between time and learning; learning has a temporal characteristic, meaning that it occurs over the passage of time (Knight et al., 2017).

The sequence of learning-associated activities can provide insight into understanding the learning process; temporal analytics is the field dedicated to exploring the learning process and its temporality (Bogarín et al., 2018; Chen et al., 2016; Knight et al., 2017). Due to the temporal nature of learning, it is crucial to use appropriate techniques to capture this aspect. Temporal analytics has gotten attention in recent years as many works stated the importance of temporality in educational studies (Gašević et al., 2017; Knight et al., 2017; Reimann et al., 2014). For example, the Journal of Learning Analytics designated a special issue to the topic, and the paper on Critical Issues in Designing and Implementing Temporal Analytics discussed the importance of temporal analytics in educational studies as well as its current status in the learning analytics community (Chen et al., 2018).

There are numerous benefits of temporal analytics for education and learning practices as it provides nuanced ways to explore data (Knight et al., 2017; Reimann et al., 2014). Many researchers utilize the techniques to further identify temporal patterns that would be unknown without temporal analysis. For instance, a study conducted by Kinnebrew et al. (2014) assessed the impact of feedback on the learning process, at the cognitive and meta-cognitive levels, during learning engagement among middle school students. Despite insignificant results from the correlational test, this study highlighted the power of the exploratory study to understand different aspects of student learning behaviour and relate them with knowledge building over time.

Despite this clear benefit, temporality has often been neglected in the applied learning research domain (Bogarín et al., 2018; Knight et al., 2017). As Reimann posited, researchers often overlook the full potential of available information regarding temporality (Reimann, 2009). He stated that human learning is inherently cumulative, and research on temporality should consider both quantitative aspects (e.g., duration, transitions) and order. Therefore, it is imperative to obtain an appropriate methodological approach to exploit the available temporal information.

Many techniques have been used for the temporal exploration of data, such as visualization (Riel et al., 2018), frequent sequence analysis (Jovanović et al., 2017; Nazeri et al., 2023), transitional analysis (Mahzoon et al., 2018), network analysis (Kinnebrew et al., 2014), fuzzy mining techniques (Beheshitha et al., 2015), and others (Bogarín et al., 2018; Hatala et al., 2023). Although we know about the technical differences between the analytical techniques, it is not clear which type of questions they are most suitable to address in the educational context, which type of applications they can furnish, or which type of data they require (Knight et al., 2017; Molenaar, 2014). For instance, a comparison study conducted by Matcha et al. (2019) on the results from three prominent temporal analytical approaches in the detection of learning tactics and strategies in a MOOC setting (Matcha et al., 2019) showed that different techniques can yield different results and lead to different interpretations for the obtained learning strategies. Another comparative study was conducted by Chen et al. (2017) to explore two prominent sequential mining models, including Lag-sequential Analysis (LsA) and Frequent Sequence Mining (Chen et al., 2017). The techniques provided different but complementary analyses of temporal patterns. Furthermore, Knight et al. (2017) noted the research on the temporal nature of learning faced several challenges, one of which is utilizing appropriate analytical techniques to exploit the temporal data. Overall, these studies showed that there is no coherent guide to selecting certain temporal techniques to lead to results that truthfully uncover underlying phenomena.

The main contribution of this study is to aid understanding of how temporal educational research is conducted and the insights it can provide. The study will analyze different components of existing studies and explore current trends in educational research that explicitly consider the temporal aspect. The study will focus on the research questions that have been answered, the analytical techniques used, and the types of insights about learning that have been uncovered through temporal educational research. Specifically, the study will identify and map the research questions addressed through temporal educational research, as well as the analytical techniques used to answer these questions. This will provide valuable insights about which techniques are most suitable for different types of research questions, which will be beneficial for researchers conducting future temporal educational research.

Another contribution of the study is to explore the types of insights about learning that have been uncovered through temporal educational research. By identifying these insights, the study will provide a better understanding of how temporal educational research can contribute to our understanding of learning processes and outcomes. Overall, the study will provide a comprehensive overview of the current state of temporal educational research and its contributions to the field of education. This will be useful for researchers and educators interested in the temporal nature of learning and who want to better understand how to incorporate temporal aspects into their research and teaching practices. To reach these goals, we constituted the following research questions:

RQ1: In educational research that used temporal studies, what (a) research questions have been answered, (b) analytical techniques were used, and (c) types of insights about learning have been uncovered?

RQ2: What are the associations between the research questions asked, the analytical techniques used, and the insights about learning discovered?

2. Methods

Kitchenham et al. (2011) suggested that a systematic mapping study can provide a wide literature review to demonstrate the quantity and structure of evidence for decision-making. Also, our mapping study can identify the direction of ongoing studies. The main difference between a systematic mapping study and a literature review is that, in a mapping study, the aim is to provide classification and structure of the research area. In a systematic literature review, the aim is to synthesize evidence to address certain research questions (Petersen et al., 2015).

According to Petersen et al. (2008), the key steps to establishing a systematic mapping study in learning analytics are these: 1) defining the protocol for the mapping study, 2) conducting an exploratory study on data collection, and 3) analyzing and summarizing the data. Figure 1 shows the process of establishing a systematic mapping study.

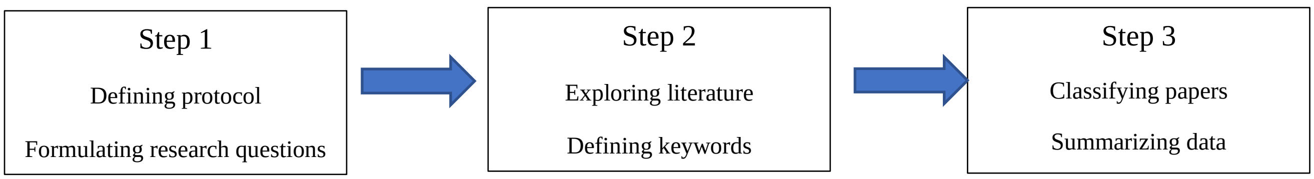

Figure 1. The process of conducting a mapping study.

2.1. Step 1: Defining the Protocol

Defining a protocol in this study includes the following stages: identifying the data sources, describing the search and selection strategies, and describing the method for extracting and analyzing the studies.

2.1.1. Data Sources

To establish an exploratory search, we used digital libraries and searched through journals, conferences, and workshop proceedings in the area of education and educational technology from 2017 to 2021. We chose December 31, 2021, as the end date for the full completed calendar year and we performed yearly searches (see below) backward, until we reached the number of papers that we could feasibly examine within the timeframe and resources available for this study, which took us back to 1 January 2017. Coincidentally, by 2017, temporal analysis in learning analytics had attracted enough attention for special issues of the *Journal of Learning Analytics*, which appeared in late 2017 (Vol. 4, No. 3) and early 2018 (Vol. 5, No. 1). Our digital search included digital libraries, including our own university library, the ACM digital library, the IEEE digital library, Science Direct, and Google Scholar. We also manually searched the publishers' websites for the top 10 publications listed in Google Scholar's venue rankings in the category of Educational Technology (Google Scholar, n.d.).[1] These venues are listed in Table 1. Although utilizing multiple search strategies yielded many duplicates, varied sources helped us to execute the complex queries.

Table 1. List of Venues Searched Manually via their Google Scholar Web Page Link

Rank	Publication
1.	Computers & Education
2.	British Journal of Educational Technology
3.	The Internet and Higher Education
4.	Journal of Educational Technology & Society
5.	Education and Information Technologies
6.	The International Review of Research in Open and Distributed Learning
7.	Educational Technology Research and Development
8.	Interactive Learning Environments
9.	Computer Assisted Language Learning
10.	International Journal of Educational Technology in Higher Education

[1] https://scholar.google.ca/citations?view_op=top_venues&hl=en&vq=soc_educationaltechnology

2.2. Step 2: Retrieving Papers

Our search strategy to identify keywords and construct search queries follows guidelines from Dickersin et al. (1994).

2.2.1. Identifying Query Keywords

We designed the following stages to ensure that our search strategy included a variety of papers covering the area of interest. Table 2 shows the identified search keywords in each stage.

Identifying the general search keywords and terms based on the study's research questions. Accordingly, our RQs generally focus on "temporal analytics" and "learning analytics."

Finding more keywords and terms used in prominent studies in the area of "temporal analytics" and "learning analytics." In this stage, we selected an editorial paper in the special issue of the *Journal of Learning Analytics* that focuses on "*critical issues in designing and implementing temporal analytics*" (Chen et al., 2018). The paper reviewed literature on temporal analytics, and we extracted the keywords from the paper. Further keywords were also extracted from other papers within the special issue (Chen et al., 2018, 2017; Knight et al., 2017; Mahzoon et al., 2018; Riel et al., 2018). As a result, we identified 55 different keywords, and we selected the top 20 of the most frequent and relevant to temporality.

Identifying synonyms and alternatives. To identify synonyms, we searched a different area of educational technology. For instance, temporal analysis is a commonly used term for the concept of time for analysis in the learning analytics field. However, there are some closely related terms to temporal analysis, and many authors used those terms interchangeably. For instance, the term educational process mining is widely used in the educational data mining (EDM) field (Bogarín et al., 2018). It seems that, in EDM, process mining is analogous to temporal analysis in LA. In the field of behavioural psychology, Bakeman used sequential analysis for the same purpose as temporal analysis (Bakeman & Gottman, 1997). Furthermore, the outcome from stage 2 helped us to identify more similar terms. In this stage, we arranged keywords into two subgroups: 1) keywords that imply learning and theory; 2) keywords associated with analytical techniques.

Simplifying the keywords to comprehend relevant terms. In this stage, we simplified the keywords to cover similar words that might not have been covered in stage 3. In doing so, we used special characters such as an asterisk (*) to specify characters in the keywords that can vary without altering meaning. For example, *sequen** includes *sequence*, *sequential*, *or sequencing.* This format is supported by our targeted online databases. In the case of not supporting this format, we manually inserted all possible keywords.

Table 2. Extracted Keywords to Generate a Search Query

Stage	Keywords
1	temporal analytics, learning analytics
2	learning analytics, sequential analysis, temporal analytics, self-regulated learning, knowledge building, educational data mining, teaching methods, discourse, discussion, community of inquiries, frequent sequence mining, sequence data mining, sequence data model, teaching method, temporal database, process analysis, lag analysis, process, interaction sequence, predictive model, cluster analysis, context effect, explanatory power, holy grain
3	learning analytics, educational technology, educational data mining, temporal analytics, sequential analysis, process analysis, process mining, sequential mining, lag analysis, knowledge building, interaction sequence, cluster analysis, predictive model
4	learning analy*, educat* tech*, sequen* analy*, temporal analy*, process analy*, lag analy*, cluster analy*, predic*, predic* model, educat* data mining, process mining, knowledge building, interaction sequen*

2.2.2. Generating Search Queries

Having the keywords, we used logical operation (AND/OR) to generate search queries (Table 3). We defined three types of queries, and used a combination of these to construct our search:

i) A query that covers the general area of educational technology
ii) A query for the specific area of temporal research; we aimed to cover the extracted keywords from literature in the previous stage, using AND/OR operations
iii) Generating the main search query by combining previous queries

Table 3. Search Queries Used to Extract Relevant Papers

Type	Search query
i	"learning analy*" OR "educat* tech*" OR "educat* data mining" OR "teach*" OR "pedagog*"
ii	("temporal*" OR "sequen*" OR "process" OR "lag") AND (analy* OR "mining" OR "model" OR "cluster" OR "predic*")
iii	Query (i) AND Query (ii)

2.2.3. Inclusion and Exclusion Criteria

To select relevant studies that address our research questions, we applied Search Query (iii) (see Table 3) in all search engines and venues over the last five years (from January 2017 to December 2021). To ensure the relevance of papers in our corpus, we excluded studies that did not focus on temporal aspects of learning. Firstly, we removed duplicate papers from different sources. Next, we carefully reviewed abstracts and selected studies that focus mainly on the temporal aspect of learning, and eliminated papers without attention to temporality in their abstract. The last excluding stage encompasses scrutinizing papers and reviewing sections of articles. This stage was accomplished during the qualitative coding of papers (discussed in the next section). Our main aim in the mapping study was to organize the studies and the information within the studies. However, for inclusion, a paper had to encompass clear objectives and methodology, as well as have a minimum description of the student learning progression or temporality in the method. As a result, 176 articles were retained. The flow chart of the selected papers in each stage can be seen in Figure 2.

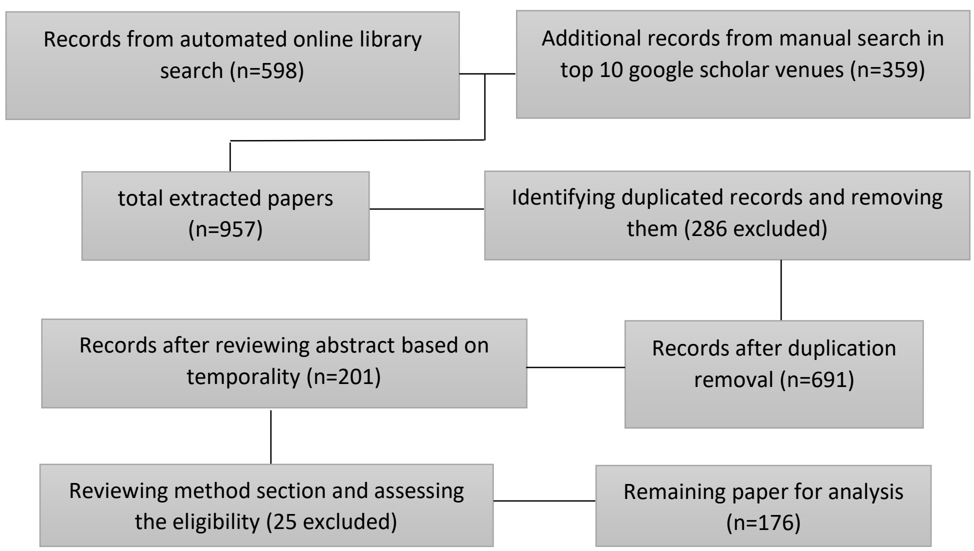

Figure 2. The number of selected papers in each stage.

2.3. Step 3: Developing a Classification Scheme and Summarizing the Results

The classification scheme was designed to characterize studies with respect to their research question focus, analytical technique, and obtained insights about learning. This study used thematic analysis to create a coding schema. The method has been widely used in qualitative research and term analysis (Basit, 2010). The thematic coding method is useful for coding descriptive terms in literature where the authors propose research questions, utilize the analytical technique, and discuss contributions and insights. At the higher level, the coding method helped us to identify the type of study and its contribution within each paper. Next, we were able to categorize different aspects of studies to address our research questions. To conduct a trustworthy thematic analysis, we followed the guidelines of Nowell et al. (2017), which provides a step-by-step approach including familiarizing ourselves with data, generating initial codes, searching for themes, reviewing themes, defining themes, and reporting.

2.3.1. Identifying Sections for Coding

In the first step, to familiarize ourselves with the literature, we reviewed different sections of studies and identified those that matched our RQs. For example, to find out what research questions have been answered, we focused on the introduction and research questions. Likewise, to code the utilized analytical technique, we reviewed the methodology section. To code the type of inferences about learning, the results and discussions were reviewed. In cases where the paper did not follow a mainstream structure, we searched for the pertinent information in other parts of the paper. The full list of the sections can be seen in Table 4.

Table 4. Coding Sections Chosen for Addressing RQs

Research coding sections	Description
Research questions/Research focus	Codes that show the main focus of the research (aims of the research).
Analytical techniques	The analytical techniques used in the research (methodology).
Inferences about learning	The type of insights and inferences about learning (results and discussion).

2.3.2. Generating the Initial Codes

In this study, we worked with three themes directly mapped to the research questions, as listed in Table 4. In the second step, through the iterative process, we produced an initial set of codes for each section in Table 4, based on a detailed reading of the identified sections in 50 papers in our corpus. In this study, the first author conducted all the coding step by step, and the reliability of the produced codes was assessed iteratively by an expert. To ensure the consistency of the codes, aside from the expert review, the data was revisited and recoded several times, as described below. As the papers in our corpus were typically coded with multiple codes in each theme, measures for interrater reliability were not used to measure the quality of the coding scheme. For full transparency, to support confirmability, Appendix 1 shows the assigned codes for all the papers.

2.3.3. Reviewing and Finalizing the Codes

After the initial codes from 50 papers were stabilized, a random sample of 10 papers was coded independently by two authors, discrepancies were discussed, and the coding schema and definitions were updated. Most adjustments in this phase involved determining the boundaries for the codes: how prominent the research question was, the analytical technique, and the level of theoretical grounding to support assigning the code. Another set of 30 papers was coded independently with the revised set of codes, and a final adjustment to the schema and code definitions were done. After discarding the codes assigned to papers in the development stage, the first author used the final schema, shown in the results section, to code all the papers.

2.3.4. Collecting Authors' Keywords from Studies

Furthermore, by examining the frequency and distribution of authors' keywords across the published papers, we can gain insights into the most common topics and themes explored in temporal educational research. We acknowledge that relying on keywords does not accurately represent all dimensions of the published research (e.g., method and conclusions); however, we feel it shows the main characteristics of temporal educational research from the authors' perspectives. It is worth noting that the trend of illustrating authors' keywords is commonly seen in mapping studies, which aim to provide an overview of a particular field or research area (Mohabbati et al., 2013; Petersen et al., 2008). Overall, while keywords are not a perfect representation, they can still provide valuable information about the overall trends and characteristics of research in the field.

3. Results

The 176 included sources were published between 1 January 2017 and 31 December 2021. We structured the results section as follows. First, we illustrated the trend in authors' keywords with a visualization. Then, to address RQ1, we organized three sections that separately discuss the components of RQ1. Next, we addressed RQ2 by providing relational visualizations for the pairs.

3.1. Authors' Keywords

To identify the current trend of the published papers, we explored the authors' keywords. We identified 571 unique keywords. Table 5 shows the topmost frequent keywords with the cut-off at n=7. As can be seen, the authors of educational temporal analysis papers predominantly associated them with the field of learning analytics (LA; n=55 keywords) followed by self-regulated learning (SRL), which is the most prominent learning theory in our corpus (n=23). The generated word cloud (Figure 3) shows 114 unique authors' keywords that appeared more than once.

Table 5. The Authors' Keywords

Authors' keywords	Counts
learning analytics	55
self-regulated learning	23
process mining	16
educational data mining	15
collaborative learning	11
knowledge tracing	9
MOOCs	9
sequence mining	9
temporal analysis	8
blended learning	7

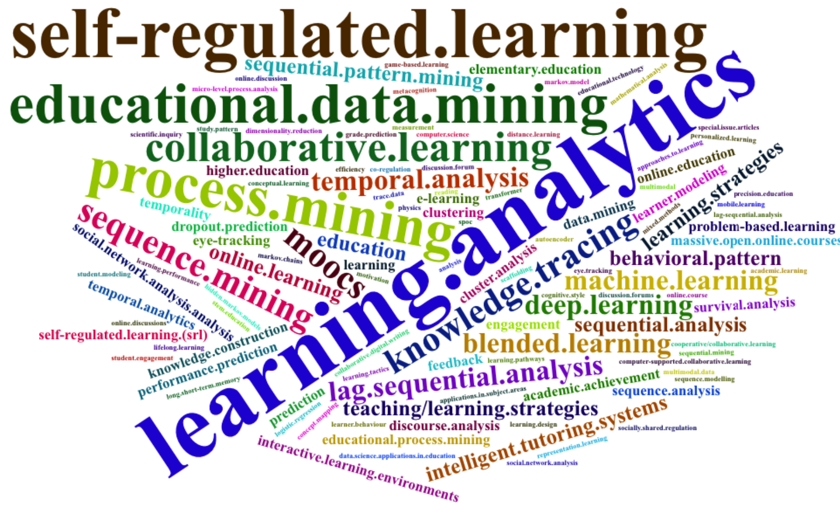

Figure 3. Word-cloud of terms that occurred more than once.

3.2. RQ1: Identifying Trends in Temporal Studies

Prior to presenting the annual trend in asked research questions, utilized techniques, and obtained insights, we provided the total number of published papers based on the published year (Figure 4). The figure shows a slight decrease from 2017 to 2018 by six papers and a sudden increase by 11 in 2019. The number remains constant at approximately 38 papers for 2019, 2020, and 2021.

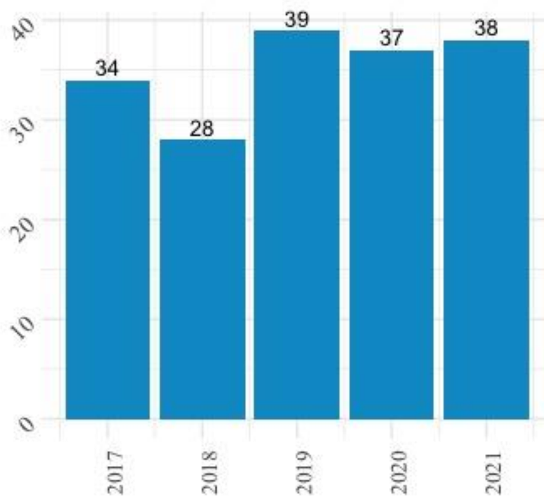

Figure 4. Number of published papers per year.

3.2.1. Identified Research Question Codes and Their Distribution

The result from the qualitative thematic coding shows 7 codes for the focus of studies' research questions (Table 6), beginning with *exploring socio-dynamic*, which captures the dynamic of interaction patterns among peers during the discourse. The next code aims to *develop a method* or improve the existing ones. This code also includes proposing a methodological framework. The next code can also be considered as a subcategory of *method development* where the studies specifically aim to identify students *at risk* of failure. The next code directs the research question to *group* the users based on their behaviour or performance. Two more codes, including *exploring SRL processes* and *identifying non-SRL learning indicators*, rely on the theoretical exploration of learning phenomenon.

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Table 6. Focus of Research Questions Being Asked in the Papers

Research Questions Focus (label)	Description
Exploring socio-dynamics	Analyzing the peer interactions and social dynamics during asynchronous discussion or collaborative tasks.
Method or algorithm development	Proposing or improving existing algorithms, methods, or frameworks. Also, authors can provide a novel framework that includes data collection, cleaning, and analysis approach. Furthermore, the study can compare the affordance of different analytical techniques.
At-risk student identification	Predicting students at risk of failure (drop out) by using a set of features and prediction model (the code is a subcategory of method development).
Group emergence/group comparison by performance	Categorizing the users based on their online behaviour or comparing the group of poor performing students vs. high-performing ones.
Exploring SRL processes	Identifying and exploring SRL-associated behaviours or engagement with materials.
Non-SRL learning indicators identification	Finding the indicators that can represent learning phenomenon that needs to be backed by learning theories (excluding SRL theory).
Time to intervention	Identifying the proper time for feedback or intervention

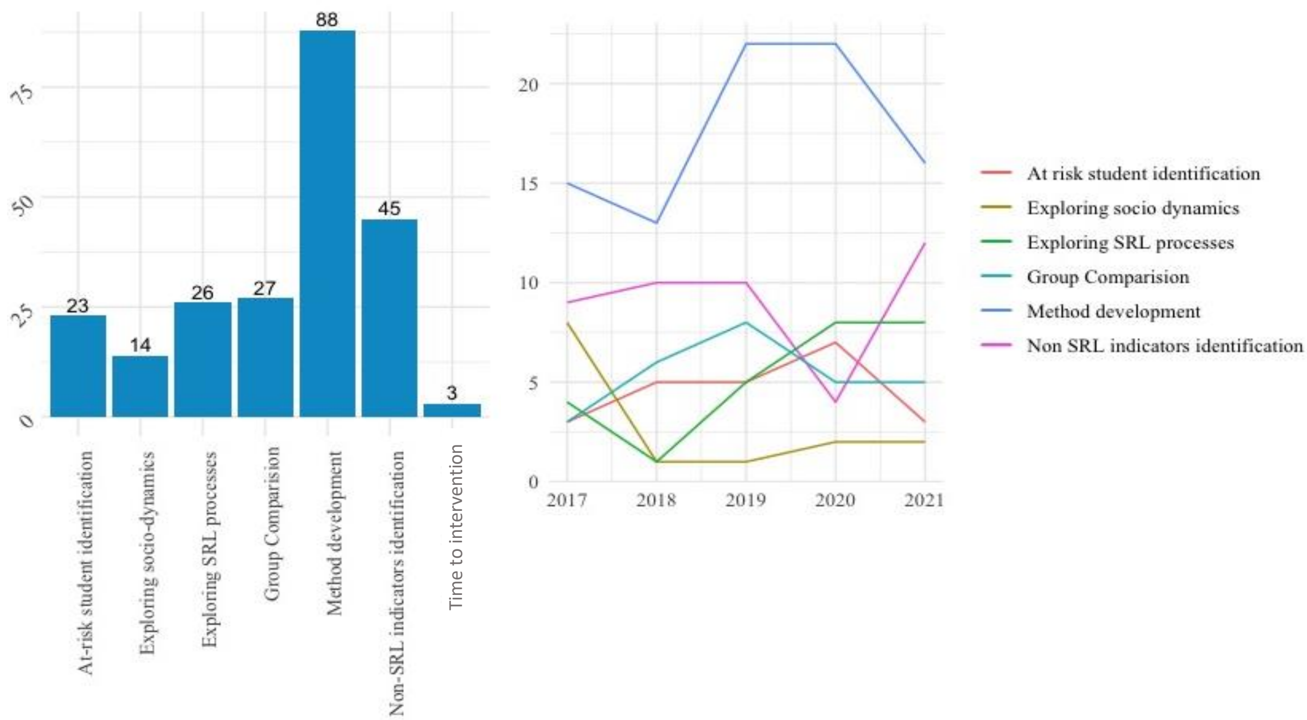

Figure 5. The distribution (left) and trend (right) of asked research questions.

Figure **5** presents the frequency of the research question codes in our corpus and their occurrence over the five-year period. Overall, 226 codes were assigned to 176 papers. The highest RQ focus was *method development* or *proposing methodological framework* (n=88). This suggests that the mainstream trend in educational temporal studies in 2017–2021 was methodological development. The next trend is *exploring behaviours*, which can be an indicator of learning but are not based on SRL theory (n=45). In this category, studies relied on other theoretical background and learning constructs to justify discovered learning phenomenon. Aiming to group users based on their online behaviour or performance (n=27), *exploring SRL-associated behaviours* (n=26), and *identifying students at the risk of failure* (n=23) are the next frequent categories, respectively. The least trending focus is to “identify when it is the time to intervene to provide constructive feedback” (n=3). The occurrence of codes over the five-year period (Figure **5**, right) does not show clear increases or decreases. The only two discernible time-related changes in focus is an increase in exploring SRL processes and a drop in exploring socio-dynamics from the initially higher count in 2017 to the lows over the next four years.

3.2.2. Utilized Analytical Techniques

This study identified 10 groups of analytical techniques used in temporal educational research. Table 7 describes the full set of identified codes; overall, 300 codes were assigned to 176 papers (since a paper can receive multiple codes). Figure 6 shows the frequency of the codes for the analytical techniques and their distribution over the five-year period. The descriptive analysis of the codes indicates that *process mining* (n=70) and *visual analysis* (n=62) are the most frequently utilized techniques, followed by *statistical analysis (stat)* (n=43) and *cluster analysis* (n=39). The high trend in the use of process mining suggests the affordance of this technique to reveal the temporal dynamics of these behaviours. Studies often interpreted the identified temporal behaviours as a study strategy or learning engagement pattern explained by learning theories. Interestingly, the high use of *visual analysis* can show the importance of visualization to discover and explain the dynamicity of behaviours. In terms of yearly trends, we did not identify dramatic shifts. However, slight uptrends in *process mining, frequent sequence mining*, and *clustering* are visible, in contrast to a slight downtrend in *statistical analysis*.

Table 7. Identified Codes for Analytical Technique

Analytical Techniques	Description
Process mining	Process mining detects the significance of the transitions between events. Some examples are lag analysis, fuzzy miner, inductive miner, etc.
Frequent Sequence Mining	Different from process mining, this technique detects frequent sequences of events that occur more often during the defined period. For instance, this technique also looks into the whole sequence of activities during a week and compares it to other weeks.
Cluster analysis	Clustering techniques group data points based on statistical similarity, and are usually followed by statistical analysis to identify the differences between clusters.
Text mining/Content analysis	Text mining or Content analysis is defined as the use of any natural language processing technique to model contextual data.
Neural network	This technique uses the network of neurons to implement a prediction model. Any type of deep neural network is considered in this category.
Qualitative analysis	Qualitative techniques are used to qualitatively examine and/or discuss the nature of the phenomenon.
Basic statistical analysis	Any statistical standalone test that is not part of another technique (e.g., comparing clusters). Examples include correlational test, ANOVA, pre-post test, entropy analysis, interaction over time, time window analysis.
Network analysis	The aim is to identify and structure the relations to explain social phenomena using nodes and relation lines.
Visualization analysis	The main aim of visual analysis is to communicate the meaning of data through visualizing it. We focused on the explanatory power of visualization as this code is assigned if the use of visualization is crucial to driving conclusions in the research. An example is that the researcher uses visualization to compare two phenomena to identify any pattern and drive a conclusion.
Other prediction models	Any other techniques used to develop a prediction model (e.g., random forest, SVM).

From a temporality perspective, some analytical techniques work exclusively with time data (process mining, frequent sequence analysis) while others are more general. In temporal educational studies, the more general techniques, such as statistics or clustering, were either applied to the outputs of the process mining or frequent sequence mining, or to features capturing temporal aspects of data, e.g., frequency of learner actions within a time window. Often studies utilized several techniques together. We presented these cross relations in Figure **7** where the main diagonal shows the number of times a sole technique was used in the study; other cells show techniques being used together. The high use of visualization analysis indicates the crucial role of this technique to reveal temporal aspects. Without extensive visualizations, it seems that studies would not be able to derive their findings; therefore, it was extensively utilized with other techniques, especially process mining. The second most utilized technique was process mining, one of the “pure” temporal techniques. As Figure **7** shows, when process mining was used, it was used solely in 23 studies. More often, it was used with other techniques, such as visualization, to interpret the process models (n=31), cluster analysis (n=18) to cluster either students or discovered processes, frequent sequence mining (n=11), and basic statistical tests to investigate other aspects of student learning behaviours (n=10).

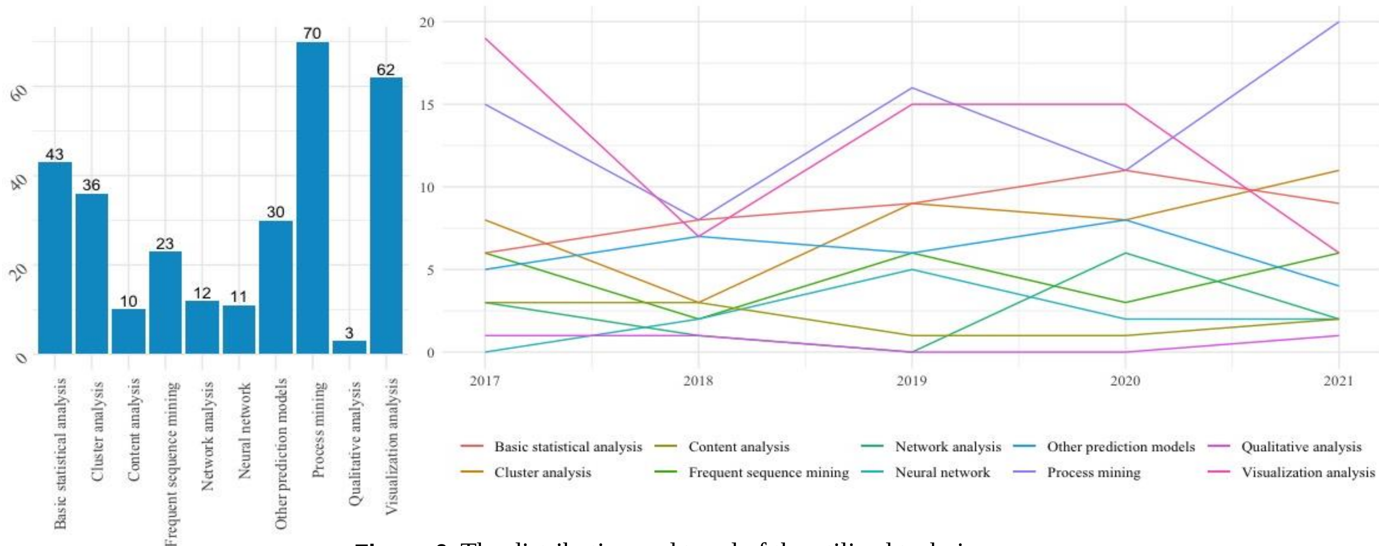

Figure 6. The distribution and trend of the utilized technique.

3.2.3. Insights About Learning

Table 8 shows the identified codes for insights about learning. Overall, 212 codes were assigned to the 176 papers. Figure 8 shows the frequency of the codes and their distribution over the five-year period. The highest learning insight trend is *identifying indicators of learning* (n=77). The next highest refers to the *no-learning-focus-outcome* (n=51) in that the studies did not (sufficiently) show the circumstances of the learning phenomenon. These studies often focused on developing a method rather than examining the impact on learning. From the time progression chart (Figure 8, right) we can discern a drop from a high in 2017 in papers contributing insight on collaboration, and a spike in 2019 for studies with no learning focus.

In the next section, we will further discuss the association between the focus of RQs, the utilized techniques, and learning insights. Overall, our identified learning insights suggest that three codes are user-centric, including *learning indicators*, *collaboration*, and *time-and-learning*. These codes reflect how student behaviour impacts their learning. Two other codes, *course-design* and *feedback*, are instructor-centric; they imply the role of the instructor to intervene or design learning materials to impact student learning.

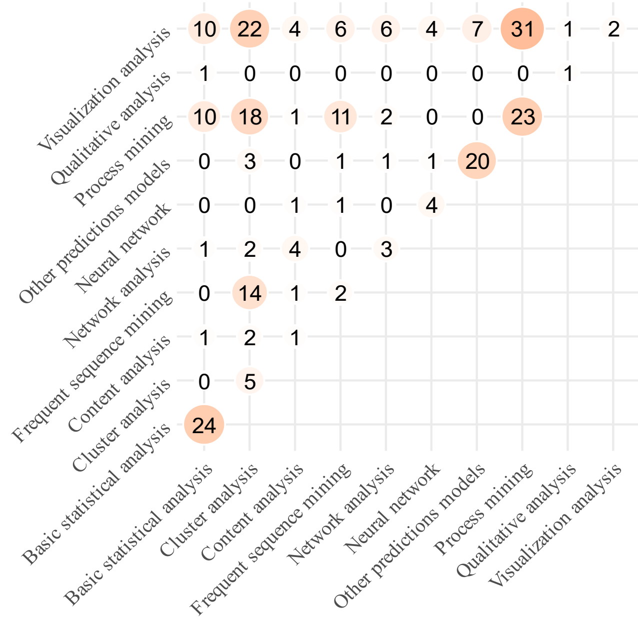

Figure 7. Analytical techniques being used together. The main diagonal shows the number of studies where the technique was the sole one used.

Table 8. Identified Codes for Insights About Learning

Insights about learning	Description
Course design	The researcher shows that specific course design can impact learning. This also includes scaffolded design experiments.
Learning indicators	The researcher identifies a set of theoretically grounded indicators that can characterize learning.
Feedback	The study finds the effect of feedback on learning.
Collaboration	The study discovers the effect of collaboration on knowledge building. This also includes investigating the progression of an idea, the quality of the idea, or the statistics of interactions during discussion. Studies often investigate how the group of users collaborate to reach a goal.
Time on learning	The researcher shows and discusses the effect of time on learning.
No learning focus outcome	The study does not provide sufficient justification for showing how learning happens or any impact on learning.

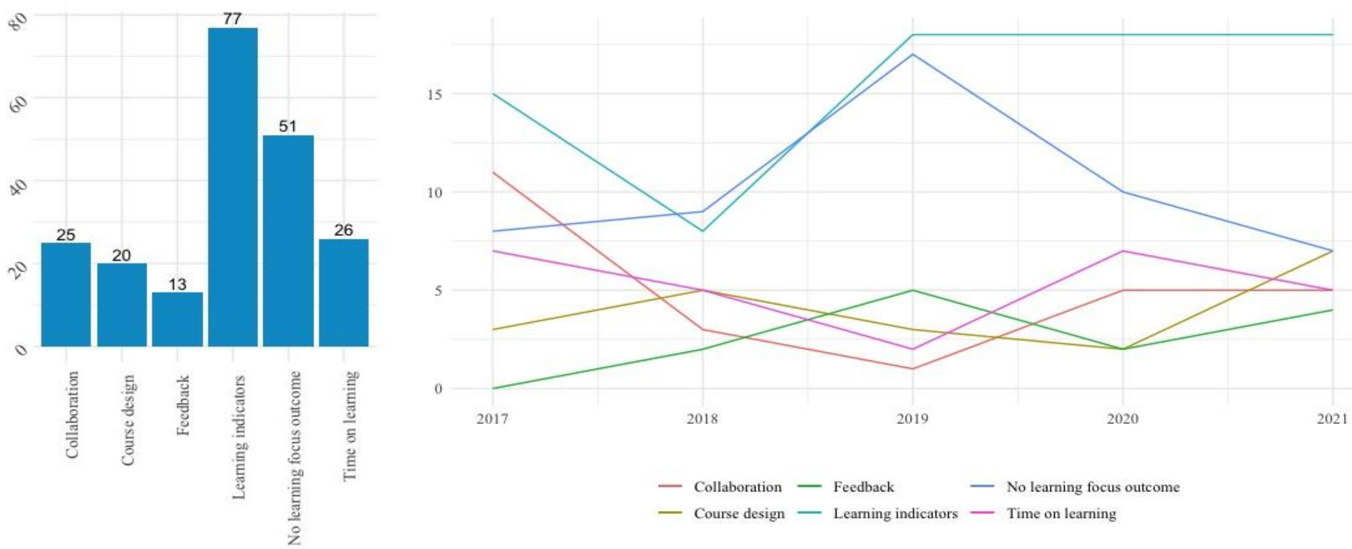

Figure 8. The distribution and five-year trend of insights about learning.

3.3. RQ2: Identifying the Associations Between the Research Questions Being Asked, the Analytical Techniques, and the Insights About Learning

In this section, we first explore the associations between the focus of the research questions and the utilized analytical techniques (Figure 9). Next, further details will be discussed by adding the dimension of learning insight **(**Figure 10**).** Figure 9 shows the relationship between the research questions crosslinked with the techniques utilized to address them. The x-axis shows our codes regarding research questions; the y-axis represents the codes regarding techniques. Each circle shows the number of papers that map to a particular RQ addressed by a particular technique.

As discussed in section 3.2, aiming to develop a method is the most common research question focus. In this category, utilizing *visualization technique* (n=35), *process mining* (n=29), *other prediction models* (n=23), and *clustering* (n=21) are the most trending techniques. The figure also shows that *process mining* is a viable technique for all types of research questions, except for identifying students at risk of failure. The high trend in utilizing process mining suggests that it can characterize temporal patterns. This means that any behaviour changes can be measured and interpreted based on underlying theory. In other words, the theory defines the meaning of each state of a particular behaviour (e.g., clicking on video content, posting a discussion), and *process mining* measures the transitions between states (e.g., from viewing a discussion to watching a video). Studies often visualized and interpreted the transitions to infer how learning happened. Moreover, some studies also incorporated *clustering* to provide a deeper comparison between behaviours (Shirvani Boroujeni & Dillenbourg, 2019; Fan & Saint, 2021; Huang & Lajoie, 2021). Similarly, *frequent sequence mining* generates sequences from different actions or states for a defined period. Therefore, the technique has strong explanatory power, especially to show how users interact with the learning management system to reveal SRL and non-SRL associated activities. For instance, Jovanović et al. (2017) utilized this analytical technique to unveil the temporal behaviour associated with the SRL phase in flipped classroom settings.

Furthermore, it is posited that frequent sequence mining and process mining can complement each other (Chen et al., 2017), and a study showed how these techniques can reveal different aspects of temporality in SRL-associated behaviours (Matcha et al., 2019). On the other hand, to identify *at-risk* students, the main focus is to achieve a high accuracy prediction rate through incorporating temporal features. Therefore, this category chiefly employed prediction models (n=18), consisting of *neural network* (n=3) and *other prediction models* (n=15), to address their research questions.

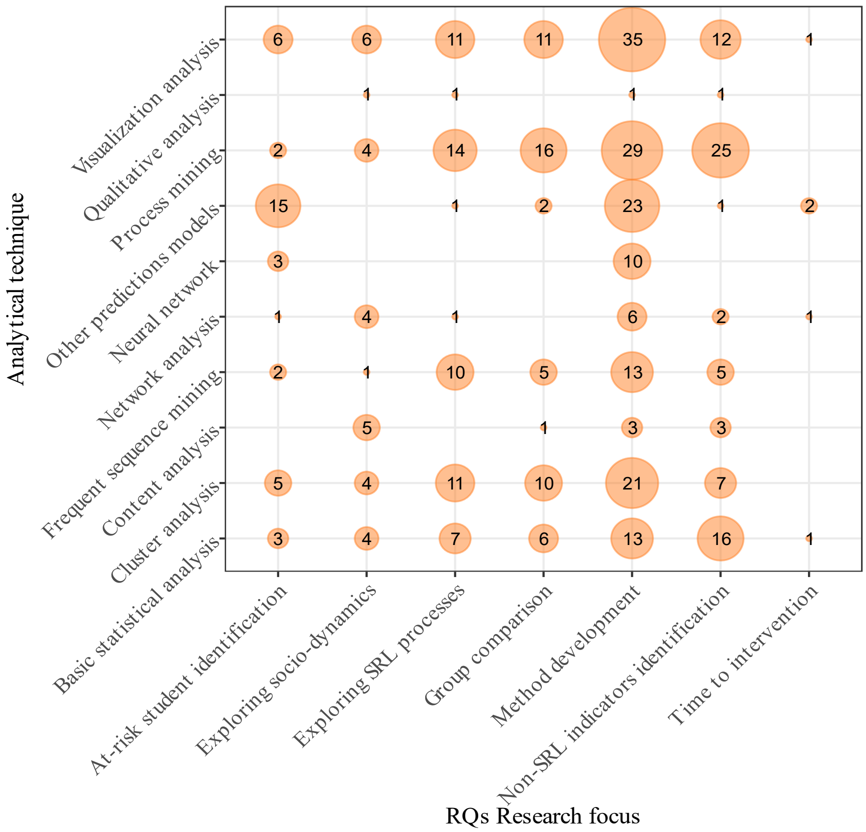

Figure 9. Relationship between asked research questions and utilized techniques.

Further analysis by considering the codes for learning insights (Figure 10) reveals the trend in the association of RQs' foci and analytical techniques based on inferred insight about learning. The plot is divided based on the revealed insights about learning, and the x-axis represents our research question codes, and the y-axis shows the technique codes. Each circle shows the number of papers that map to a particular RQ addressed by a particular technique respecting revealed learning insights.

Starting with capturing *indicators of learning* (user-centric insight), which constitutes the highest attentions of research foci, studies that focus on *developing a method* mainly utilized *visualization* (n=15), *process mining* (n=14), *clustering* (n=9), and *frequent sequence techniques* (n=8). Studies in this category often developed a methodological framework to generate sequences of activities based on underpinning theory to reveal the dynamicity of learning phenomenon. In this learning insight, the main difference between *exploring SRL processes* and *exploring non-SRL learning indicators* was that SRL studies substantially used more *frequent sequence mining* and *clustering techniques* (n=8, n=9, respectively), in comparison with non-SRL studies (n=3, n=4, respectively). The comparison suggests that tools such as TraMineR (Gabadinho et al., 2011), based on *frequent sequence mining* techniques, are popular to create sequences of activities associated with SRL processes. Then, these activities can be clustered to characterize and compare student behaviours. *Content analysis technique* is not used frequently; it was used most often (n=3) for *exploring non-SRL learning indicators*. Finally, studies concerned with identifying students at risk of failure and the time to enter intervention are more action-oriented; they did not result in revealing learning indicators.

Two other user-centric insights — *collaboration* and *time on learning* — had a distinctive trend in terms of the foci of RQs and the utilized techniques. Studies that illustrate the impact of collaboration in learning focused on *exploring socio-dynamic* factors and mainly utilized *text mining* (n=4), *visualization* (n=4), *process mining* (n=3), and *network analysis* (n=3). These types of studies trace the progression of the idea through online discourse (Liu et al., 2021; Wang et al., 2020). *Network analysis* was utilized relatively more in *collaboration*. It is likely that the authors reported using this method to show the connections of interactions through discourse. This allowed them to follow how adding a new idea can trigger higher discussion activity (Lee & Tan, 2017; Sher et al., 2020). Overall, the technique can provide a deeper understanding of the construction of collaboration. On the other hand, studies that inferred the impact of *time on the learning* process had *method development* as an RQ focus, mostly using *visualization* (n=6) and *process mining* (n=5).

Two instructor-centric insights (*feedback* and *course design*) demonstrated a similar pattern, that *method development* and *exploring non-SRL indicators* were the highest foci of RQs. In *course design*, authors often proposed a new framework for learning and then explored the impact of their proposed method on user behaviour, mainly using *process mining* or *basic statistical tests*. A similar rationale was used to examine the impact of feedback.

Lastly, studies *without learning insight focus* outcomes mainly focused on *developing method* and identifying *students at risk* of failure. These types of studies extensively used methodological description to improve or create a novel approach to address their research questions. Often found in the area of educational data mining (EDM), which is more algorithm-centric, these studies pay less attention to studying impacts on learning. In our corpus, EDM constituted 15 papers, nine of which were coded as having no learning outcome focus. Overall, papers without learning insight aimed to improve the performance of the existing model by utilizing a new set of temporal features or proposing a new algorithm based on temporal data (n=46 of 51). Notably, deep neural networks are gaining attention in this category.

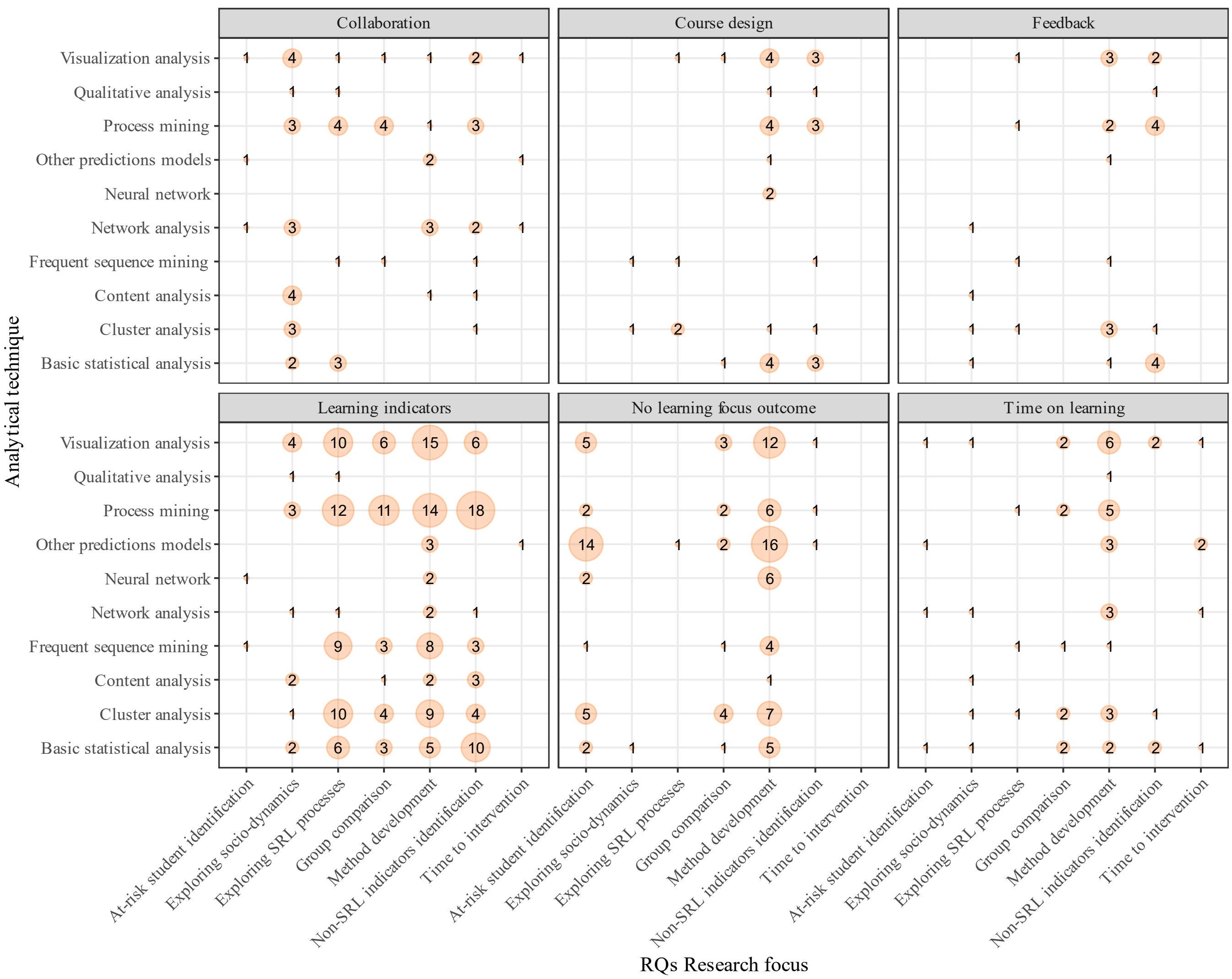

Figure 10. Relationship between research question foci and analytical technique respecting learning insight.

4. Discussion

Learning is a process that occurs over time. The circumstances of the learning process can provide insight into understanding the learning phenomenon. Temporal analysis is the field dedicated to exploring the learning process in relation to time. In recent years, the temporal aspect of learning has received increased attention in the learning analytics community, and studies have utilized several methods to exploit temporal information. Despite research efforts to date, however, it is not clear what the associations are between asked research questions, utilized techniques, and inferred insights about learning. In this study, we investigated the affordance of temporal techniques and showed how authors used them to reveal learning.

The findings in this mapping study can help orient and guide researchers in preparation for conducting their temporal studies by providing a list of relevant works that can lead them to selecting proper techniques based on their research questions and what type of insight they are anticipating. For this purpose, before conducting a study, researchers can start their investigations by exploring the lists of published temporal studies in different categories (provided in Appendixes 1 and 2). Starting with the type of research questions asked, researchers can look up which of ours are closely related to their own inquiries. For example, researchers interested in learning indicators for SRL processes using temporal approaches can quickly identify the list of 22 studies for closer examination, gaining an overview and helping them to select appropriate techniques and data features to answer their research questions. They can choose a set of papers that developed a sequential model to characterize learning strategies (Fan & Saint, 2021; Jovanović et al., 2020, 2017; Saint et al., 2021). These papers defined a learning strategy as "Any thoughts, behaviors, beliefs or emotions that facilitate the acquisition, understanding, or later transfer of new knowledge and skills" (Jovanović et al., 2017). Learning strategies define how students use a different sequence of activities that show the characteristics of an individual's learning. They can then compare these papers with approaches used in another study, where researchers utilized various techniques to explore the temporality of a learning strategy and compare the results from each technique (Matcha et al., 2019).

Second, we provide a list of inferred insights about learning that can help researchers to explore their own anticipated insights. Appendix 2 helps researchers locate studies that focus on particular learning insights from the research question perspective, and what techniques were used to accomplish it. As we discussed earlier, the most prevalent learning insight from temporal studies was to identify learning indicators in order to develop a method to characterize the online behaviour of users. In this category, studies often define a set of activities associated with the theoretical background, and then identify temporal changes or interpret the sequences of activities as learning progression. For instance, studies identified a certain sequence of student activities to be associated with an SRL phase (e.g., enactment of learning tactics), and the recurrences of the phases to indicate learning progression (Fan & Saint, 2021; Huang & Lajoie, 2021; Jovanović et al., 2020; Wang et al., 2021). After learning indicator insight, the second-largest group of temporal studies were not aimed toward theoretical insights from the perspective of learning theories. These studies often harnessed the predictive power of temporal features (e.g., time and order of activity) for their proposed model, contributing new algorithms or proposing a set of new (temporal) features to improve the performance of their model.

Our findings showed that when conducting temporal studies, researchers often use a combination of techniques. Some techniques work exclusively with the time data, namely *process mining* and *frequent sequence analysis*. These two techniques differ in several important ways and are complementary in what they can uncover (Chen et al., 2017). *Frequent sequence mining* finds concrete sequences of learning actions that can be directly observed in an individual student's log files or higher-level derived constructs, such as SRL phases. As a result, the presence of these sequences can indicate that a student belongs to a particular group or demonstrates certain characteristics, potentially leading to intervention. The outcomes of the *process mining* techniques are probabilistic in nature, specifying frequencies or probabilities of transitions between steps in the learning process, such as frequency of transitions between course activities. Although such models allow us to understand the underlying learning process, they are generally unsuitable for relating individual student activity to the discovered models. Visualization techniques, through their affordances, have the power to show temporality by depicting steps of learning activities as they unfold over time. However, the visualizations were used in this capacity quite rarely. They were often used in combination with other techniques, as we detailed in the results section.

Other techniques are more general, examining the temporal nature of learning using data features designed to capture temporality. For example, a study by Du et al. (2022) investigated the temporal pattern in engaging with learning materials by computing the time and physical location of the students. They then used statistical analysis to show the correlation with academic performance. Another study used the activity session feature, which included a trace log, based on a 30-minute threshold, and a clustering technique to differentiate groups of students with different levels of SRL behaviours (de Barba et al., 2020). As a potential direction for further analysis, our findings can be used to identify data features that capture temporality to examine particular research questions and learning insights.

4.1. Limitations

Our mapping study had several limitations. First, the papers were collected through database searches, and some journal websites might have less accurate search mechanisms. Furthermore, some did not support the search query in Table 3 (e.g., using AND, OR, and asterisk (*) operations). To address this issue, we manually inserted combinations of search terms individually. Second, the relational analysis had redundancy and overlapping issues, which means that a paper can simultaneously have several codes, and thus the relational codes multiplied. This is why the relational numbers are more than distribution numbers. However, this issue did not deter showing the trend in associations between the asked research questions, utilized techniques, and obtained insights. We also provided a cross-relational table to show the techniques used together (Figure 7). Another limitation is the five-year time frame, for reasons listed in section 2.1.1. We believe the codes provided in this study to be stable; however, we cannot claim this mapping study to be exhaustive, but rather exploratory in nature. New codes may be uncovered by expanding the mapped period. Similarly, the relationships between research foci, analytical techniques, and learning insights are representative only of the period covered.

5. Conclusions

By providing a list of insights gained about learning, we showed how temporal studies could unveil learning processes using different analytical techniques. This paper contributed to widening the understanding of the current trend in temporal educational studies. We showed the connections between research questions and analytical techniques while considering the learning insights. This evolves the field and adds an extra layer to previous overviews of temporality in education (Gašević et al., 2017; Knight et al., 2017; Reimann et al., 2014). Knowing what techniques have been used can help researchers in two ways. First, it can quickly identify effective techniques used before, based on the similarity of research focus and desired outcomes. Second, it can support exploratory research by selecting novel techniques rarely utilized before, with the aim of unravelling different aspects of temporality. Furthermore, this study found that to provide learning insights, it is important to utilize interpretable techniques to demonstrate temporal patterns that represent learning activities. Furthermore, these patterns should be theoretically justifiable. This finding is aligned with previous studies that discuss the importance of theory in learning analytics (Gašević et al., 2017; Wise & Shaffer, 2015).

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Appendix 1

Research Focus / Insight / Technique	Works
At-risk student identification	
Collaboration	
Network Analysis	[31]
Other Prediction Models	[31]
Visualization Analysis	[31]
Learning indicators	
Frequent Sequence Analysis	[91]
Neural Network	[91]
Time and learning	
Network Analysis	[31]
Other Prediction Models	[31]
Statistical Analysis	[39]
Visualization Analysis	[31]
No learning focus outcome	
Cluster Analysis	[127], [151], [70], [7], [138]
Frequent Sequence Analysis	[138]
Neural Network	[168], [123]
Other Prediction Models	[71], [33], [93], [9], [151], [7], [13], [85], [88], [100], [101], [102], [123], [175]
Process Mining	[127], [70]
Statistical Analysis	[153], [103]
Visualization Analysis	[168], [127], [33], [70], [7]
Non-SRL learning indicators identification	
Collaboration	
Cluster Analysis	[75]
Frequent Sequence Analysis	[166]
Network Analysis	[86], [113]
Process Mining	[8], [164], [166]
Text Mining	[75]
Visualization Analysis	[75], [86]
Course design	
Cluster Analysis	[52]
Frequent Sequence Analysis	[52]
Process Mining	[158], [23], [169]
Qualitative Analysis	[98]
Statistical Analysis	[108], [23], [109]
Visualization Analysis	[108], [98], [109]
Feedback	

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Research Focus / Insight / Technique	Works
Cluster Analysis	[10]
Process Mining	[10], [165], [169], [170]
Qualitative Analysis	[98]
Statistical Analysis	[99], [87], [165], [174]
Visualization Analysis	[10], [98]
Learning indicators	
Cluster Analysis	[47], [75], [84], [133]
Frequent Sequence Analysis	[47], [84], [133]
Network Analysis	[86]
Process Mining	[61], [8], [23], [24], [58], [59], [72], [84], [133], [135], [145], [144], [146], [148], [149], [150], [167], [170]
Statistical Analysis	[99], [157], [23], [51], [53], [66], [72], [83], [145], [161]
Text Mining	[75], [83], [148]
Visualization Analysis	[59], [75], [83], [86], [133], [135],
Time and learning	
Cluster Analysis	[154]
Statistical Analysis	[108], [126]
Visualization Analysis	[108], [126]
No learning focus outcome	
Other Prediction Models	[46]
Process Mining	[62]
Visualization Analysis	[62]
Exploring socio-dynamic	
Collaboration	
Cluster Analysis	[12], [74], [75]
Network Analysis	[76], [19], [74]
Process Mining	[18], [82], [171]
Qualitative Analysis	[78]
Statistical Analysis	[78], [82]
Text Mining	[76], [19], [74], [75]
Visualization Analysis	[76], [12], [75], [171]
Course design	
Cluster Analysis	[52]
Frequent Sequence Analysis	[52]
Feedback	
Cluster Analysis	[74]
Network Analysis	[74]
Statistical Analysis	[156]
Text Mining	[74]

Research Focus / Insight / Technique	Works
Learning indicators	
Cluster Analysis	[75]
Network Analysis	[112]
Process Mining	[56], [82], [171]
Qualitative Analysis	[78]
Statistical Analysis	[78], [82]
Text Mining	[75], [112]
Visualization Analysis	[56], [75], [112], [171]
Time and learning	
Cluster Analysis	[12]
Network Analysis	[19]
Statistical Analysis	[156]
Text Mining	[19]
Visualization Analysis	[12]
No learning focus outcome	
Statistical Analysis	[37]
Exploring SRL processes	
Collaboration	
Frequent Sequence Analysis	[173]
Process Mining	[43], [92], [142], [173]
Qualitative Analysis	[78]
Statistical Analysis	[32], [78], [142]
Visualization Analysis	[142]
Course design	
Cluster Analysis	[67], [122]
Frequent Sequence Analysis	[67]
Visualization Analysis	[67]
Feedback	
Cluster Analysis	[97]
Frequent Sequence Analysis	[97]
Process Mining	[97]
Visualization Analysis	[97]
Learning indicators	
Cluster Analysis	[97], [67], [96], [45], [28], [30], [57], [65], [132], [172]
Frequent Sequence Analysis	[97], [67], [96], [45], [28], [65], [147], [162], [172]
Network Analysis	[79]
Process Mining	[97], [43], [45], [17], [28], [36], [57], [60], [92], [115], [132], [162]
Qualitative Analysis	[78]
Statistical Analysis	[32], [36], [60], [78], [79], [141],

Research Focus / Insight / Technique	Works
Visualization Analysis	[97], [67], [17], [30], [57], [60], [65], [115], [141], [162]
Time and learning	
Cluster Analysis	[122]
Frequent Sequence Analysis	[173]
Process Mining	[173]
No learning focus outcome	
Other Prediction Models	[101]
Group emergence/ group comparison by performance	
Collaboration	
Frequent Sequence Analysis	[173]
Process Mining	[8], [22], [164], [173]
Visualization Analysis	[22]
Course design	
Statistical Analysis	[108]
Visualization Analysis	[108]
Learning indicators	
Cluster Analysis	[125], [64], [47], [172]
Frequent Sequence Analysis	[47], [162], [172]
Process Mining	[64], [8], [22], [24], [54], [72], [115], [144], [146], [148], [162]
Statistical Analysis	[25], [72], [141]
Text Mining	[148]
Visualization Analysis	[125], [64], [22], [115], [141], [162],
Time and learning	
Cluster Analysis	[2], [44]
Frequent Sequence Analysis	[173]
Process Mining	[2], [173]
Statistical Analysis	[108], [4]
Visualization Analysis	[108], [2]
No learning focus outcome	
Cluster Analysis	[127], [70], [3], [7]
Frequent Sequence Analysis	[3]
Other Prediction Models	[3], [7]
Process Mining	[127], [70]
Statistical Analysis	[38]
Visualization Analysis	[127], [70], [7]
Method or algorithm development	
Collaboration	
Network Analysis	[31], [113], [137]

Research Focus / Insight / Technique	Works
Other Prediction Models	[31], [49]
Process Mining	[128]
Text Mining	[42]
Visualization Analysis	[31]
Course design	
Cluster Analysis	[120]
Neural Network	[129], [140]
Other Prediction Models	[68]
Process Mining	[106], [73], [119], [176]
Qualitative Analysis	[63]
Statistical Analysis	[73], [81], [124], [176]
Visualization Analysis	[106], [129], [120], [176]
Feedback	
Cluster Analysis	[10], [97], [120]
Frequent Sequence Analysis	[97]
Other Prediction Models	[68]
Process Mining	[10], [97]
Statistical Analysis	[174]
Visualization Analysis	[10], [97], [120]
Learning indicators	
Cluster Analysis	[97], [64], [96], [27], [65], [84], [95], [132], [133]
Frequent Sequence Analysis	[97], [91], [96], [65], [84], [95], [133], [160]
Network Analysis	[131], [137]
Neural Network	[80], [91]
Other Prediction Models	[29], [107], [15]
Process Mining	[97], [64], [131], [17], [27], [73], [84], [95], [114], [130], [132], [133], [160], [176]
Statistical Analysis	[5], [157], [51], [73], [176]
Text Mining	[80], [42]
Visualization Analysis	[5], [97], [64], [131], [107], [48], [15], [17], [27], [41], [65], [95], [114], [133], [176]
Time and learning	
Cluster Analysis	[2], [152], [136]
Frequent Sequence Analysis	[20]
Network Analysis	[31], [152], [134]
Other Prediction Models	[31], [29], [117]
Process Mining	[2], [152], [155], [6], [20]
Qualitative Analysis	[63]
Statistical Analysis	[5], [124]

Research Focus / Insight / Technique	Works
Visualization Analysis	[31], [5], [2], [152], [6], [41],
No learning focus outcome	
Cluster Analysis	[3], [7], [11], [50], [90], [118], [138],
Frequent Sequence Analysis	[16], [69], [3], [138]
Neural Network	[168], [34], [55], [163], [1], [105],
Other Prediction Models	[139], [71], [77], [33], [93], [104], [9], [26], [3], [7], [40], [46], [111], [100], [101], [143]
Process Mining	[14], [94], [11], [50], [89], [118],
Statistical Analysis	[110], [116], [159], [121], [35]
Text Mining	[69]
Visualization Analysis	[14], [139], [168], [33], [34], [116], [105], [26], [7], [11], [50], [118]
Time to intervention	
Collaboration	
Network Analysis	[31]
Other Prediction Models	[31]
Visualization Analysis	[31]
Learning indicators	
Other Prediction Models	[29]
Time and learning	
Network Analysis	[31]
Other Prediction Models	[31], [29]
Statistical Analysis	[21]
Visualization Analysis	[31]

Appendix 2

Insight / Research Focus / Technique	Works
Collaboration	
At-risk student identification	
Network Analysis	[31]
Other Prediction Models	[31]
Visualization Analysis	[31]
Exploring socio-dynamic	
Cluster Analysis	[12], [74], [75]
Network Analysis	[76], [19], [74]
Process Mining	[18], [82], [171]
Qualitative Analysis	[78]
Statistical Analysis	[78], [82]
Text Mining	[76], [19], [74], [75]
Visualization Analysis	[76], [12], [75], [171]

Insight / Research Focus / Technique	Works
Exploring SRL processes	
Frequent Sequence Analysis	[173]
Process Mining	[43], [92], [142], [173]
Qualitative Analysis	[78]
Statistical Analysis	[32], [78], [142]
Visualization Analysis	[142]
Group emergence/ group comparison by performance	
Frequent Sequence Analysis	[173]
Process Mining	[8], [22], [164], [173]
Visualization Analysis	[22]
Method or algorithm development	
Network Analysis	[31], [113], [137]
Other Prediction Models	[31], [49]
Process Mining	[128]
Text Mining	[42]
Visualization Analysis	[31]
Non-SRL learning indicators identification	
Cluster Analysis	[75]
Frequent Sequence Analysis	[166]
Network Analysis	[86], [113]
Process Mining	[8], [164], [166]
Text Mining	[75]
Visualization Analysis	[75], [86]
Time to intervention	
Network Analysis	[31]
Other Prediction Models	[31]
Visualization Analysis	[31]
Course design	
Exploring socio-dynamic	
Cluster Analysis	[52]
Frequent Sequence Analysis	[52]
Exploring SRL processes	
Cluster Analysis	[67], [122]
Frequent Sequence Analysis	[67]
Visualization Analysis	[67]
Group emergence/ group comparison by performance	

Insight / Research Focus / Technique	Works
Statistical Analysis	[108]
Visualization Analysis	[108]
Method or algorithm development	
Cluster Analysis	[120]
Neural Network	[129], [140]
Other Prediction Models	[68]
Process Mining	[106], [73], [119], [176]
Qualitative Analysis	[63]
Statistical Analysis	[73], [81], [124], [176]
Visualization Analysis	[106], [129], [120], [176]
Non-SRL learning indicators identification	
Cluster Analysis	[52]
Frequent Sequence Analysis	[52]
Process Mining	[158], [23], [169]
Qualitative Analysis	[98]
Statistical Analysis	[108], [23], [109]
Visualization Analysis	[108], [98], [109]
Feedback	
Exploring socio-dynamic	
Cluster Analysis	[74]
Network Analysis	[74]
Statistical Analysis	[156]
Text Mining	[74]
Exploring SRL processes	
Cluster Analysis	[97]
Frequent Sequence Analysis	[97]
Process Mining	[97]
Visualization Analysis	[97]
Method or algorithm development	
Cluster Analysis	[10], [97], [120]
Frequent Sequence Analysis	[97]
Other Prediction Models	[68]
Process Mining	[10], [97]
Statistical Analysis	[174]
Visualization Analysis	[10], [97], [120]
Non-SRL learning indicators identification	
Cluster Analysis	[10]

Insight / Research Focus / Technique	Works
Process Mining	[10], [165], [169], [170]
Qualitative Analysis	[98]
Statistical Analysis	[99], [87], [165], [174]
Visualization Analysis	[10], [98]
Learning indicators	
At-risk student identification	
Frequent Sequence Analysis	[91]
Neural Network	[91]
Exploring socio-dynamic	
Cluster Analysis	[75]
Network Analysis	[112]
Process Mining	[56], [82], [171]
Qualitative Analysis	[78]
Statistical Analysis	[78], [82]
Text Mining	[75], [112]
Visualization Analysis	[56], [75], [112], [171]
Exploring SRL processes	
Cluster Analysis	[97], [67], [96], [45], [28], [30], [57], [65], [132], [172]
Frequent Sequence Analysis	[97], [67], [96], [45], [28], [65], [147], [162], [172]
Network Analysis	[79]
Process Mining	[97], [43], [45], [17], [28], [36], [57], [60], [92], [115], [132], [162]
Qualitative Analysis	[78]
Statistical Analysis	[32], [36], [60], [78], [79], [141]
Visualization Analysis	[97], [67], [17], [30], [57], [60], [65], [115], [141], [162]
Group emergence/ group comparison by performance	
Cluster Analysis	[125], [64], [47], [172]
Frequent Sequence Analysis	[47], [162], [172]
Process Mining	[64], [8], [22], [24], [54], [72], [115], [144], [146], [148], [162]
Statistical Analysis	[25], [72], [141]
Text Mining	[148]
Visualization Analysis	[125], [64], [22], [115], [141], [162]
Method or algorithm development	
Cluster Analysis	[97], [64], [96], [27], [65], [84], [95], [132], [133]
Frequent Sequence Analysis	[97], [91], [96], [65], [84], [95], [133], [160]
Network Analysis	[131], [137]
Neural Network	[80], [91]
Other Prediction Models	[29], [107], [15]

Insight / Research Focus / Technique	Works
Process Mining	[97], [64], [131], [17], [27], [73], [84], [95], [114], [130], [132], [133], [160], [176]
Statistical Analysis	[5], [157], [51], [73], [176]
Text Mining	[80], [42]
Visualization Analysis	[5], [97], [64], [131], [107], [48], [15], [17], [27], [41], [65], [95], [114], [133], [176]
Non-SRL learning indicators identification	
Cluster Analysis	[47], [75], [84], [133]
Frequent Sequence Analysis	[47], [84], [133]
Network Analysis	[86]
Process Mining	[61], [8], [23], [24], [58], [59], [72], [84], [133], [135], [145], [144], [146], [148], [149], [150], [167], [170]
Statistical Analysis	[99], [157], [23], [51], [53], [66], [72], [83], [145], [161]
Text Mining	[75], [83], [148]
Visualization Analysis	[59], [75], [83], [86], [133], [135]
Time to intervention	
Other Prediction Models	[29]
No learning focus outcome	
At-risk student identification	
Cluster Analysis	[127], [151], [70], [7], [138]
Frequent Sequence Analysis	[138]
Neural Network	[168], [123]
Other Prediction Models	[71], [33], [93], [9], [151], [7], [13], [85], [88], [100], [101], [102], [123], [175]
Process Mining	[127], [70]
Statistical Analysis	[153], [103]
Visualization Analysis	[168], [127], [33], [70], [7]
Exploring socio-dynamic	
Statistical Analysis	[37]
Exploring SRL processes	
Other Prediction Models	[101]
Group emergence/ group comparison by performance	
Cluster Analysis	[127], [70], [3], [7]
Frequent Sequence Analysis	[3]
Other Prediction Models	[3], [7]
Process Mining	[127], [70]
Statistical Analysis	[38]
Visualization Analysis	[127], [70], [7]

Insight / Research Focus / Technique	Works
Method or algorithm development	
Cluster Analysis	[3], [7], [11], [50], [90], [118], [138]
Frequent Sequence Analysis	[16], [69], [3], [138]
Neural Network	[168], [34], [55], [163], [1], [105]
Other Prediction Models	[139], [71], [77], [33], [93], [104], [9], [26], [3], [7], [40], [46], [111], [100], [101], [143]
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Statistical Analysis	[110], [116], [159], [121], [35]
Text Mining	[69]
Visualization Analysis	[14], [139], [168], [33], [34], [116], [105], [26], [7], [11], [50], [118]
Non-SRL learning indicators identification	
Other Prediction Models	[46]
Process Mining	[62]
Visualization Analysis	[62]
Time and learning	
At-risk student identification	
Network Analysis	[31]
Other Prediction Models	[31]
Statistical Analysis	[39]
Visualization Analysis	[31]
Exploring socio-dynamic	
Cluster Analysis	[12]
Network Analysis	[19]
Statistical Analysis	[156]
Text Mining	[19]
Visualization Analysis	[12]
Exploring SRL processes	
Cluster Analysis	[122]
Frequent Sequence Analysis	[173]
Process Mining	[173]
Group emergence/ group comparison by performance	
Cluster Analysis	[2], [44]
Frequent Sequence Analysis	[173]
Process Mining	[2], [173]
Statistical Analysis	[108], [4]
Visualization Analysis	[108], [2]
Method or algorithm development	

Insight / Research Focus / Technique	Works
Cluster Analysis	[2], [152], [136]
Frequent Sequence Analysis	[20]
Network Analysis	[31], [152], [134]
Other Prediction Models	[31], [29], [117]
Process Mining	[2], [152], [155], [6], [20]
Qualitative Analysis	[63]
Statistical Analysis	[5], [124]
Visualization Analysis	[31], [5], [2], [152], [6], [41]
Non-SRL learning indicators identification	
Cluster Analysis	[154]
Statistical Analysis	[108], [126]
Visualization Analysis	[108], [126]
Time to intervention	
Network Analysis	[31]
Other Prediction Models	[31], [29]
Statistical Analysis	[21]
Visualization Analysis	[31]

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