Chapter 2
Rich Representations for Analyzing Learning Trajectories: Systematic Review on Sequential Data Analytics in Game-Based Learning Research

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Abstract This chapter focuses on sequential data analytics (SDA), which is one of the prominent behavior analysis frameworks in game-based learning (GBL) research. Although researchers have used a variety of SDA approaches in GBL, they have provided limited information that demonstrates the way they have employed those SDA approaches in different learning contexts. This study used a systematic literature review to demonstrate findings that synthesize SDA's empirical uses in various GBL contexts. In this chapter, we recapitulate the characteristics of several SDA techniques that salient GBL studies have used first. Then, we address the underlying theoretical foundations that explain the proper uses of SDA in GBL research. Lastly, the chapter concludes with brief guidelines that illustrate the way to use SDA, as well as reveal major issues in implementing SDA.

1 Introduction

In game-based learning (GBL) research, a question exists regarding how to capture a wide spectrum of students' learning trajectories during their gameplay [1]. Compared to the emerging learning analytics (LA) and educational data mining (EDM) fields, GBL research highlights primarily the interpretation of students' behavioral data while engaged in gameplay. Researchers require iterative design actions to use evidence-centered design (ECD) in GBL studies [2, 3]. During the phases of ECD, understanding students' learning trajectories is the key to establish and corroborate game design rationales that are associated strongly with their learning outcomes. Further, tracing students' learning trajectories also can help researchers examine the students' performance unobtrusively [4, 5].

Several researchers in GBL have examined prominent factors as precursors of students' learning performance by tracking their behavioral changes

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during a game [6, 7]. Students' behavioral changes usually indicate their sequential patterns, which refer to a series of gameplay actions intended to accomplish tasks in a game [8, 9]. Identifying students' gameplay actions is also believed to indicate their mindful learning processes, including decision-making, problem-solving, and affective status during gameplay [8, 10].

To envision students' learning trajectories clearly through their behavior patterns, GBL research has validated and adopted sequential data analytics (SDA) increasingly [8, 11, 12]. Principally, SDA seeks to identify the meaningful associations between a series of game actions and learning outcomes. While prior evaluation frameworks in GBL relied largely on estimating performance differences among groups of learners, SDA pays more attention to capturing hidden causal associations between salient game actions and each student's learning performance, respectively. Thus, SDA is a powerful tool for researchers who attempt to discover which students' game actions are likely to promote their learning outcomes [6, 13, 14].

Although many studies in GBL primarily demonstrated the effects of either digital games or gamified learning applications on students' learning performance [15, 16], few researchers yet have aggregated and synthesized the findings of the way previous GBL studies implemented SDA in different circumstances. Moreover, prior work in GBL has not differentiated the types of SDA depending upon each technique's features and associated GBL design cases.

In response to the aforementioned issues, this chapter explores the underlying issues and procedures used when implementing SDA in GBL research. First, to facilitate the readers' understanding, the chapter explains how SDA has been introduced and adopted in different learning contexts. Further, the chapter describes the ways to conduct SDA and offers examples of the multiple analysis techniques used to portray how learners behave in GBL environments. To collect and analyze the data, this study carried out a systematic literature review that depicted varied SDA's characteristics extensively. During the discussion, the chapter addresses a few key issues in implementing SDA in GBL research. There are two research questions relevant to the scope of this chapter: (1) *How has SDA been used in GBL research? and* (2) *Which key analytics in SDA have been used in GBL research?*

2 Method

2.1 Procedure

A systematic search of multiple online bibliographic databases (i.e., ERIC, IEEE Explore, ScienceDirect, ACM Library, and ISI Web of Science) was conducted on SDA in the GBL environments. In addition to academic bibliographic databases, Google Scholar was also used to provide a wide coverage of relevant studies. This study also examined the reference lists of seminal articles and traced productive authors' work to expand the initial inclusion.

Synonyms of the keywords were used because both GBL and SDA have many related but different expressions. Search terms included combinations of "game-based learning," "educational game," "serious game," "game analytics," "sequential mining," "sequential analysis," "sequence analysis," "sequential data mining," and "sequential pattern mining." If the database provided a thesaurus (e.g., ERIC), an additional search was also made.

The initial search returned 932 results, and the researchers conducted the first round of screening at the title and abstract level. The initial search result was read by two researchers independently to see if both educational game and SDA appear. If only SDA appears, the article is selected only if it is a methodological or commentary publication that informs the application of SDA in GBL. As a result, 129 articles were screened in their entirety. Finally, based on the inclusion and exclusion criteria below, 102 articles were maintained for coding. The flowchart (Fig. 1) shows the search procedure.

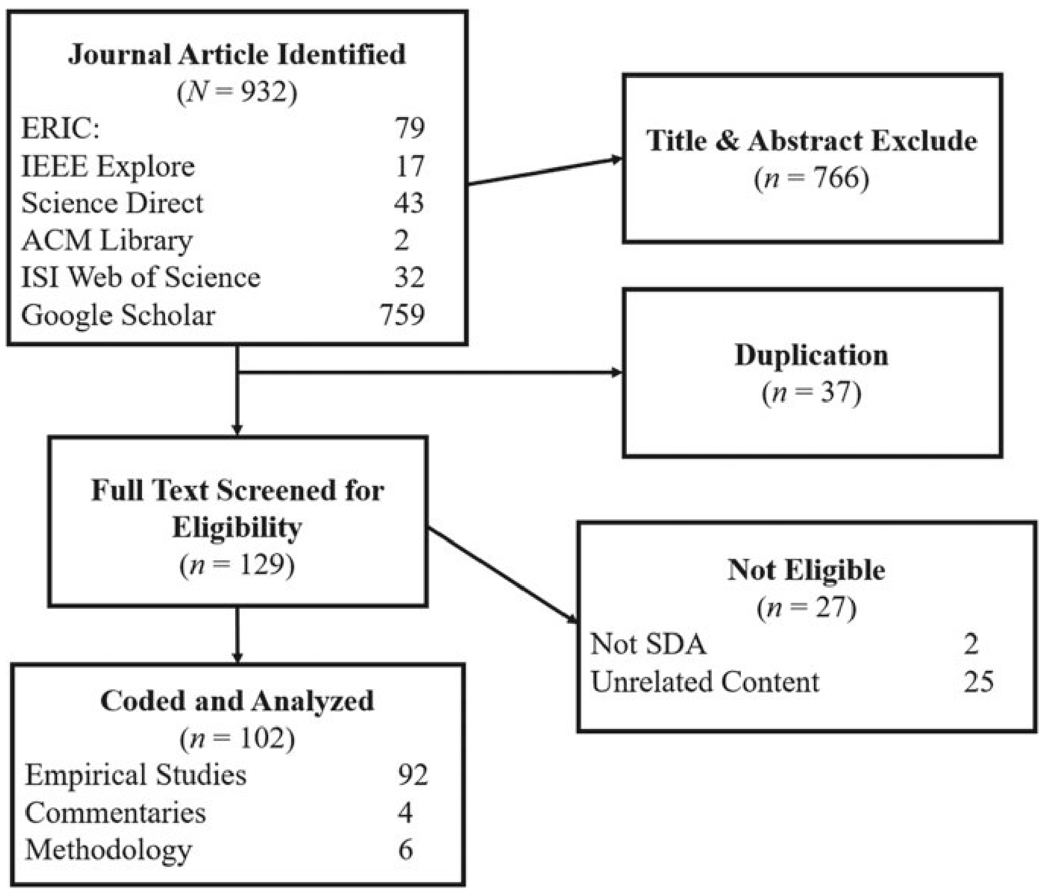


Fig. 1 Study identification flow diagram

2.2 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were as follows:

(1) Environment relevance: Studies were required to be conducted in a digital GBL environment in which the instruction had to be delivered via game-like interactions. Studies on sports games environments were excluded.
(2) Method relevance: Studies were required to use sequential analytical approach(es) to examine participants' in situ data (e.g., game behavior, affective states, biometric data). Studies that used only other analytical approaches (e.g., cluster analysis) were excluded.
(3) Content relevance: Studies were required to use sequential analytic approach(es) to draw meaningful conclusions. Studies that only focus on adaptivity and usability without clear presentation of SDA were excluded.
(4) Language and quality: Studies were required to be empirical studies written in English and published in peer-reviewed journals, as chapters, or in refereed conference proceedings.
(5) Because this study is a review of a method used widely, several non-empirical articles (e.g., commentaries on game analytics, methodological articles, cases/simulations from other related disciplines) were included but reviewed separately.

2.3 Coding Procedure

This study particularly focused on keeping high reliability of the literature reviews to include high-quality articles that would provide key themes regarding SDAs. The researchers established the initial coding framework that classified seminal articles based on the aforementioned criteria. In particular, this study adopted a qualitative coding framework proposed by constant comparative method [17]. This study paid special attention to maintaining the consistency of the content analysis results by using two coders, who aimed at inter-reliability checking. Two individual coders independently coded the articles. Through in-depth discussions, the coders attained 100% agreement through iterative refinements of the coding results.

3 Findings

3.1 How Has SDA Been Used in GBL Research?

3.1.1 Trends of SDA in the Literatures

The figure shows the trend of SDA publication in the literature (Fig. 2). It shows a growing trend of the empirical studies over the years: Before 2000, very few empirical studies used SDA; between 2000 and 2010, one or two empirical studies were published each year; after 2010, SDA has been more frequently used by researchers. This trend agrees with the growing trend of game analytics GBL in general [18]. However, compared to the massive body of GBL literature, SDA application is still under-studied. Although SDA has been used frequently in many other fields (e.g., economics, behavioral psychology, linguistics), and GBL has been studied long before this decade, many early educational games generally do not capture enough students' behavioral data that can be analyzed with SDA approach. As a result, SDA is less used. Thanks to the advancement of technology of data capturing and storage, GBL researchers today can study the learning experience at a finer granularity with in situ data. Therefore, it is likely that SDA will be used more frequently in GBL in the future.

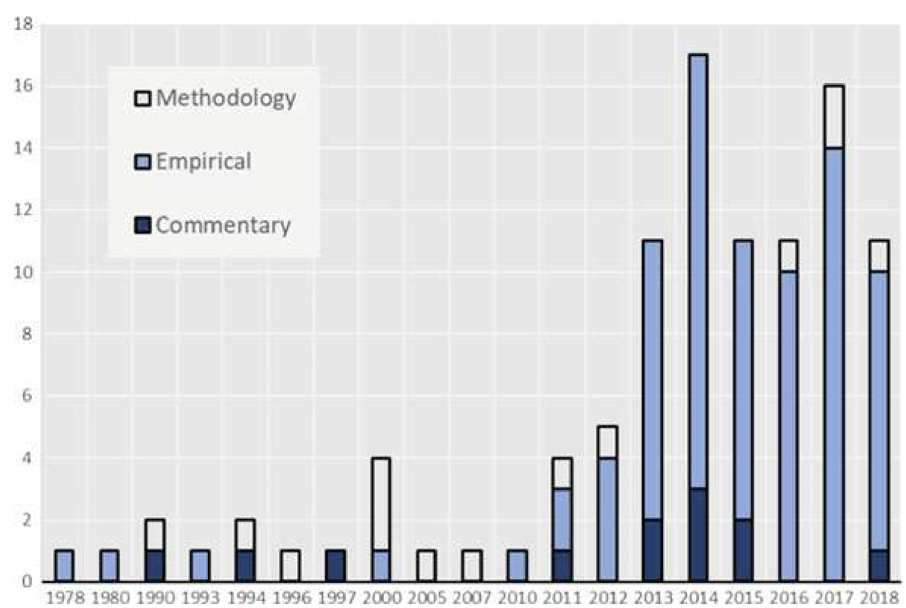


Fig. 2 Tentative trend of SDA publication in the literature

3.1.2 The Advantages of Using SDA

Identifying and understanding users' behavioral patterns in computer-mediated environments have been a major interest of most informatic studies. Early researchers attempted to extract a series of information paths that users experience frequently during their explorations of given information systems [19]. These researchers have used SDA to identify interesting associations among observable variables in data mining. While some early SDA approaches in prior studies were criticized due to their possible commitments of a Type 1 error [20]. SDA has been used widely because it is able to collect micro-level behavioral changes in interactions better [21]. Researchers have stated the possibility of a Type 1 error commitment in implementing SDA because SDA largely relies on the distribution of behavior event data. Basically, SDA flexibly sets its required sample sizes in data analysis. In other words, it indicates that SDA generates its result by repeated behavior events of the same sample. The higher repetition of data observation and analysis a researcher has in the same sample, the higher probabilities of a Type 1 error the data analysis has. Specifically, due to uncorrected z scores in normal distributions, an inflated Type 1 error is a danger, which leads to wrong estimation of a significance in identifying key behavior transition paths. To avoid this issue, a group of researchers suggested the required number of events to analyze the statistical significances of each behavior transition path, respectively.

Despite the fact that there is a likelihood of Type 1 errors in the statistical significance testing of SDA, micro-level SDA investigation still largely contributes to monitoring in-depth and rich representations of behavioral changes during users' interactions. Further, fine-grained SDA also provides baseline data that gauges students' future behaviors and relevant learning support designs [22]. In the wide-ranging spectrum of the SDA field, there are two notable SDA approaches most researchers have conducted: (1) sequential analysis in human observations [20] and (2) sequential pattern mining (SPM) [23]. Sequential analysis in human observations originated from a rudimentary computational model in behavioral analyses. The sequential analysis is based on the statistic that focuses on inferring prominent human decisions or actions as unobservable external stimuli. In using sequential analysis, researchers attempt to condense the scope of their outcome measures, such as human behavior events or actions. Then, the researchers extract the most frequent actions associated with certain stimuli. If the frequency of behavior events and actions from the analysis increases significantly, it suggests a possible association between the outcome measures and specific stimuli. Thus, sequential analysis focuses on estimating the probability of a single variable that is likely to influence the outcome in all series of behavior sequences. Since Bakeman and Brownlee [24] introduced sequential analysis, particularly to collect observable and explicit interactions among people's behaviors, this technique has been fundamental in encouraging researchers' versatile adoption of sequential analysis in different learning environments.

Compared to sequential analysis, which seeks to identify unobserved human behaviors, SPM attempts primarily to capture notable behavior sequences. SPM is designed to collect a variety of series of explicit actions in behavior combinations. In data mining research [15, 19], SPM refers to the approach in which a set of multiple behavioral events in a computer system is identified. The sequences in this analysis can be computer logs archived automatically [6] or behavioral codes [25] that human observers label. Specifically, the logs archived are computer-based trigger events saved in databases, while the behaviors human observers code are generated manually using in-depth transcriptions in qualitative research. By comparison to sequential analysis, SPM aggregates the total number of data-sequence combinations. When implementing SPM, most researchers have used different types of computer algorithms that extract the frequent use of multiple sets of sequence combinations. Kang et al. [6] used SPM to infer the most frequent set of action sequences during students' play in the science game *Alien Rescue*. The researchers adopted a *C-SPADE* algorithm [19] that emphasizes identifying temporal associations as well as chains of gameplay sequences. In addition, Taub et al. [4] employed the *SPAM* algorithm to portray students' gameplay sequences that represent their scientific reasoning skills in GBL. The algorithm in this study emphasized demonstrating all sequences of students' gameplay within the boundary the researchers set.

3.1.3 Applying SDA in GBL Research

GBL research has employed SDA to examine meaningful game behaviors or sequences in response to the nature of SDA techniques mentioned above. In underlying GBL research, emerging topics, such as stealth assessment [1, 26] and serious game analytics [22], have been key notions that explain the importance of in-depth and quantitative analytics. Researchers have used various methods to estimate students' meaningful behaviors following improvements in GBL studies. Under a few key evaluation frameworks in GBL, researchers emphasize using implicit evaluation approaches that prevent students themselves from being aware that they are being assessed during their gameplay. In accordance with the nature of implicit assessment in GBL studies, SDA has been particularly useful to explore the in situ learning contexts that may influence students' gameplay patterns. Compared to other analytics, SDA is able to depict better the way a game evokes certain learning actions. Those learning actions can be an indicator that helps us understand the way students attain meaningful learning experiences and what experiences they may undergo in a game. The following characteristics of GBL demonstrate why SDA is especially helpful in analyzing such data.

SDA and Narrative Design in GBL

In GBL, learners interact with educational games in various ways to develop concepts, learn skills, understand rules, apply knowledge, and solve problems [27]. If we treat all of the interactions as events, a sequence of events can be mapped to represent the learning experience. From a qualitative inquiry perspective, it is important to describe learners' lived experiences in GBL environments [28]. Therefore, rather than treating an educational game as a "black box," researchers should strive to understand the way learners' gameplay leads to learning outcomes. Although a pure narrative research design is uncommon in GBL research, it provides a good way to study gameplayers' learning experiences (i.e., gaming experience). SDA is a useful tool with which to narrate "the story" of gameplay. Both sequential analysis and SPM can help researchers describe the experience (e.g., the frequency of actions, the transition probability between actions) and generate insights (e.g., patterns and notable sequences that emerge).

Although using SDA alone is not narrative research, adopting this approach in GBL is consistent with narrative design. As mentioned before, the primary purpose of the narrative design is to tell the story of people's lives [29]. SDA allows GBL researchers to represent and analyze gamers' learning experiences quantitatively. By describing the sequences and discovering their attributes, researchers can understand the nature of the experience and the way it prepares students. In addition, the narrative design in GBL focuses on representing an individual's experience in chronological order [30]. One of the SDA's most important characteristics is that the sequence of "events" is ordered in a time series. This helps researchers describe a learner's trajectory and understand thereby the way a particular trajectory may lead to a certain learning outcome.

SDA in Inquiry-Based and Discovery Learning

Inquiry-based and discovery learning are common approaches in designing GBL experiences. Educational games often use engaging storytelling to establish the context and propose meaningful problems to the learners [31]. For example, the game *Crystal Island* is designed as a narrative-centered learning environment. To promote knowledge of microbiology, students are asked to play the role of a medical researcher to solve multiple puzzles in an epidemic illness on a remote island [4, 32]. The game's narrative nature provides students with a self-regulated learning experience with which they can acquire the target knowledge through interactions with different modules of the game (e.g., investigative actions, inventory collection, learning resources, NPC dialogue, and game logs).

Because inquiry and discovery learning emphasize the learning interaction significantly, it makes sense to monitor students' actions and their learning trajectories [33]. Fortunately, if the actions occur in the digital GBL environment, computerized systems can capture and record a history log with very high fidelity. If not captured by the computerized system, researchers also can use qualitative observations to capture the actions. Once the sequence of gaming actions is obtained, researchers can use it to accomplish multiple goals by using SDA (e.g., capturing in situ learning contexts, predicting future behaviors, providing personalized suggestions).

3.1.4 SDA Objectives

Capturing In Situ Learning Contexts

In accordance with the key nature of GBL research, SDA is effective in elucidating in situ learning contexts in which students' interactions occur during gameplay [34]. Generally, GBL highlights the examinations of students' adaptive processes when they attend to the game rules and contextual limitations given [35]. Prior studies using SDA have demonstrated clearly the ways in which GBL research seeks to monitor students' behavioral changes during gameplay. Taub et al. [36] employed multi-channel data mining with SDA to identify learners' cognitive- and metacognitive-self-regulatory learning processes. The study implemented the game *Crystal Island*, which is designed to promote students' scientific reasoning skills via exploratory learning. The study sampled 50 students' eye-tracking responses associated with their game sequence logs. The study findings stressed the importance of game sequence mining that collects all combinations of game behaviors that are associated strongly with meaningful learning. Another study by Taub et al. [4] implemented SDA to depict all of the processes in the way students exploited their self-regulated learning strategies by testing students' gameplay patterns in *Crystal Island*. This study sought to determine efficient game behaviors that reached the goal of a single game task and then examined the way in situ game contexts influenced their efficient game behaviors. In addition, Kinnebrew et al. [37] used SDA to determine the affordances of game events that are most likely to be associated with students' learning contexts. They used the game *SURGE Next*, which addresses major physics concepts related to Newton's law. The students in this game were supposed to identify different types of forces that influenced game results. This study aimed at identifying how gameplay data provides researchers with clues to the potential baseline performance that categorizes learners' differences in gameplay. By capturing in situ data, researchers are believed to understand students' contextual adaptation acts, indicating students' engaged behaviors.

Collecting Baseline Data for Future Prediction

SDA has been used not only to capture in situ learning contexts during gameplay, but also to collect baseline data to predict students' future gaming actions. In GBL, prediction is a persistent research goal that gauges students' future learning behaviors in a game. In particular, when designing an educational game, identifying students' typical interactions during gameplay is vital when adopting the design of an adaptive learning system. Generally, an adaptive learning system underscores the responsiveness of a system that adjusts either the level or types of formative feedback.

With respect to an intelligent system's adaptability [38], several researchers have proposed that identifying students' routinized behaviors in a learning environment is necessary to offer sufficient background about the way to provide proper scaffolding in a timely manner. Sun and Giles [9] emphasized sequence prediction as a key category that explains the way human high-order reasoning takes place. To build sequence prediction in an intelligent system, gauging users' prior sequential patterns is indispensable.

Among many GBL studies, several researchers designed different types of prediction models associated with students' baseline gameplay data. Kinnebrew et al. [37] implemented SDA to build their prediction model, which clusters students' gameplay patterns according to their game performance. To corroborate their initial game interaction design in the game *SURGE Next*, they triangulated the findings of students' prior knowledge, learning outcomes, and gameplay behaviors. By implementing SDA, the study collected 65 differential patterns during iterative mining processes. Although the scope of the analysis was largely the demonstration of different game behavior patterns based on the students' prior knowledge, it is noticeable that the study was specifically designed to identify basic game behavior patterns, which is essential to design adaptive game level changes and learning support. In addition, making predictions based on the baseline data enabled the researcher to make the best use of the understanding of the in situ learning trajectory. Inferences also can be made for further analysis (e.g., clustering and regression). Chen [2] displayed how SDA can be employed to establish the design framework of competition-driven educational games. The key design question in this study was how to design game interactions that consider both characteristics of peer competition and task-based learning. This study illustrated the way students used the mini-game *Pet-Master*, which focuses on students' animal-raising skills. To perform the skills required in the game, they needed to use basic math computations and Chinese idioms during gameplay. The study finding reported that the students tended to employ their competition-driven behaviors in the early stages of their gameplay. This study showed a notable behavior cycle in that students were likely to switch their gameplay stages from social dimensions to an economic system. The result of the study indicates that identifying the game behavior cycle was useful to understand the way students are likely to act adaptively in each step of all the game interactions (i.e., peer competition → strengthening the power of their surrogate → finding an equipping system → attending to an economic system).

Providing Personalized Learning Experiences

SDA has been useful to address the way personalized GBL should be designed for GBL research. After predicting students' game actions in GBL, researchers design adaptive learning support to elicit their gameplay to promote meaningful learning. Associated with this issue, the notion of personalized learning has been a key design idea in that a learning system is believed to provide adaptive learning support based on students' prior learning paths and their changes in affective state [39]. The learning system is encouraged to propose different types of scaffolding and external visual stimuli based on both occurrence frequency and types of students' learning actions. Researchers have assessed temporal associations between particular student actions and the timing of using personalized learning support in GBL environments. Through the system framework, GBL can provide contextual feedback that may help students perform their game tasks effectively based on their improvement level. This personalized learning framework reveals the way GBL researchers consider the gradual increase in task complexity based on students' game actions in the personalized system. Students' game actions are vital clues to address the way GBL supports learners' meaningful learning process adaptively. Relevant to this issue, SDA can acquire the entire sequential occurrence of various gameplay actions and identify the relation between gameplay patterns and learning outcomes.

With an understanding of in situ learning trajectories and salient prediction based on baseline data, researchers can use SDA to provide learners with personalized learning experiences in a game. Personalization based on sequential data considers both the context and history of learning and emphasizes the person's experience. Hwang et al. [40] explored the interrelation between students' English listening performance and behavior patterns in a problem-based learning game. In this study, SDA was used to show students' gameplay patterns that are associated with their problem-solving solutions in learning English. The study focused on designing a personalized learning support that considers students' gameplay paths necessary to their problem-solving. With the help of SDA, the researchers extracted the notable combinations of students' explicit game behaviors and proposed a game design framework that considers students' problem-solving approaches, which are represented by their gameplay paths. Other case studies [41–43] also have exploited SDA results to build adaptive learning support systems. For example, Andres et al. [41] evaluated students' behavioral sequences in applying physics concepts in the game *Physics Playground*. The study collected the students' behavior sequences in computed logs that were associated with their problem-solving in physics. They emphasized depicting which set of behavioral sequences indicates students' affective states of their gameplay. The study findings contributed to determining the way a game system detects potential affective variables that may influence their learning automatically.

3.2 Which Key Analytics in SDA Have Been Used in GBL Research?

3.2.1 Data Source and Behavior Coding

Behavior Coding Scheme

Although SDA is one of the quantitative techniques, it is rooted in qualitative inquiry, as noted previously (i.e., narrative research). Therefore, a major data source is observational data based on coding schemes. A behavior coding scheme is a human observation guideline that illustrates which explicit actions should be measured by human observation in accordance with the goals of the study's research questions. The field of SDA has allowed GBL researchers to establish behavior coding schemes that demonstrate the entire list of observable variables. Researchers have used behavior coding schemes due to several reasons. First, a behavior coding scheme helps researchers reliably specify each game behavior state that multiple behavior analysis coders can capture. Detailed descriptions of the coding scheme focus on explaining explicit features of a certain behavior. For example, Hou [25] used a refined behavior coding scheme that features iterative behavior coding steps. They implemented three successive steps of behavior analyses. After they archived all student players' in-game actions for behavior coders' references, two experts in GBL research were joined to build an exploratory coding scheme including students' meaningful in-game behaviors, such as all possible game motions, events, and interactions. Through the axis coding from a qualitative research framework, they distilled 10 major behavior categories. At the last phase of the behavior coding, trained behavior coders labeled the behavior logs of students' behaviors in the archived data. To ensure the coding scheme's reliability, the study checked the *Kappa* coefficient to indicate the inter-reliability of behavior observations among multiple coders. Chang et al. [44] also showed their systematic design of a behavior coding scheme to identify study participants' peer interaction behaviors when using a game. To capture students' social interactions, they recorded the students' behaviors when playing a game. They sampled a total of 3600 interaction actions from the students of 21 groups. This study also reported a *Kappa* coefficient to ensure their high inter-reliability of behavior coders. Those approaches to report the inter-reliability of coders demonstrate how behavior analyses according to their coding schemes were systematically implemented. Second, a behavior coding scheme is also key in quantifying qualitative data [45]. Using a coding scheme gives an opportunity to transform observational to measurable data, such as state and static events. The data analysis hosted by a behavior coding scheme enables researchers to investigate whether an intervention increased the tendency of certain target behavior by indicating numerical changes of the behavior in the coding scheme. Bakeman and Quera [46] demonstrated their sequential data interchange standard (SDIS), including three data types (untimed event, timed event, and interval). Specifically, in their classification, *untimed events* are a kind of static behavior type that displays the frequency of each action in a time frame. Differently, *interval* type refers to the time duration, indicating how long certain behavior lasts. Prior GBL studies have used two kinds of behavior data to examine which in-game action sequences appeared. In addition, researchers aimed at estimating how long learners maintain the state of a specific action when playing a game over time. Conclusively, those two types of behavioral data allow researchers to conduct various association analyses either to test statistical significance of the associations or to illustrate how a set of gameplay patterns appears.

Data Types

Researchers have used several types of behavioral data when they have employed SDA in GBL studies [46–48]. SDA emphasizes the temporal association between two independent behavior states and attempts to identify hidden relations among multiple behavior variables. Further, the technique synthesizes the occurrences of behaviors and simulates students' general learning trajectories during GBL. In prior GBL studies, researchers have adopted behavior variables, including students' in-game action, explicit body actions during gameplay, and groups' game actions as behavior variables. Those types of behavior variables could refer to students' cognitive, affective, and/or metacognitive states and indicate the occurrence of meaningful learning.

The measurement of behavior variables has varied in GBL studies. First, some researchers have employed human observations to evaluate students' behaviors based on a certain behavior coding scheme the researchers developed conceptually in advance. Human observations collected by multiple behavior coders can make it easier to reveal hidden patterns in learning sequences during students' gameplay. It is also likely to generate qualitative themes underlying students' reactions to a game. Prior studies have proven that using behavior coding schemes designed systematically yields reliable measures. Ocumpaugh et al. [47] proposed a systematic behavior coding manual, *BROMP* (Baker Rodrigo Ocumpaugh Monitoring Protocol), that is designed to measure students' explicit behaviors in a classroom setting and has been exploited in various educational data mining studies. For example, several studies have used *BROMP* to capture students' work context, actions, utterances, and facial expressions accompanied by gestures. To replace the necessity of stealth learning indicators, *BROMP* has been introduced to adopt multi-data sensor analysis, which does not rely only on students' learning achievement.

Other GBL research tends to use computer-log analyses that can extract and rearrange all game sequences automatically [5, 6]. By comparison to using human observations, analyzing computer logs requires GBL researchers to represent either a single log or a certain loop of multiple logs as combinations of learning actions in GBL. While a log itself may not include any meaning, the researcher can identify the associations among computer logs and the relevant conceptual variables they show explicitly. Martínez and Yannakakis [5] demonstrated how they generated and defined their behavior logs in gameplayers' log files. First, they defined three major game log types (performance, navigation, and, physiological events). Through iterative dimension reduction as data refinement, they collected a total of 41 gameplay features from the collection of game logs. Afterward, they implemented sequence mining to extract key gameplay sequence patterns. This study was designed to collect multimodal information from players and furnish the features of each game log types to build a predictor of players' affective status in their gameplay. Another study [49] collected students' performance logs with their timestamps to illustrate how students' discovery learning occurred at two specified learning conditions. Their computer logs were used for indicating how students reacted to prompted questions of their learning environment system. The logs were examined to identify whether students understood their learning task regarding the control of variable strategy (CVS). Kang et al. [6] also used their game logs to compute the frequency of major game sequences. Before implementing sequence mining, the researchers defined several log types, which refer to students' meaningful interactions of tools to support their scientific inquiries (e.g., sharing cognitive load, supporting cognitive process, and supporting out-of-reach activities). This study inclusively arranged students' multiple navigation log data and implemented sequential pattern mining.

3.2.2 Analytics Approaches

Behavior Frequency Analysis

Although behavior frequency analysis technically does not include any SDA features, estimating the frequency of game behaviors helps GBL researchers gauge the extent to which students are likely to perform certain game actions associated with either game interactions or events. This analysis focuses only on demonstrating the ratio of certain game actions in the total of game interaction variations. Those studies have adopted behavior frequency analysis as a preliminary analytic technique that captures salient game features to narrow the scope of further sequential analysis. GBL researchers have employed this analysis to determine the way students' game actions tend to occur. However, this analysis has limited ability to explain hidden associations between the occurrences of game actions and the particular period of game interactions. Some studies by Hou [25, 50] have reported the results of behavior frequency analysis. Hou [25] attempted to explain potential gender differences in game patterns and reported the proportion of each in-game behavior on which the students acted, respectively. In addition to reporting the descriptive statistical findings, this study also performed a simple ANOVA to investigate whether there was a statistically significant difference between genders. Further, Hou [50] also employed a behavior frequency analysis that depicted the distribution of game behaviors students used. This study adopted the analysis to explore whether there is a notable tendency in the game actions to be investigated in detail.

Progressive Sequential Analysis

Since coined the term *progressive sequential analysis*, several GBL studies have adopted progressive sequential analysis that grasps students' gradual changes in game behaviors over time during gameplay. In comparison to behavioral frequency analysis, this approach highlights temporal associations in each game behavior students perform. Although the analysis itself does not address the statistical significance of associations among students' game behaviors, it is helpful in portraying sequential connections among the game behaviors. Specifically, a progressive sequential analysis encourages GBL researchers to scrutinize the way students evolve their game sequences associated with learning goals. Hou [50] conducted a progressive sequential analysis to identify students' behavioral transactions that occur by learning phases in a problem-based learning game in English literacy. This study divided the game into three learning phases and then investigated the way students change their behaviors when they encounter each phase during gameplay. This approach has been employed using cluster analysis to examine different transaction patterns according to learning anxiety level. Progressive sequential analysis also has been implemented in qualitative analyses to infer which learning contexts are likely to influence students' behavior changes over time. Li and Liu [51] employed a progressive sequential analysis with in-depth content analysis and explored various transaction types of collaborative problem-solving skills in students' online discussions.

Transitional Probability Matrix

While a behavior frequency analysis reports only the frequency with which certain behaviors occur, a transitional probability matrix allows researchers to identify the extent to which they can estimate whether particular action states may trigger certain actions. Under the *hidden Markov* chain theorem, a stochastic statistical table represents this matrix. As supervised learning in data mining [52], the *hidden Markov* chain underlies the inter-dependency of behavior states. Specifically, the theorem presumes that behavior states in the model influence each other. In the theorem, key behavior patterns in observations are invisible, but each state in outcome behavior states is shown that indicates the likelihood of major behavior states. The *hidden Markov* chain consists of two types of probabilities: *transition* and *emission*. Once GBL researchers highlight the probability distribution of sequential patterns, the *transition probabilities* among various behavior states explain the way transitions among game behaviors take place with a certain probability. On the other hand, the *emission probabilities* show how likely it is that one game behavior promotes conclusively the outcome behaviors on which the researchers may focus.

GBL studies have made several attempts to use transitional probability matrices to explain hidden relations among game behaviors. Chen [2] explored primary school students' gameplay patterns related to their learning actions in the context of a competition-based game. This study used a transitional probability matrix to extract salient game sequences most students were likely to perform. The matrix can filter in salient game actions that exceed a *Z*-score distribution and imply that the behaviors are statistically significant. The study findings showed that two such combinations of behavior states (Learning/Pet-feeding → Item-Shopping → Competing) appeared to be meaningful during gameplay. Snow et al. [53] employed the analysis of transitional probability matrices to infer students' choice patterns in accordance with their reading abilities over time. By using transitional probability matrices, the researchers examined whether low-ability students' regulatory behaviors progressed. To extract meaningful game sequences in all variations of behaviors, this study conducted a residual analysis of each behavior state. The results demonstrated that low-ability students' regulatory behaviors tended to use generative practice game in comparison to those of high-ability students.

Lag Sequential Analysis

Many researchers have used lag sequential analysis (LSA) in behavioral psychology studies. This analysis focuses primarily on identifying a particular chain of behavior sequences statistically. Gottman et al. [20] indicated that this analysis investigates associations in sequenced series of dichotomous behavior states. Researchers usually carry out a chi-squared test to confirm a statistical difference that indicates a particular association among two different behavior states in various combinations of behavior sequences.

In favor of the features aforementioned, GBL researchers have implemented LSA particularly to explore the way certain game interactions are likely to promote the occurrences of certain outcome variables. GBL supposes largely that students' explicit actions intended to solve problems in tasks in their gameplay are associated with meaningful learning. GBL researchers believe that students' learning actions and relevant affective states can be labeled by behavior coding and have attempted to elucidate highly probable connections between students' game experiences and certain learning states, such as engagement and motivation. For example, Hou [25] employed a LSA to demonstrate the sequences in a total of 100 student players' gameplay patterns. By examining the adjusted residuals of each behavior transaction in a Z-distribution, the study found 21 statistically significant game sequences that occurred during students' gameplay. Sun et al. [10] sampled a total of 2362 behavioral codes and then implemented a LSA to extract salient game sequences the students demonstrated and cluster them according to multiple group differences (e.g., flow, anxiety, and boredom).

In comparison to behavior frequency analysis and sequential pattern mining (SPM), LSA has been exploited largely to determine whether a particular behavior association is statistically meaningful. While behavior frequency analysis and SPM are designed generally to portray frequent occurrences of behaviors and their combinations, LSA concentrates on identifying a particular chain that is statistically significant. The statistical findings in the analysis usually are deemed a major causal factor in the outcome variables during the analysis.

Sequential Pattern Mining

Sequential pattern mining (SPM) is among the algorithmic processes that archive a salient set of behavior associations. Since the field of learning analytics emerged, SPM has been adopted in a wide array of informatics studies. Codocedo et al. [54] defined SPM as data analysis that identifies notable patterns in symbols, sets, or events. Lin et al. [55] stated that SPM functions as a decision-maker that discovers new patterns from various perspectives. A series of the analysis procedures in SPM emphasizes pattern identification in time series data. While *LSA* seeks primarily to determine statistically significant associations among behavior states, SPM's entire goal is to describe frequent occurrences of actions. Thus, SPM decomposes all of the variations in action states labeled by systematic behavior coding and then archives all cases of behavior combinations that take place.

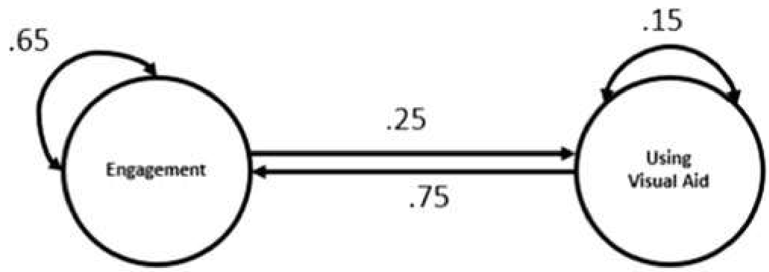
To employ SPM, researchers must use several major data algorithms, such as *generalized sequential pattern* (GSP) [23], *sequential pattern discovery using equivalence classes* (SPADE) [19], and *frequent pattern-projected SPM* (FreeSpan) [56]. First, GSP is a prominent algorithm that computes the number of occurrences of the unit for the analysis very simply. The unit of the algorithm's analysis may refer to a unique behavior state on which a researcher focuses. By using the a priori-based rule [57], this algorithm can generate easily multiple candidate sequence combinations that occur frequently in time series data. The SPADE algorithm also is designed to collect frequent sequences.

This approach has been highlighted specifically because it arranges ID-based sequences in the table vertically. This mining technique draws a table that includes the name of a certain event and its frequency. *FreeSpan* projects a small set of sequence databases and allows the database to increase by adding subsequent fragments of the data. This algorithm has been used because it can process sequential data faster than the a priori-based GSP can, which concentrates primarily on reducing the number of data transaction paths.

GBL researchers' academic interest in SPM has increased steadily. This interest focuses specifically on identifying students' paths in decision-making and capturing behavior patterns that may refer to their game interactions in approaches to problem-solving. To indicate the students' improvement with associated sequences during the game, some studies have attempted to cluster groups by students' learning outcomes. For example, Kang et al. [6] employed a serious game, Alien Rescue, for elementary school students. They adopted SPM with the SPADE algorithm to identify the most frequent game sequences that the students performed. Further, they grouped students by their learning performance. Based on the two groups in the study, the study visualized path diagrams that indicated different sequential patterns a group of students demonstrated. Kinnebrew et al. [37] adopted differential sequence mining (DSM), which implements group clustering to reduce the noise in data preprocessing in SPM. This approach is similar to the adoption of cluster analysis with SPM. However, DSM includes cluster analysis as one of the steps required during data mining. The study divided the participants into two groups and then illustrated their sequential patterns based on their prior learning achievement.

3.2.3 Interpreting and Visualizing Results

SDA is used in GBL research to portray students' learning sequences in different ways. Relevant to sequential analysis in human behaviors, researchers have attempted to demonstrate multiple path diagrams that represent the direction and probability of a single transaction between two independent behavior states [10, 25, 58]. In GBL research, this path diagram depicts the way students change their behavior state to achieve the game's goal. Figure 3 is an example path diagram drawn from sequential analysis of human observations. The arrow denotes a single transaction, indicating



	Engagement	Using Visual Aid
Engagement	.65	.25
Using Visual Aid	.75	.15

Fig. 3 A path diagram based on a transition probability matrix

that one behavior occurs with a certain probability depending on another behavior. As Fig. 3 shows, engagement follows a student using visual aids with a probability of 0.75, while engagement follows the previous engagement status with a probability of 0.65. On the other hand, using visual aids follows engagement with a 0.25 probability, although using visual aids drives another using visual aid behavior state with a 0.15 probability. The path diagram shows by this result, and the matrix table demonstrates the way the findings drawn from sequential analysis can be visualized and interpreted in empirical studies.

On the other hand, SPM adheres to archiving students' major behavior patterns. In students' gameplay, SPM lists either students' frequent behavior-log combinations or salient action patterns that appear to indicate students' attempts to solve game tasks. Although SPM has limited ability to capture hidden associations among multiple behaviors in the pattern the algorithm computed statistically, SPM still is able to map which game stage challenges students and suggest whether embedding scaffolds are needed. SPM usually implements a decision tree diagram that provides an overview of which adaptation should be provided in each stage of students' gameplay. The *IF-THEN* rule in a decision tree diagram helps researchers emphasize providing additional learning support in certain game events that are likely to challenge students.

Interestingly, students' behavior transactions in GBL studies are not always linear; rather, they may be compound because multiple behavior states are interconnected and occur concurrently in students' gameplay. In particular, when students encounter ill-structured game tasks in their play, they are inclined to explore their surrounding circumstances first and attempt to test latent problem-solving solutions while still examining other problems. The behaviors in which students engage to reach their game goal vary and the behavior associations tend to be complex.

3.2.4 Practical Guidelines for Using SDA in GBL Research

The table summarizes six different SDAs with short description, examples, and existing tools. The purpose of this table is to map some techniques that are used most frequently and their examples. It is not exhaustive and not intended to capture all of these SDAs' technical details (Table 1).

4 Discussion

4.1 Uses of SDA in GBL Research

As presented above, we identified three main objectives of using SDA in GBL research: (1) capturing in situ learning context, (2) collecting baseline data for future prediction, and (3) providing personalized learning experiences. Although they appear to be separate objectives, they build upon each other. Capturing in situ learning context is the foundation of the other two objectives because SDA provides a rich representation of the learning trajectory and further analyses are possible only with the meaningful data. At this level, the in situ learning context is represented from a descriptive perspective [4, 25]. Next level of SDA is to use baseline data (i.e., in situ learning context) to make further predictions and draw inferences. For example, if the pattern of behavior is identified, the next possible step(s) can be predicted [8, 22]. Furthermore, based on the correlation between students' behavior sequence pattern and learning outcomes, we can predict the possible outcome given the observed sequence [34, 37]. Finally, based on predictions and inferences, SDA can help to design adaptive learning experiences and personalized support to optimize the learning trajectory. With SDA, scaffolding in GBL can be done at a finer grain level comparing to overall analyses (e.g., Bayesian Network). Hwang et al. [31] argued that based on the identifying students' problem-solving style, additional support should be designed to facilitate the diverse needs of each type of learners.

SDA is a promising technique that can be applied in GBL design and research. The literature also shows an increasing trend of the empirical articles. However, we noticed that most of the work collected in this current review is only at the first level. Predictions and inferences (i.e., level 2) are conducted post hoc instead of a priori. Therefore, the results from SDA analyses may not necessarily transfer beyond the participants. Level 3 objective is based on both level 1 representation and level 2 prediction. Although theoretical papers are published, and small-scale usability examples are presented, we did not see any full example of using SDA for designing adaptivity in GBL.

Table 1 Practical guidelines of six SDAs in GBL research

SDA	Description	Examples	Tools
Behavior frequency analysis	Investigating a simple distribution of behaviors. ANOVA or chi-squared can be used to examine the difference between groups	Andres et al. [41] Hou [25] Hou [50] Neuman et al. [59]	*Software*: GSEQ; BORIS; Observer XT
Sequential analysis (Lag = 1)	Investigating directional transition probabilities among behaviors. Adjusted residual often is used to determine whether a correlation exists Transition probability distribution also can be investigated through Markov chain or hidden Markov model (HMM)	Hsieh et al. [34] Hou [50]	*Software*: GSEQ; BORIS; Observer XT; SADI R packages for HMM
Lag sequential analysis	A general approach of sequential analysis (lag ≥ 1). For example: the sequence is A $\rightarrow$ B $\rightarrow$ C. The lag 1 transition is A $\rightarrow$ B or B $\rightarrow$ C. The lag 2 transition is A $\rightarrow$ C. Behaviors are assumed to be sequenced, but not necessarily at equal time intervals	Biswas et al. [60] Jeong et al. [61] Wallner [21] Yang et al. [16]	*Software*: GSEQ; BORIS; Observer XT; SADI *R packages*: HMM; dempmixS4 Sequential; behavseq
Sequential pattern mining	Discovering a set of sequences measured with respect to particular criteria (e.g., frequency, length). Popular algorithms include GSP, SPAM, SPADE, and C-SPADE	Kang et al. [6] Kinnebrew et al. [37]	*R package*: arulesSequences *Free software*: SPMF
Differential sequence mining	Measuring the similarity or difference in behavior patterns between two sets of sequences	Kinnebrew and Biswas [8] Kinnebrew et al. [37] Sabourin et al. [26] Loh et al. [22]	*R packages*: TraMineR; arulesSequences; cluster

4.2 Implementing SDA in GBL

Implementing SDA in GBL research is not only about feeding data to models. As Baker and Inventado [18] pointed out, most educational data mining (EDM) and learning analytics (LA) researchers use learning science and educational theories to guide their selection of analyses techniques and aim to feed back to the theory with the results. SDA should be a systematic research approach guided by theoretical frameworks or specific focus. The first step is to determine the objective and scope of the research which have great implications on what data should be collected and how the results should be interpreted.

With determining the objective and scope of the research, the following things should be considered: (1) what is the data source (e.g., game action, keystroke, utterance, facial expression, biophysical information, interaction among peers)? (2) What data is going to be collected (e.g., selected behavior based on theoretical framework)? (3) How the data is going to be collected (e.g., human observation, automated log file)? These questions should be answered thoroughly before applying SDA.

After collecting the data, cleaning data is usually a major task of SDA. Although studies generally do not report this process, according to general EDM practice, data cleaning is essential to prepare the data for analyses [62]. Similar to establishing a coding scheme in qualitative inquiries, SDA data cleaning can also be an iterative process. Guided by theories, cleaning the data involves (1) formatting the data, (2) omitting irrelevant information, (3) computing variables, and (4) dealing with missing data.

With cleaned data, the researchers can then choose different SDA techniques based on the proposed research questions. The question can range from a simple descriptive question about what behaviors happened to an exploratory question about what the patterns emerged.

4.3 Limitation of Using SDA in GBL

Although SDA in GBL seems to be a promising analytical and mining approach to understand the in situ learning data, the application of the technique might be limited by the following two challenges. First, SDA requires a large volume of data and sometimes high computational power. Although the quantity of analyzable data has increased over the years [18], not all researchers are well-equipped with the ability to access fine-grain data required by SDA easily. Even if the data can be captured, cleaning analyzing the data might consume a lot of computational power. Second, SDA is often performed as post hoc analysis. Therefore, it is challenging to ensure the validity of the results without cross-validating with the participants. In addition, the participants may not even recall some certain behaviors because the data is captured at a fine granularity. Another issue with post hoc analysis is if the scope of the study is biased, data collection will be biased which in turn leads to an unvalidated biased result. Whereas the first challenge is relatively easy to solve because it is almost completely at the hardware level, the second one can be tricky because it relies on the carefully planning and scoping beforehand, information triangulation, and awareness of bias. The section below will highlight two important things to be mindful about when using SDA in GBL research.

4.4 Key Issues in Implementing SDA

4.4.1 Examining Implicit Behaviors with SDA

Commonly, researchers model the learning sequence with the logged game interactions. As mentioned above, computerized systems usually archive the data automatically. However, in some cases, modeling the observed sequence alone is insufficient, because many other variables (e.g., metacognition and affective states) also may affect the game interaction observed. Without introducing these variables, the sequence or patterns observed may not have a clear meaning. In addition, some behaviors or relations (e.g., off-task behavior and dialogue relation) are not manifested explicitly in the game interaction observed. Thus, examining the implicit behaviors/relations can help researchers map the learning trajectory better.

As a result, it is important to examine the variables that also affect the game interaction observed. Because the game interaction is examined with SDA, it also makes sense to examine these variables from a time series perspective. For example, Biswas et al. [60] measured students self-regulated learning skills in gaming interactions with the *hidden Markov model* (HMM). In addition to the activities observed in the game environment (i.e., Betty's Brain, a learn-by-teaching ITS), they constructed three hidden states of problem-solving processes (i.e., information gathering, map building, and monitoring). Based on the HMM probabilistic transition between hidden and observed events, students who learned with teachable agents demonstrated a better metacognitive behavior pattern than did those who learned by themselves. Martínez and Yannakakis [5] proposed a method of multimodal sequential pattern mining. Physiological signals data (i.e., blood volume pulse and skin conductance) were recorded in addition to the game logs. By examining the data from multiple sources, the sequential pattern obtained predicted the user's effect better compared to single modal data. Although combining data from multiple sources or introducing additional variables to the sequential analytics may be complicated and time-consuming, this approach provides more information compared to SDA only on interactions observed and it is easier to frame the discussion based on theoretical foundations.

Another approach is to examine the implicit interactions in game interactions. For example, it may be important to examine off-task behaviors, not only in the GBL experience, but also in general educational research. First, off-task behavior sometimes indicates inattention [63]. Further, students may collaborate with each other sometimes when they are off task. These are all important pieces of information for researchers, because they either can provide an explanation for failure or indication of treatment integrity as a reliability threat. Similarly, when students are not playing, we cannot assume that time freezes. It makes sense to code the off-task behaviors, or away-from-keyboard (AFK) behaviors as well, which may be as simple as a pause. Unfortunately, the authors did not find any GBL study that analyzed these types of behavior.

4.4.2 Post hoc Analysis in SDA and Establishing Causality

Although SDA provides a rich representation of the learning trajectory, it is important to note that it does not provide sufficient evidence to conclude the causation between specific sequence patterns and learning outcomes. Typically, researchers not only describe the learning sequence and discover patterns, but conduct post hoc analyses as well [14, 50, 52]. For example, researchers may categorize learners into multiple groups based on their learning achievement (e.g., high versus low performance groups). Subsequently, they may try to establish a sequential model for each category and compare the differences among groups (e.g., frequency of a behavior and/or pattern, the probability of transition between states). However, there is a potential logical fallacy (i.e., cum hoc ergo propter hoc) when drawing further causal conclusions.

Like observational studies, SDA cannot provide rigid causal relations between variables. Normally, a causal relation is established with the results of randomized controlled trials. If a causal relation exists, one must identify clearly: (1) the cause, (2) relation between cause and effect, and (3) that there is no alternative explanation of the effect [64]. If one attempts to draw any causal conclusion based only on the relation between sequential data and the outcome, there is no alternative explanation for the outcome. Even if the sequence or pattern occurs before the outcome and it seems to occur step by step, the sequence may not necessarily lead to the outcome. Thus, because there is no alternative explanation, a causal relation cannot be established. Similarly, if the “potential cause” is the descriptive data in the sequence model (e.g., frequency of behavior or transition probability between states), the effect of the entire trajectory, other instances, and students’ psychological states is all neglected. Therefore, both researchers and readers of SDA should be very cautious about drawing such causal conclusions.

A conservative but safer approach to report post hoc analyses in SDA is to remind the readers of the potential of a logical fallacy. If the goal is to provide implications of causal inferences, to differentiate groups, the researchers should examine not only the sequence per se, but all a priori information available. Similar approaches can be found in studies that have adopted a retrospective cohort design, which will not be discussed in detail here [65]. Based on a closer look at the data, the conclusion should shed light on the possible causes of learning outcomes. Subsequently, randomized controlled trials should be used to examine the proposed causes and the learning outcomes.

5 Conclusion

SDA's primary purpose in many GBL studies has been to identify hidden behavior associations that lead to students' meaningful learning through certain gameplay interactions. Through a systematic literature review, this chapter explored current research using SDA in the context of GBL. Generally, GBL requires students to perform given game tasks and change their actions adaptively based on the surrounding game contexts they encounter. Using SDA not only reveals students' learning sequences, but also provides background channel data that reinforce an adaptive learning system. This chapter also addressed key GBL design features that explain why SDA is effective. Researchers have attempted to measure largely to what extent students are engaged with a game's narratives. By comparison to learning engagement in students' gameplay, researchers have noted that conducting SDA is effective in gauging the effect of the quality of a game narrative's design on students' engagement. In addition, SDA is associated with learning design principles, such as discovery and inquiry learning that elicit students' self-regulated explorations and help them achieve their learning goal.

Although SDA has been limited in confirming the causalities among students' game actions associated with their learning trajectory, there is a clear indication that SDA is able to collect a variety of information datasets that may refer to students' game behaviors related to the occurrence of meaningful learning. SDA research has been employed with a variety of analytic approaches, such as behavior frequency analysis, progressive sequential analysis, transitional probability matrix, lag sequential analysis, and sequential pattern mining. While some SDAs emphasize demonstrating sequential patterns and frequent occurrences of actions primarily, others tend to reveal statistically significant associations between two independent game behavior states. To highlight the salient association among behaviors in SDA, depicting multiple transactions of students' game behaviors in GBL also has been considered as a way to visualize information. This chapter demonstrated an example path diagram to explain the way sequential paths can be interpreted.

References

1. Shute, V. J. (2011). Stealth assessment in computer-based games to support learning. *Computer Games and Instruction, 55*(2), 503–524.
2. Chen, Z.-H. (2014). Exploring students' behaviors in a competition-driven educational game. *Computers in Human Behavior, 35,* 68–74.
3. Ke, F., & Shute, V. (2015). Design of game-based stealth assessment and learning support. In *Serious games analytics* (pp. 301–318). New York: Springer.
4. Taub, M., Azevedo, R., Bradbury, A. E., Millar, G. C., & Lester, J. (2018). Using sequence mining to reveal the efficiency in scientific reasoning during STEM learning with a game-based learning environment. *Learning and Instruction, 54,* 93–103.
5. Martínez, H. P., & Yannakakis, G. N. (2011). Mining multimodal sequential patterns: A case study on affect detection. In *13th International Conference on Multimodal Interfaces* (pp. 3–10).

6. Kang, J., Liu, M., & Qu, W. (2017). Using gameplay data to examine learning behavior patterns in a serious game. *Computers in Human Behavior, 72,* 757–770.
7. Loh, C. S., Sheng, Y., & Ifenthaler, D. (2015). Serious games analytics: Theoretical framework. In *Serious games analytics* (pp. 3–29). New York: Springer.
8. Kinnebrew, J. S., & Biswas, G. (2012). Identifying learning behaviors by contextualizing differential sequence mining with action features and performance evolution. In *International Educational Data Mining Society*.
9. Sun, R., & Giles, C. L. (2001). Sequence learning: From recognition and prediction to sequential decision making. *IEEE Intelligent Systems, 16*(4), 67–70.
10. Sun, J. C.-Y., Kuo, C.-Y., Hou, H.-T., & Lin, Y.-Y. (2017). Exploring learners' sequential behavioral patterns, flow experience, and learning performance in an anti-phishing educational game. *Journal of Educational Technology & Society, 20*(1).
11. Biswas, G., Kinnebrew, J. S., & Segedy, J. R. (2014). Using a cognitive/metacognitive task model to analyze students learning behaviors. In *International Conference on Augmented Cognition* (pp. 190–201).
12. Liao, C. C., Chen, Z.-H., Cheng, H. N., & Chang, T.-W. (2012). Unfolding learning behaviors: A sequential analysis approach in a game-based learning environment. *Research & Practice in Technology Enhanced Learning, 7*(1).
13. Hsieh, Y.-H., Lin, Y.-C., & Hou, H.-T. (2016). Exploring the role of flow experience, learning performance and potential behavior clusters in elementary students' game-based learning. *Interactive Learning Environments, 24*(1), 178–193.
14. Hung, Y. H., Chang, R. I., & Lin, C. F. (2016). Hybrid learning style identification and developing adaptive problem-solving learning activities. *Computers in Human Behavior, 55,* 552–561.
15. Drachen, A., Thurau, C., Togelius, J., Yannakakis, G. N., & Bauckhage, C. (2013). Game data mining. In *Game analytics* (pp. 205–253). New York: Springer.
16. Yang, T.-C., Chen, S. Y., & Hwang, G.-J. (2015). The influences of a two-tier test strategy on student learning: A lag sequential analysis approach. *Computers & Education, 82,* 366–377.
17. Kolb, S. M. (2012). Grounded theory and the constant comparative method: Valid research strategies for educators. *Journal of Emerging Trends in Educational Research and Policy Studies, 3*(1), 83.
18. Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning analytics* (pp. 61–75). New York: Springer.
19. Zaki, M. J. (2000). Sequence mining in categorical domains: Incorporating constraints. In *9th International Conference on Information and Knowledge Management* (pp. 422–429).
20. Gottman, J., Gottman, J. M., & Roy, A. K. (1990). *Sequential analysis: A guide for behavioral researchers*. Cambridge University Press.
21. Wallner, G., & Kriglstein, S. (2015). Comparative visualization of player behavior for serious game analytics. In *Serious games analytics* (pp. 159–179). New York: Springer.
22. Loh, C. S., Li, I.-H., & Sheng, Y. (2016). Comparison of similarity measures to differentiate players' actions and decision-making profiles in serious games analytics. *Computers in Human Behavior, 64,* 562–574.
23. Srikant, R., & Agrawal, R. (1996). Mining sequential patterns: Generalizations and performance improvements. In *International Conference on Extending Database Technology* (pp. 1–17). New York: Springer.
24. Bakeman, R., & Brownlee, J. R. (1980). The strategic use of parallel play: A sequential analysis. In *Child development* (pp. 873–878).
25. Hou, H.-T. (2012). Exploring the behavioral patterns of learners in an educational massively multiple online role-playing game (MMORPG). *Computers & Education, 58*(4), 1225–1233.
26. Sabourin, J. L., Shores, L. R., Mott, B. W., & Lester, J. C. (2013). Understanding and predicting student self-regulated learning strategies in game-based learning environments. *International Journal of Artificial Intelligence in Education, 23*(1–4), 94–114.
27. Clark, D. B., Tanner-Smith, E. E., & Killingsworth, S. S. (2016). Digital games, design, and learning: A systematic review and meta-analysis. *Review of Educational Research, 86*(1), 79–122.

28. Bogdan, R., & Biklen, S. K. (1997). *Qualitative research for education*. MA: Allyn & Bacon Boston.
29. Connelly, F. M., & Clandinin, D. J. (1990). Stories of experience and narrative inquiry. *Educational Researcher, 19*(5), 2–14.
30. Cortazzi, M. (2014). *Narrative analysis*. Routledge.
31. Hwang, G.-J., Chiu, L.-Y., & Chen, C.-H. (2015). A contextual game-based learning approach to improving students' inquiry-based learning performance in social studies courses. *Computers & Education, 81,* 13–25.
32. Lester, J. C., Ha, E. Y., Lee, S. Y., Mott, B. W., Rowe, J. P., & Sabourin, J. L. (2013). Serious games get smart: Intelligent game-based learning environments. *AI Magazine, 34*(4), 31–45.
33. Woo, Y., & Reeves, T. C. (2007). Meaningful interaction in web-based learning: A social constructivist interpretation. *The Internet and Higher Education, 10*(1), 15–25.
34. Hsieh, Y.-H., Lin, Y.-C., & Hou, H.-T. (2015). Exploring elementary-school students' engagement patterns in a game-based learning environment. *Journal of Educational Technology & Society, 18*(2), 336.
35. Vandercruysse, S., & Elen, J. (2017). Towards a game-based learning instructional design model focusing on integration. In *Instructional techniques to facilitate learning and motivation of serious games* (pp. 17–35). New York: Springer.
36. Taub, M., Mudrick, N. V., Azevedo, R., Millar, G. C., Rowe, J., & Lester, J. (2017). Using multi-channel data with multi-level modeling to assess in-game performance during gameplay with Crystal Island. *Computers in Human Behavior, 76,* 641–655.
37. Kinnebrew, J. S., Killingsworth, S. S., Clark, D. B., Biswas, G., Sengupta, P., Minstrell, J., et al. (2017). Contextual markup and mining in digital games for science learning: Connecting player behaviors to learning goals. *IEEE Transactions on Learning Technologies, 10*(1), 93–103.
38. Sabourin, J., Mott, B., & Lester, J. (2013). Discovering behavior patterns of self-regulated learners in an inquiry-based learning environment. In: Lane H.C., Yacef K., Mostow J., Pavlik P. (Eds), *Artificial Intelligence in Education AIED. Lecture Notes in Computer Science* (Vol. 7926). Springer, Berlin, Heidelberg.
39. Lin, C. F., Yeh, Y.-C., Hung, Y. H., & Chang, R. I. (2013). Data mining for providing a personalized learning path in creativity: An application of decision trees. *Computers & Education, 68,* 199–210.
40. Hwang, G.-J., Hsu, T.-C., Lai, C.-L., & Hsueh, C.-J. (2017). Interaction of problem-based gaming and learning anxiety in language students' English listening performance and progressive behavioral patterns. *Computers & Education, 106,* 26–42.
41. Andres, J. M. L., Rodrigo, M. M. T., Baker, R. S., Paquette, L., Shute, V. J., & Ventura, M. (2015). Analyzing student action sequences and affect while playing physics playground. In *International Conference on Educational Data Mining*.
42. Serrano-Laguna, Á., Martínez-Ortiz, I., Haag, J., Regan, D., Johnson, A., & Fernández-Manjón, B. (2017). Applying standards to systematize learning analytics in serious games. *Computer Standards & Interfaces, 50,* 116–123.
43. Shih, W.-C. (2017). Mining learners' behavioral sequential patterns in a Blockly visual programming educational game. In *International Conference on Industrial Engineering, Management Science and Application (ICIMSA)* (pp. 1–2).
44. Chang, C. J., Chang, M. H., Liu, C. C., Chiu, B. C., Fan Chiang, S. H., Wen, C. T., et al. (2017). An analysis of collaborative problem-solving activities mediated by individual-based and collaborative computer simulations. *Journal of Computer Assisted Learning, 33*(6), 649–662.
45. Heyman, R. E., Lorber, M. F., Eddy, J. M., & West, T. V. (2014). *Behavioral observation and coding*.
46. Bakeman, R., & Quera, V. (2011). *Sequential analysis and observational methods for the behavioral sciences*. Cambridge University Press.
47. Ocumpaugh, J., Baker, R. S., & Rodrigo, M. M. T. (2015). *Baker Rodrigo Ocumpaugh monitoring protocol (BROMP) 2.0 technical and training manual*. New York, NY and Manila, Philippines: Teachers College, Columbia University and Ateneo Laboratory for the Learning Sciences.

48. Ocumpaugh, J., Baker, R. S. d., Gaudino, S., Labrum, M. J., & Dezendorf, T. (2013). *Field observations of engagement in reasoning mind* (pp. 624–627).
49. Gobert, J. D., Sao Pedro, M. A., Baker, R. S., Toto, E., & Montalvo, O. (2012). Leveraging educational data mining for real-time performance assessment of scientific inquiry skills within microworlds. *Journal of Educational Data Mining, 4*(1), 104–143.
50. Hou, H.-T. (2015). Integrating cluster and sequential analysis to explore learners' flow and behavioral patterns in a simulation game with situated-learning context for science courses: A video-based process exploration. *Computers in Human Behavior, 48,* 424–435.
51. Li, C.-H., & Liu, Z.-Y. (2017). Collaborative problem-solving behavior of 15-year-old Taiwanese students in science education. *Eurasia Journal of Mathematics, Science and Technology Education, 13*(10), 6677–6695.
52. Wen, C.-T., Chang, C.-J., Chang, M.-H., Chiang, S.-H. F., Liu, C.-C., Hwang, F.-K., et al. (2018). The learning analytics of model-based learning facilitated by a problem-solving simulation game. *Instructional Science, 46*(6), 847–867.
53. Snow, E. L., Jackson, G. T., & McNamara, D. S. (2014). Emergent behaviors in computer-based learning environments: Computational signals of catching up. *Computers in Human Behavior, 41,* 62–70.
54. Codocedo, V., Bosc, G., Kaytoue, M., Boulicaut, J.-F., & Napoli, A. (2017). A proposition for sequence mining using pattern structures. In: Bertet K., Borchmann D., Cellier P., Ferré S. (Eds) *Formal concept analysis. ICFCA 2017. Lecture Notes in Computer Science* (Vol. 10308, pp. 106–121).
55. Lin, T.-J., Duh, H. B.-L., Li, N., Wang, H.-Y., & Tsai, C.-C. (2013). An investigation of learners' collaborative knowledge construction performances and behavior patterns in an augmented reality simulation system. *Computers & Education, 68,* 314–321.
56. Han, J., Pei, J., Mortazavi-Asl, B., Chen, Q., Dayal, U., & Hsu, M.-C. (2000). FreeSpan: Frequent pattern-projected sequential pattern mining. In *ACM SIGKDD* (pp. 355–359).
57. Agarwal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. In *20th International Conference on Very Large Data Bases (VLDB)* (pp. 487–499).
58. Tsai, M.-J., Huang, L.-J., Hou, H.-T., Hsu, C.-Y., & Chiou, G.-L. (2016). Visual behavior, flow and achievement in game-based learning. *Computers & Education, 98,* 115–129.
59. Neuman, Y., Leibowitz, L., & Schwarz, B. (2000). Patterns of verbal mediation during problem solving: A sequential analysis of self-explanation. *The Journal of Experimental Education*, *68*(3), 197–213.
60. Biswas, G., Jeong, H., Kinnebrew, J. S., Sulcer, B., & Roscoe, R. (2010). Measuring self-regulated learning skills through social interactions in a teachable agent environment. *Research and Practice in Technology Enhanced Learning, 5*(02), 123–152.
61. Jeong, A. C. (2010). Assessing change in learners' causal understanding using sequential analysis and causal maps. *Innovative assessment for the 21st century* (pp. 187–205). Boston, MA: Springer.
62. Vialardi, C., Bravo, J., Shafti, L., & Ortigosa, A. (2009). Recommendation in higher education using data mining techniques. In *International Working Group on Educational Data Mining*.
63. Rowe, J. P., McQuiggan, S. W., Robison, J. L., & Lester, J. C. (2009). Off-task behavior in narrative-centered learning environments. In *AIED* (pp. 99–106).
64. Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston: Houghton Mifflin.
65. Mann, C. (2003). Observational research methods. Research design II: Cohort, cross sectional, and case-control studies. *Emergency Medicine Journal, 20*(1), 54–60.