A Systematic Literature Review of Empirical Studies on Learning Analytics in Educational Games

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Abstract

Learning analytics (LA) in educational games is considered an emerging practice due to its potential of enhancing the learning process. Growing research on formative assessment has shed light on the ways in which students' meaningful and in-situ learning experiences can be supported through educational games. To understand learners' playful experiences during gameplay, researchers have applied LA, which focuses on understanding students' in-game behaviour trajectories and personal learning needs during play. However, there is a lack of studies exploring how further research on LA in educational games can be conducted. Only a few analyses have discussed how LA has been designed, integrated, and implemented in educational games. Accordingly, this systematic literature review examined how LA in educational games has evolved. The study findings suggest that: (1) there is an increasing need to consider factors such as student modelling, iterative game design and personalisation when designing and implementing LA through educational games; and (2) the use of LA creates several challenges from technical, data management and ethical perspectives. In addition to outlining these findings, this article offers important notes for practitioners, and discusses the implications of the study's results.

Keywords

I. Introduction

Educational games are immersive, interactive and can engage students in dynamic learning-and-playing processes. They have therefore been used in various disciplines, such as computer architecture [1], mathematics [2], language learning [3][4] and science [5], as well as in online contexts [6][7]. Unlike in traditional learning management systems, users generate massive data while interacting with educational games. Therefore, collecting and synthesising students' en-route behaviour patterns, intellectual states and emotional level in gameplay become essential to identifying how their playful learning occurs. Researchers have sought various ways to utilise this data to identify how to accurately observe students' learning process through learning analytics (LA) [8]. LA refers to the collection and analysis of learners' intellectual and behavioural attributes to optimise learning experiences [9]. Several studies on educational games have

also focused on adopting unobtrusive ways to use LA approaches to measure students' progressions without interrupting the flow of their gameplay [10] [11]. In particular, using stealth assessment in educational games has broadened the role of real-time and automatic assessments in educational games [12]. Moving away from existing approaches that rely on external measures (e.g. post-test), recent research has sought ways to promptly measure how students' in-situ learning occurs while they are experiencing ongoing gameplay.

The LA field has expanded in recent years because it allows educators to perform formative assessments that accompany fine-grained and contextual feedback tailored to the various needs of individuals in learning environments. For instance, recent implementations of educational games have integrated formative assessments with LA [13] [14]. Serving as a mechanism of such assessment, LA in educational games aims to identify and interpret students' meaningful progressions or task challenges in gameplay. Subsequently, game elements and supports (e.g. feedback, learning sequence and presentation of materials) are tailored to individual needs (e.g. domain knowledge, cognitive competence, or affective states).

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Despite the emerging significance of LA when implementing educational games, a limitation also remains. There is a lack of comprehensive guidelines for LA design, development, and implementation, because analytic approaches are game- and context-specific, resulting in high variations in adoption. Specifically, this issue limits developers' ability to define general analytics to effectively incorporate LA in educational games [15]. In other words, the applications of LA in educational games still appear complex, and generally acceptable approaches have rarely been reported [16]. This fact implies that it is necessary to perform a comprehensive review to explore how LA has been integrated and implemented in educational games.

Accordingly, this study conducts a systematic literature review to better understand the potential implementations of educational games across various contexts. The goal of this study is to advance this field by (1) exploring why and how LA has been implemented across various learning contexts and (2) discussing existing limitations and challenges in integrating LA in educational games. This study is structured as follows: Section II presents the background of LA in educational games and highlights the research gap this study aims to address. Section III presents the research method followed to conduct the systematic literature review. Section IV presents the findings of this study, while section V discusses these findings. Finally, section VI concludes the study with general notes and future directions.

II. Background of LA in Educational Games

LA is an interdisciplinary field associated with many domains, including data science, artificial intelligence, practices of recommender systems, and online marketing and business intelligence [17]. LA is defined as 'the measurement, collection, analysis and reporting of data about learners and their context, for purposes of understanding and optimising learning and the environments in which it occurs' [18]. Powell and MacNeill [19] highlighted key applications of LA, namely to: (1) offer feedback for students about their learning performance; (2) predict at-risk students who may fail to pass their final exams; (3) help educators to provide interventions when needed; (4) improve the design of courses; and (5) support decision-making when it comes to administrative tasks. LA has been increasingly prominent because it enables researchers to collect, interpret and share meaningful data that inform how learners interact with a learning environment.

The applications of LA are rooted in the usage of formative assessment in learning. A formative assessment is one that is integrated into the learning experience without interruptions during students' gameplay [11]. Research suggests the importance of formative assessments in informing educators about which cognitive and emotional challenges students may experience. In addition, formative assessment can prompt educators to decide on the types of adaptive learning supports (in-game help and game tasks) to use to foster students' deep learning [12]. Specifically, a current stream of a stealth assessment has explored feasible implementations of formative assessment in educational games [21][22]. Since educational games yield highly interactive and massive traces of learners' in-game behaviours, researchers have considered the latent uses of LA in educational games. In the same vein, Alonso-Fernandez, Calvo, Freire, Martinez-Ortiz and Fernandez-Manjon [23], as well as Tlili and Chang [24], have stated that educational games without analytics are like black boxes that barely offer meaningful clues to students' learning process during their play.

Hence, LA is applied in educational games to better capture how students' improvement and challenges occur without interrupting their flow, and then to inform tailored feedback for game-based learning experiences. However, previous studies rarely suggested how and why LA techniques are capable of supporting learners' play in educational games. This gap demonstrates that it is essential to understand (1) what are the objectives of implementing LA in educational games; (2) what are the educational game contexts; and (3) how such factors (objectives and game contexts) can influence various LA implementations in educational games.

Despite the potential of future combinations of LA and educational games, integrating those two systems remains challenging. Papamitsiou and Economides [25] asserted that further explorations using LA in educational games are necessary because understandings of the intersection between LA and interactive learning environments are still vague. Saveski et al. [26] revealed that 21 European game studies demonstrated a high interest in applying LA in educational games, but the researchers were concerned with the complexity of implementation. Like previous researchers, Perez-Colado, Perez-Colado, Freire-Moran, Martinez-Ortiz and Fernandez-Manjon [16] mentioned that the application of LA in educational games is still a complicated process, despite the fact that there are several platforms which combine both educational games and analytics. Therefore, given the gap between the advancement of LA technologies and their practical implementations in educational games, a further systematic literature review is necessary to gain insights that can close the gap. To address the questions above, we proposed four primary research questions in this study.

- RQ1. What are the objectives of applying LA in educational games?
- RQ2. What genres of educational games have applied LA, and what types of game metrics were used in the application of LA?
- RQ3. What types of LA approaches were used in educational games?
- RQ4. What are the challenges in applying LA in educational games?

III. Method

A systematic literature review of empirical studies using LA in educational games was conducted based on the major steps outlined by Okoli and Schabram [27].

A. Data Collection and Search Criteria

Several keywords, including 'learning analytics AND educational games', 'learning analytics AND game-based learning' and 'educational data mining in games' were used in searches in different electronic databases, namely Taylor & Francis Online, IEEE Xplore Digital Library, ScienceDirect, AIS Electronic Library, Springer, Wiley Online Library, ACM Digital Library, ProQuest and Semantic scholar. As shown in Fig. 1, these searches yielded a total of 405 studies conducted from 2012 to 2019. Of those, 180 studies were removed since they were found to be duplicated. The remaining 225 studies were then evaluated by title, abstract and, if necessary, by full text, based on the inclusion and exclusion criteria described in Table I. In the end, only 36 studies met the inclusion criteria, and those studies were double-checked again through readings of the full text.

TABLE I. Inclusion and Exclusion Criteria

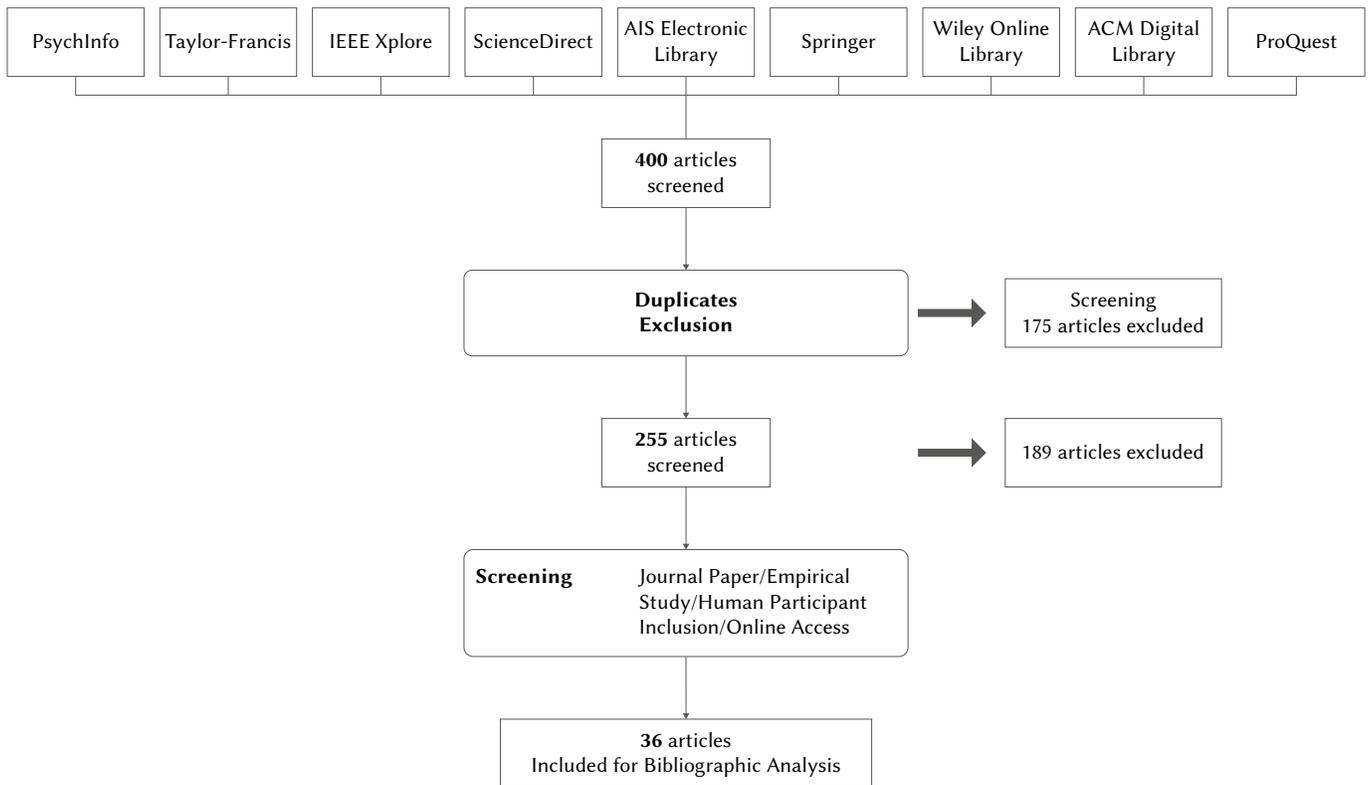| Inclusion and Exclusion Criteria technique |
|---|
| Articles that are published in peer-reviewed journals. |
| Articles that are empirical studies and report rigorous study procedures and their findings. |
| Articles that involve human subjects. |
| Articles that have their full text available online. |
| Articles that apply LA in educational games. |

Fig. 1. Flowchart of the systematic review process.

B. Coding Procedure

Each study in the literature was coded for different characteristics. As this study aimed to explore LA designs and implementations in educational games, we took into consideration existing integrations of LA in combination with major features of educational games discussed in the sampled studies. Hence, two major coding schemes presented in two systematic literature reviews guided our coding scheme in this study, namely Papamitsiou and Economides [25] for LA and Connolly et al. [28] for educational games. In addition to the basic article information (e.g. year of the study, journal name), we evaluated the LA objective and technical information (i.e. LA approach, whether the LA was embedded in the game or not and LA challenges). In addition, we evaluated environmental information (i.e. game genre and game mode) and the metrics of the educational games highlighted in these studies. Table II presents the detailed coding scheme of this study. Finally, suggested by Webster and Watson [29], the coding results were then organized in a table (see Appendix I), which formed the abstract of this systematic literature review.

We designed an initial coding protocol for multiple coders who are experts on educational games and LA. Based on the coding scheme presented in Table II, we carried out training using a subset of the literature for this study. The coder training was conducted until all coders reached consensus. When individuals' coding results differed, all coders iteratively discussed their results to reach an agreement. A detailed summary of the articles reviewed based on the coding variables is presented in Appendix I.

TABLE II. Coding of Reviewed Research Papers Examining LA in Educational Games

Variables	Description	Coding Criteria
Year	Year study was conducted	Year
LA objective	Goal of applying LA in educational games	• Understanding and modelling students' in-game behaviours • Formative design of educational games • Implementing teaching supports • Conducting learning assessments • In-game personalisation
LA approach	The approach used to analyse data	• Data mining and analytics (e.g. lag-sequential analysis and social network analysis) • Data visualization • Sequential data analytics
Challenge	The challenges of LA application in educational games	Report the mentioned challenges during the application of LA in educational games
Embedded analytics	Was the LA procedure incorporated within the educational game?	Yes / No
Game mode	The mode of the educational game used while applying LA	Single player / multi-player / massively multiplayer
Game metrics	The metrics used within educational game for LA	Report the actual collected traces for LA

IV. Findings

A. RQ1. What Are the Objectives of Applying LA in Educational Games?

This section found major objectives of LA in educational games: understanding and modelling students' in-game behaviours (13 studies); creating formative designs for educational games (7 studies); implementing teaching support (8 studies); conducting learning assessments (13 studies); personalising in-game features (2 studies). It should be noted that several studies applied LA in educational games for more than one purpose [30]. Each key application is described in the subsequent sections. Appendix I includes the details of coded articles for this study.

1. Understanding and Modelling Students' In-game Behaviours

A group of studies has examined students' in-game behaviours [31] [32] [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] to identify gameplay patterns. Using collected data about such behaviours, researchers aimed at understanding students' behaviour patterns and their inherited characteristics during gameplay. For example:

- [40] Liu et al. used LA to implement in-game behaviour log analysis to collect students' time- and date-stamped actions. They implemented data visualisations of collected student log data to represent students' pattern of use of in-game tools (e.g. database, notebook, and probes).

- [42] Martin et al. used LA to explore how groups of students solved in-game tasks related to fractions. Using hierarchical clustering, this study identified three gameplay patterns.

Furthermore, researchers also observed students' in-game behaviours to obtain evidence of modelling that reflected either affective or cognitive states attained during gameplay.

- Affective state: Denden et al [33] and Essalmi et al [34] modelled the students' personalities, specifically extraversion and openness dimensions, based on their gaming behaviours and LA [9, 10].

- Cognitive state: Khenissi et al. [39] implemented LA in a memory match game to implicitly model the students' working memory capacity using a fuzzy logic algorithm.

2. Formative Design of Educational Games

Using LA was also beneficial in carrying out formative designs of educational games [15] [44] [45] [46] [47] [48] [49]. Specifically, LA enabled game designers and educators to understand how educational games can be better designed through assessments of students' play logs and observed behaviour. As examples of such design studies on educational games:

- [15] Serrano-Laguna, Torrente, Moreno-Ger and Fernández-Manjón carried out data visualisations to detect cases of outlier behaviour from students. Using collected data, they identified the types of learner challenges that appeared during gameplay.

- [49] Chaudy and Connolly used the LA engine EngAGe integrated with an educational game. This engine is designed to allow both game developers and educators to conduct iterative designs of an assessment that is capable of in-game adaptions to players.

3. Implementing Teaching Supports

LA played a role in the development of teaching supports to foster students' learning in educational games [30] [45] [46] [50] [51] [52] [53] [54]. First, researchers used LA to provide students' records of learning profiles in a game system. The use of teaching supports was found to enhance students' attention and then help them cope with challenges during gameplay. Some studies included examples of how teaching supports were applied and implemented across different domains.

- Providing a visual dashboard demonstrating real-time behaviour data

  - [30] Minović, Milovanović, Šošević and González incorporated an analytical tool in an educational game that generated a real-time dashboard (e.g. using circular graphs) for teachers to use when teaching computer networks. They used this dashboard to keep track of their students' trajectories and support their learning when needed.

  - [51] Chen and Lee applied LA to help students learn English vocabulary in an educational game. The game in this study tracked students' answers to inform teachers of students' learning states, providing warning messages and suggestions to enhance the learning process.

- Providing learner profile data for teachers' decision-making

  - [54] Rodríguez-Cerezo, Sarasa-Cabezuelo, Gómez-Albarrán and Sierra created an analytics tool in generated educational games for teaching computer language implementation to help teachers control their students while learning occurred and to assess their performance.

4. Conducting Learning Assessments

LA in educational games served as learning assessments. The key to assessment in educational games was to unobtrusively measure students' learning progressions across various subjects. A collection of studies implemented LA to identify learners' progression in in-game performance, problem-solving skills or knowledge acquisition [11] [15] [30] [52] [55] [56] [57] [58] [59] [60] [61] [62] [63].

- In-game performance [58][59][60]: a group of researchers used LA in an educational game to model students' knowledge levels, in order to allow researchers to compare expert and novice scores. Such studies used similarity indices that represented to what extent students' in-game performance emerged.

- Problem-solving [56]: Hernández-Lara, Perera-Lluna and Serradell-López applied LA in a simulation game that taught students decision-making and management skills. They aimed to implicitly observe students' interaction behaviours in relation to target learning outcomes.

- Knowledge [61]: Rowe et al. considered LA approaches in two developed educational games (Impulse and Quantum Spectre). Using game log data, this study detected learners' strategic behaviours concerning various scientific concepts (e.g. Newtonian physics).

5. In-game Personalisation

Research has implemented personalisation to automatically provide students with adaptive learning experiences in educational games [11] [53]. Adaptivity in educational games refers to providing appropriate level of challenge and tailored feedback in an educational game [5]. In accordance with this rationale, some studies have adjusted game designs to reflect learners' needs and challenges.

- [11] Reese, Tabachnick and Kosko adopted their actionable measurement system to indicate learners' progress on their in-game performance. In their educational game CyGaMEs, the game system provided students with embedded learning support and a performance progression bar showing personalised data visualisations that indicated how close students were to meeting their in-game goals.

- [53] Kiili, Moeller and Ninaus applied LA in an educational game for teaching fractions and decimals to provide personalised hints based on each student's misconceptions.

B. RQ2. What Genres of Educational Games Have Applied LA, and What Types of Game Metrics Were Used in the Application of LA?

As Fig. 2(a) shows, the educational game genres in which LA is most often applied are role-playing games (11 studies) and puzzle games (9 studies). This finding suggests that research tend to use role-playing games because those games enable students to experience playful learning in correspondence to a given narrative in a virtual environment. Moreover, role-playing games provide a media-rich environment, including interactions, activities, and places; hence, behaviour traces can be generated, tracked and used in LA everywhere in such a game environment. Puzzle games have also been used extensively, primarily because they can facilitate students' problem-solving and reasoning [64] [65]. On the other hand, as Fig. 2(b) shows, the most used educational game type in which LA is applied is the single-player game (31 studies out of 33). This result suggests that previous games were designed to promote individuals' self-regulated actions in individual adventures.

Prior studies have used several types of in-game metrics across different game genres. Such games have applied LA to meet different
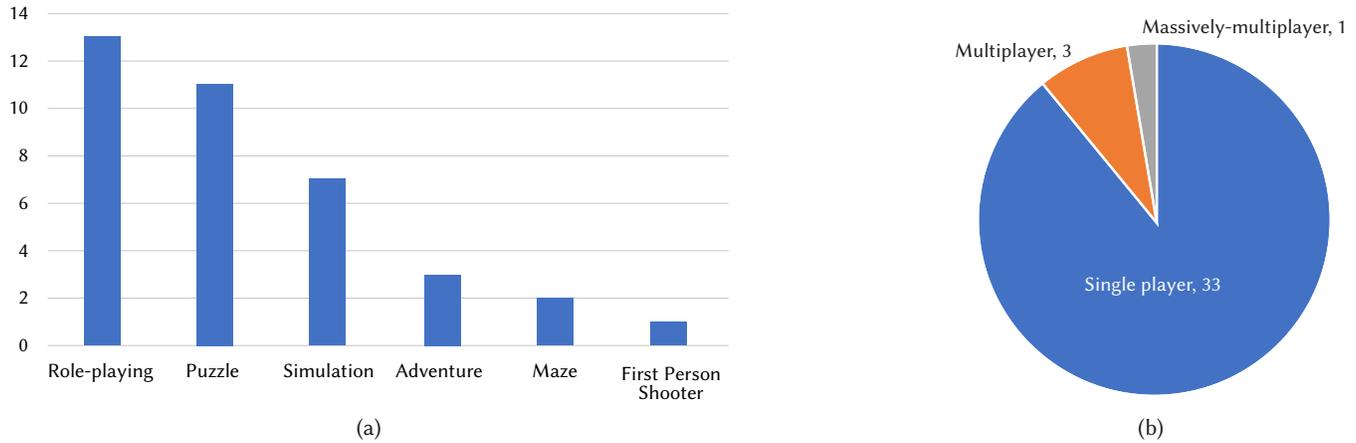

Fig. 2. Used game genres and types for la (a= game genres, b= game types).

TABLE III. Coding of Reviewed Research Papers Examining LA in Educational Games

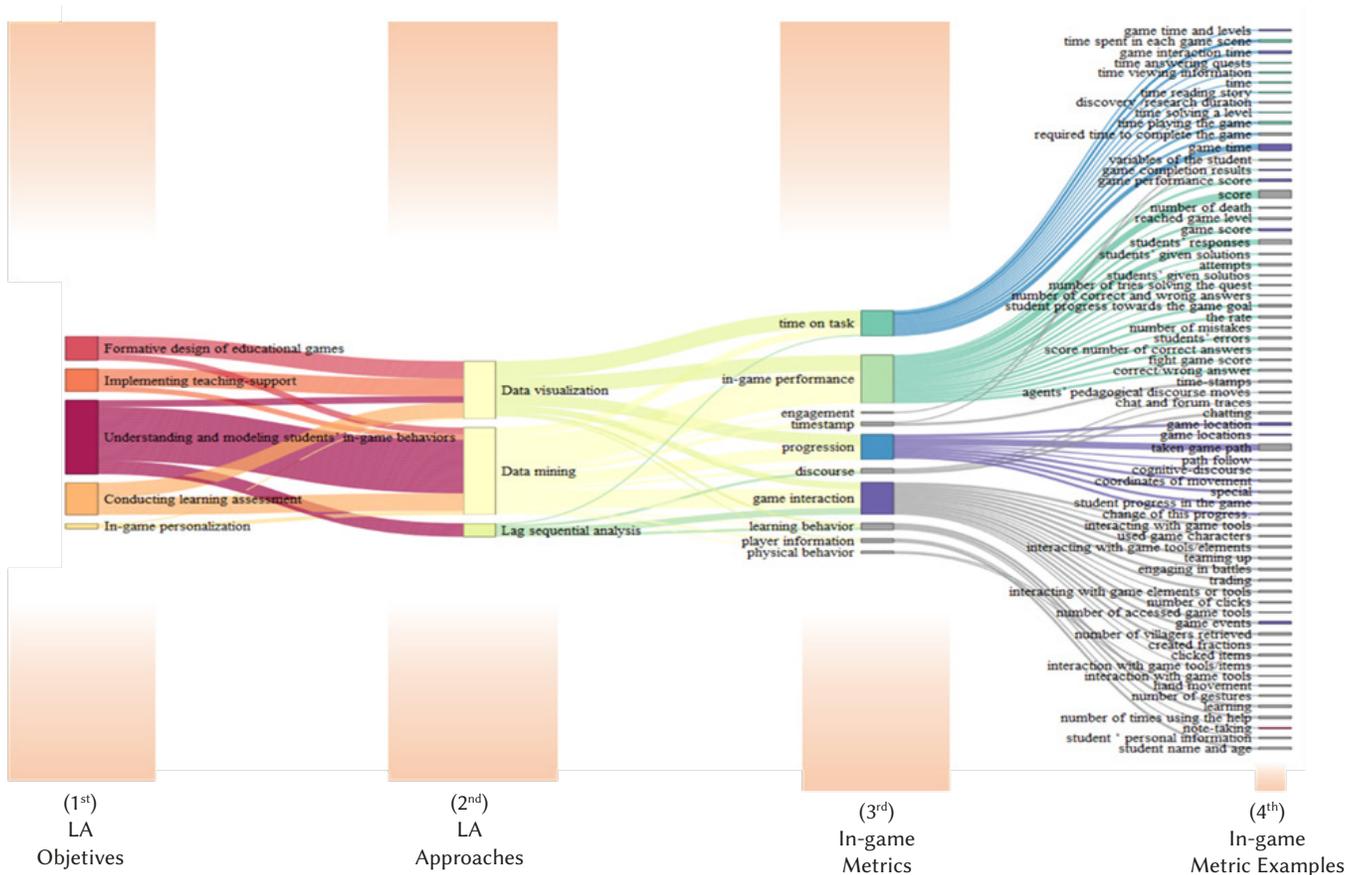| Target measures	Type of game metrics	Examples	Description
Performance measure	In-game performance	• Game score • Reached game level • Number of correct/wrong answers	In-game performance measures can keep track of students' in-game performance in relation to learning.
	Time on task	• Time spent in each scene • Interaction time • Time solving a level	Researchers focused on measuring the time duration by either students' performance in the game in general or in a particular in-game activity or quest. This metric was specifically used to measure either how much time they paid attention to gameplay or how they efficiently accomplish game tasks.
Behavioural measures	Game interaction	• Used game characters • Interacting with game tools/elements • Number of clicks	In terms of interaction with the game tools/elements, research focused on using the interaction of students with different game elements (found in the game environment) or game tools (provided by the game as tools to further support the learning process). The purpose of game interaction is to capture all the interactions of players.
	Learning behaviour	• Number of times using the help • Note-taking	Learning behaviours refer to the specific game interactions that are identified to be related to learning. The purpose of learning behaviour is only to capture the meaningful interactions of players.
	Progression	• Game location • Followed path • Progress in the game	These metrics focus on tracking the students' game trajectories or paths while learning in the game environment.
	Timestamp		Timestamping usually works with the game interactions, learning behaviours and progression to mark the chronological sequence of gameplay.
Multi-faceted measure	Discourse	• Dialogue • Verbal communication	Researchers focused on collecting chat/forum communications among students generated while those students were playing an educational game.
	Player information	• Personal information • Student name and age	These metrics are out of the game but can provide background information on players.
Challenge	Physical behaviour	Gesture	This type of metric looks beyond in-game performance. Bioinformation can be tracked similarly.

Fig. 3. Sankey diagram of LA objectives, approaches, and in-game metrics.

objectives (identified by RQ 1). Table III shows the major types of in-game metrics with their examples. In general, performance has been the most frequently emphasised target measure in previous studies. Previous studies measured either in-game performance or time on task. Another major type of measure was behavioural (e.g. game interactions, learning behaviours and progression). These metrics provided researchers with analytical information that represented 'en-route' variables of students' behaviours. Lastly, a group of LA metrics – such as discourse, player information and physical behaviour – helped researchers understand students' learning behaviours through multiple facets (e.g. discourses and physical behaviours). This type of measure proved beneficial in corroborating the results of both performance and behavioural measures but was shown to be highly dependent on inherited game contexts and data availability.

C. RQ3. What Types of LA Approaches Were Applied and Used in Educational Games?

As shown Appendix I, the most used analytics approach was data mining (28 studies), followed by data visualisation (13 studies) and sequential data analytics, or SDA (i.e. lag-sequential analysis, 2 studies). We also confirmed that several studies applied multiple analytics approaches in combination (e.g. both data mining and data visualisation). Data mining aims to discover hidden information and meaningful patterns from massive data, while SDA captures sequential transitions in behaviour events representing learning paths in gameplay [66]. Data visualisation is used to display a variety of visual stimuli, such as pie charts and histograms, to represent data indicating students' learning progression.

Most (60%) studies applied LA to educational games offline. Specifically, these studies collected the students' traces during the learning process first. They then used external data-mining software, such as Weka, to analyse these traces and extract meaningful information. The rest of the studies (40%), on the other hand, incorporated LA within the educational games to provide real-time reports for stakeholders, such as teachers and students. This result is explained by the existing limitation that designing educational games with incorporated analytics systems (i.e. automatic data collection and adaptations) is likely to be more complex and challenging. This is because to provide an adaptive game scenario, game designers and developers need to adapt all the involved game elements (e.g. mechanics, graphics, sounds, etc.) in that scenario to different profiles, which could be time consuming and with high cost. For instance, Denden et al. [33] highlighted that to provide an adaptive educational game based on personality, the game environments that a student can visit, as well the non-player characters to interact with should be personalized.

Fig. 3 is a visual synthesis of our study findings, which mapped the relationship among LA objectives, LA approaches, and the specific in-game metrics from the collected studies. It outlines a visual path indicating how LA objectives, approaches, outcome variables, and in-game metrics are interconnected. Across types of LA objectives in educational games (1st layer, 5 categories), researchers have adopted LA approaches (2nd layer, 3 categories) by drawing on a list of in-game metrics (3rd layer, 10 categories). To evaluate such outcome variables, research has used a collection of in-game metrics (4th layer, 67 examples) in the diagram. The dominant goal of LA in previous studies was to understand and model students' in-game behaviours. Accordingly, the majority of the collected studies have used data-mining techniques (2nd layer) to track students' learning as indicated by in-game performance, progression and game interactions (3rd

layer). Surprisingly, few studies assessed students' outcomes in terms of learning behaviours. Most tended to focus on capturing students' in-game trajectories in relation to game performance. Our study findings suggest that to date, research on LA in educational games has mostly focused on the growth of data-mining techniques to capture, collect and explicate learners' in-game actions.

D. RQ4. What Are the Challenges in Applying LA in Educational Games?

After identifying ways of incorporating LA in educational games, this section discusses the reported challenges which can hinder such incorporation. The identified challenges (Appendix I) can be grouped into three categories: (1) techniques; (2) data; and (3) ethics.

1. Challenges on Techniques

These concerns are related to the provided infrastructure, including tools for the application of LA in educational games. They are as follows:

- Validations of learning analytics implementations in educational games:
  - Previous research also stated the difficulty of incorporating analytic systems in educational games, due to the complexity of designing educational games that contain such systems [48].
  - Fine-tuning learning analytics systems across different educational game contexts is necessary to validate the feasible adoptions of the systems (e.g. configuring either universal or contextual sets of variables and tracing rules).

- Lack of game environments to capture students' collaboration:
  - Few studies in the sampled literature configured students' collaborations during gameplay [36] [55] [56].
  - A lack of collaboration settings in previous studies suggests that there are likely limits on providing social learning experiences through group interactions (e.g. how students collaborate and what type of communication occurs). Further investigation about the application of LA in other game types, namely multiplayer and massively multiplayer, is suggested to capture the effect of social dynamics on game-based and playful learning.

- Reusability of the analytics system: According to existing studies, integrations of LA into educational games appear not to be reusable, because a high degree of variation between educational game developers and educators exists when game metrics are used [15]. Consequently, the cost of designing educational games with analytics systems is high. Therefore, researchers need to focus on developing and providing standardised and scalable LA approaches that can be used across different educational games.

- Big data storage: Educational games encourage learners to be interactive, so that their many traces can be generated and stored. This raises a question of how massive trace data from students can be stored securely [15] [54] [63]. Hence, game developers need to consider ways to store all generated trace data while avoiding losses due to network constraints.

2. Challenges in Data Collection

- Identification of important data: Research suggests that the failure to select the important data to be collected from big data storage is likely to limit the application of LA by resulting in the collection of data that cannot be useful later on. Important data should reflect, for instance, students' performance [38] [61]. In this context, Tlili et al. [67] mentioned that data generated during the application of LA should be carefully studied and selected before the collection process begins.

- Identifying relationships between data: Research states that in educational games, it is difficult to see the relationship between traces in order to extract useful information [38]. Therefore, specific metrics should be predefined (depending on the LA goal) and considered during the educational game design. This can facilitate identifying the relationships between metrics that have been previously defined.

3. Challenges in Ethics

These challenges relate to the duties and obligations that arise when applying LA in educational games.

- *Students' privacy*: Existing studies rarely consider how students' privacy is secured when collecting student data in educational games [33]. Pardo and Siemens [68] have suggested that it is necessary to consider appropriate legislation methods for data collection to avoid unintentional violations of students' privacy.

- *Transparency of LA*: Researchers have highlighted the need to ensure the transparency of collected data, which should be fully open for students. This statement implies that students should be able to retrieve their performance results when they want to during gameplay [33]. This approach can help students feel safe while applying LA and assist in immediately monitoring their learning progress by enabling a 'watch the watcher' process [69].

- *Storage time*: Researchers were not clearly aware of how long the collected data should be securely stored [33].

- *Equity challenge:* Only a few studies suggested how LA in educational games could be used to support students with disabilities. The study findings outlined in Appendix I show that 91% of educational games with LA were aimed at typical-developing students without any disabilities.

V. Discussion

A. Academic Implications

We found that existing LA practices tend to be exploratory (e.g. cluster analysis and sequential analysis). LA implementations in educational games were intended to identify learners' behaviour patterns, as well as their characteristics. Some studies employed cluster analysis to identify either individual or group learning styles and behavioural patterns [32] [38] [42]. The others used SDA to extract and visualise a major set of behaviour sequences representing strategic and engaged gameplay patterns [40] [43]. Such exploratory LA implementations were intended as a means of qualitatively analysing students' gameplay contexts and behaviour patterns through a quantitative lens.

Despite the benefits of exploratory LA studies outlined above, a challenge also exists. Existing exploratory LA practices are post-hoc analyses, which focus on showing what happens during gameplay, and are therefore limited in predicting students' learning challenges in different gameplay paths [39]. In other words, the exploratory post-hoc analyses have limited implications without validating the model performance in context. For example, existing LA practices scarcely address the question of how to provide adaptive supports to assist students in meeting challenges in educational games. Predicting learners' difficulties or challenging experiences is essential to choosing adaptive supports tailored to learners' progressions in gameplay. Hence, once an educational game aims at providing personalised game experiences to students having learning challenges, building a pipeline to connect an adaptive system with such exploratory LA can be suggested in future research.

1. Validations of Learning Analytics Measures

When using LA in educational games, only a few researchers implemented validations of various in-game data with external assessments [11] [61]. In addition to observing learners' trajectories unobtrusively, researchers should also aim to ensure that such game metrics represent target outcome variables as intended. Educational games involve multiple types of game metrics. We can build a bigger picture through multiple learner traces from gameplay. This will enable researchers to implement finer-grained data analyses (e.g., microactions), triangulate the data collected and understand learning processes in detail. For example, synthesising and validating multiple data sources from learners' gameplay is necessary to confirm how such game metrics consistently indicate learners' achievement through gameplay. Especially considering different game design contexts, validating different types of game metrics can be useful in capturing learners' meaningful gameplay reliably.

2. Lack of Learning Analytics Implementations in Collaborative Educational Games

We confirm that there is a lack of multiplayer and massively multiplayer games applying LA. This result indicates not only the necessity of designing games that foster collaboration, but also that of implementing LA to understand collaborative experiences. Although the field of LA includes various data-mining and analytics approaches used to understand learners' social dynamics, existing educational games have rarely focused on students' social interactions. Traditional ways of understanding collaboration and peer interactions among learners (e.g. observation, interview, video analysis) are generally time-consuming. LA, however, can distill emerging information much faster, sometimes with greater and unbiased detail, than those methods. It thus raises the question of how future LA practices can be contextualised in educational games that require learners' social interactions.

3. The Need for Mastery Learning Design in Educational Games

Despite the increasing growth of data-mining techniques in educational games, there is a dearth of empirical research on how to design and implement an educational game system that supports students' mastery of learning experiences. We have confirmed that previous studies largely focused on understanding and modelling students' in-game behaviours instead of on learning assessment and in-game personalisation. While the former LA objective highlights unobtrusive and externalised data collection related to students' in-game behaviours, the latter influences how likely an educational game is to be designed to enable students' mastery of learning objectives [70]. Specifically, learning assessments and in-game personalisation are means to indicate students' learning progressions and provide automatic and responsive feedback tailored to their learning states. The reported challenges in data collection are also related to the discrepancy between current and potential LA practices. The automation of learning assessments and personalisation requires an educational game to select and define important data features in relation to students' cognitive, behavioural and emotional states. However, limitations in choosing and embedding important data features into educational games and their assessment system still exist [38] [61]. This recalls our study result that few studies on educational games have focused on students' learning behaviours as a major measure in LA. Future educational games should consider ways to reinforce students' mastery of learning experiences.

B. Practical Implications

In terms of practical implications, we suggest important means through which stakeholders can understand this research field and further work better. First, a collection of game metrics (e.g. interaction with the game tools/elements, followed game path or trajectory, game time, game score, number of wrong/correct answers and chat/forum communication) has been used for different LA applications in educational games. Future educational games can use these and other metrics for different purposes, including to help researchers collect evidence that identifies learners' status in different domains (e.g. cognitive, affective and behavioural) and across various game contexts.

Second, we suggest that educators and practitioners further investigate applications of LA in educational games. Specifically, LA techniques benefit educators by enabling data-driven decisions in communication among all stakeholders. Although educational games have been increasingly used by educators in K-12 settings [5] [42], the integration of LA into educational games is still at the early stage. Such integration should foster communications between teachers and students. Besides, future LA in educational games could take more stakeholders (e.g. parents and administrators) into consideration.

Third, it is important to address the accessibility of educational games with LA. Research has shown the possibility of using LA to help students with disabilities [15] [46] [57]. However, relevant educational policies and acts, as well as inclusive game design standards are scarce. LA can help create a novel way of facilitating access to education by students with disabilities, which will further increase equity and support inclusive learning. In addition, policymakers should emphasise and address the ethical challenges of using LA. Privacy and transparency have been issues not only in educational games with LA, but also in adopting LA into educational systems.

VI. Conclusion, Limitations, and Future Work

In this study, we systematically reviewed educational games studies with LA to investigate how LA implementation has evolved. The study findings suggest that: (1) LA in educational games has been used for different purposes, such as student modelling, iterative game design, providing teaching supports and personalisation. (2) Role-playing games and puzzle games in single-player mode are the most common game-setting implementing LA. When LA has been implemented, various game metrics (e.g. interaction with the game tools/elements, followed game path or trajectory, game time, game score) have been used for data input. (3) The most frequently used analytics approaches include data mining and data visualisation. We confirmed that most of the LA approaches are post-hoc and focus on exploring students' in-game trajectories. (4) It is important to address challenges from three perspectives, namely techniques, data and ethics, to ensure the successful integration of LA applications into educational games.

It should be noted that this study has also some limitations that should be acknowledged and further researched. This study included only study findings from empirical journal articles. The narrow scope of data collection in this study limited the number of sampled data and failed to address emerging LA practices expansively. Despite such limitations, this study provides a solid basis for better understanding the ways in which LA in educational games has been contextualised. Future research could investigate ways to integrate LA solutions in educational games by providing a variety of LA examples in educational game contexts.

Appendix

APPENDIX I. A List of Selected Literatures As to Learning Analytics in Educational Games

Num	LA Goal [a]	LA Approach [b]	Game Genre [c]	Game Mode [d]	Embedded Analytics [e]	Challenges [g]	Game Metrics
[11]	Ca, Ip	Dm	Pz	Sg	No	N/A	Student progress towards the game goal, the rate and change of this progress
[15]	Fo, Ca	Dv	Ad, Pz	Sg	Yes	App	Students' responses
[30]	It, Ca	Dv	Ad	Sg	Yes	N/A	Student progress in the game, score
[31]	Un	Dm	Si	Sg	Yes	N/A	Game completion results, game performance score
[32]	Un	Dm	St	Sg	No	N/A	Score, Used game characters, Time viewing information
[33]	Un	Dm, Dv	Rp	Sg	Yes	App	Interacting with game tools/elements, time, score, Taken game path
[34]	Un	Dm	Rp	Sg	Yes	N/A	Interacting with game tools/elements, path follow, time reading story
[35]	Un	Dm	Rp	Sg	No	N/A	Agents' pedagogical discourse moves, Cognitive-discourse variables of the student
[36]	Un	Dm, Lg	Rp	Mm	No	N/A	Teaming up, engaging in battles, learning, trading, interacting with game elements or tools, and chatting
[37]	Un	Dm	Ad	Sg	No	N/A	Game performance score
[38]	Un	Dm	Pz	Sg	No	N/A	Students' given solutions and attempts
[39]	Un	Dm	Pz	Sg	Yes	N/A	Number of clicks, Discovery /research duration
[40]	Un	Dv	Rp	Sg	No	App	Number of accessed game tools
[41]	Un	Dm	Pz	Sg	No	N/A	Student's personal information, Number of correct and wrong answers, Score, and number of gestures
[42]	Un	Dm	Pz	Sg	No	N/A	Created fractions
[43]	Un	Lg	Si	Sg	No	N/A	Note-taking, Interaction with game tools, Game time
[44]	Fo	Dv	N/A	N/A	Yes	N/A	N/A
[45]	Fo, It	Dv	Rp	Sg	Yes	N/A	Time spent in each game scene, Game location, Reached game level
[46]	Fo, It	Dv	Si	Sg	Yes	N/A	Game interaction time, interacting with game tools, game time
[47]	Fo	Dm	Pz	Sg	No	N/A	Students' given solutions and attempts
[48]	Fo	Dm	Pz	Sg	No	App	Game score, Fight Game score
[49]	Fo	Dm, Dv	N/A	N/A	Yes	N/A	N/A
[50]	It	Dm	FPS	Sg	No	N/A	Game time and levels, score, number of deaths
[51]	It	Dv	Rp	Sg	Yes	N/A	Students' responses and game locations
[52]	It, Ca	Dm	Rp	Sg	Yes	N/A	Students' responses
[53]	It, Ip	Dm	Rp	Sg	Yes	N/A	Students' responses
[54]	It	Dv	Pz	Sg	Yes	App	Number of mistakes, Time solving a level
[55]	Ca	Dv	Si	Mp	Yes	N/A	Game score, time answering quests
[56]	Ca	Dm	Si	Mp	No	N/A	Chat and Forum traces
[57]	Ca	Dm	Pz	Sg	No	N/A	Number of tries solving the quest, Hand movement
[58]	Ca	Dm	Rp	Sg	Yes	N/A	Coordinates of movement, time-stamps, special
[59]	Ca	Dm	Rp	Sg	Yes	N/A	Game events, number of villagers retrieved
[60]	Ca	Dm	Rp	Sg	Yes	N/A	Coordinates of movement, time-stamps, special game events, number of villagers retrieved
[61]	Ca	Dm, Dv	Pz	Sg	Yes	App	Students' errors
[62]	Ca	Dm, Dv	Si	Sg	No	N/A	Student name and age, Correct/wrong answer, game time
[63]	Ca	Dm	Pz	Sg	No	N/A	Interaction with game tools/items

[a] LA Goal (Un = Understanding and modeling students' in-game behaviors, Fo = Formative design of educational games, It = Implementing teaching support, Ca = Conducting learning assessment, Ip = In-game personalization), [b] LA approach (Dm = Data mining, Lg = Lag sequential analysis, Dv = Data visualization), [c] Game Genre (Puzzle = Pz, Adventure = Ad, Roleplaying = Rp, Strategy = St, Simulation = Si, First person shooting = FPS, Not applicable = N/A), [d] Game Mode (Single player = Sg, Multiplayer = Mp, Massively Multiplayer, = Mm), [e] Embedded Analytics (Yes or No), [f] Game Traces, [g] Challenges (Applicable = App, Non applicable = N/A).

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Zhichun "Lukas" Liu

Dr. Zhichun "Lukas" Liu is a postdoctoral fellow at Kaput Center of Research and Innovation in STEM Education, University of Massachusetts Dartmouth. His current work aims at using game-based learning to promote the development and learning transfer of computational thinking among K-12 students and teachers. His research interests also include using quantitative analytics methods to understand learners' behavior, competence, discourse, and interactions.

Daniel Burgos

Daniel Burgos received a postgraduate in artificial intelligence & machine learning from MIT, and the Ph.D. degree in communication, the Dr.Ing. degree in computer science, the Ph.D. degree in education, the Ph.D. degree in anthropology, and the D.B.A. degree in business administration. He works currently as a Full Professor of technologies for education & communication and Vice-Rector for International Research, UNESCO Chair of eLearning, and ICDE Chair of open educational resources at Universidad Internacional de La Rioja. He is also the Director of the Research Institute for Innovation & Technology in Education (UNIR iTED). Further, he is a Professor with An-Najah National University, Palestine, an Adjunct Professor with the Universidad Nacional de Colombia (UNAL), Colombia, an Extraordinary Professor with North-West University, South Africa, a Visiting Professor with Coventry University, U.K., and the Universidad de las Fuerzas Armadas (ESPE), Ecuador. He has published over 150 scientific articles, 20 books, and 15 special issues on indexed journals. He has developed +55 European and Worldwide Research and Development projects. His research interests include adaptive, personalised and informal eLearning, learning analytics, open education and open science, eGames, and eLearning specifications.

Nian-Shing Chen

Nian-Shing Chen is currently Chair Professor in the Department of Applied Foreign Languages at the National Yunlin University of Science and Technology, Taiwan. He has published over 400 academic papers in the international referred journals, conferences and book chapters. One of his papers published in Innovations in Education and Teaching International was awarded as the top cited article in 2010. He is the author of three books with one textbook entitled "e-Learning Theory & Practice". He has received the national outstanding research awards for three times from the National Science Council in 2008, 2011-2013 and the Ministry of Science and Technology in 2015-2017. His current research interests include assessing e-Learning course performance; online synchronous teaching & learning; mobile & ubiquitous learning; gesture-based learning and educational robotics.

Kinshuk

Kinshuk is currently a Professor of Computer Science and the Dean of the College of Information at the University of North Texas, USA. He received the Ph.D degree in computer science from the University of De Montfort, England, in 1996. He held the NSERC/CNRL/Xerox/McGraw Hill Research Chair for Adaptivity and Personalization in Informatics, funded by the Federal government of Canada, Provincial government of Alberta, and by national and international industries. Area of his research interests include learning analytics; learning technologies; mobile, ubiquitous and location aware learning systems; cognitive profiling; and interactive technologies.