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A review on learning analytics in mobile learning and assessment

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ABSTRACT

Employers are facing difficulties in selecting the most suitable candidates for employment and the transition from education to work is challenging for young graduates. Therefore, it is important to have indicators that could show the suitability of a potential candidate for his/her chosen job. A person who possesses knowledge but lacks confidence may struggle to perform assigned tasks, while an overly confident person with limited knowledge is likely to make errors in their job. Although there is existing research on learning analytics related to assessments, the research on learning analytics specifically focused on the confidence-knowledge relationship based on assessment data is still lacking. This article aims to examine the application of analytics in providing insights based on assessment data that can be utilized by potential employers. To achieve this, a systematic review was carried out, analyzing a total of 141 articles. The findings contribute to a better understanding of the use of assessment analytics in identifying the knowledge-confidence quadrants of students.

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1. INTRODUCTION

Mobile learning facilitates ubiquitous learning by providing learners with access to educational content and resources anytime and anywhere, and by enabling them to collaborate with others and share knowledge and ideas [1]. Besides, it allows students to have positive emotions during their learning thus, improving their learning outcomes [2]. For mobile learning to be more useful, the mobile learning environment must provide valuable insights that can facilitate the teaching and learning process. Jia and Zhang [3] proposed clear navigation, simple layout, linear display, harmonious colouring, smooth video, and full interaction. An interactive test dashboard with high-quality visualized test feedback, including response time and answer correctness, can enhance learning performance, and increase technology acceptance levels [4]. To provide insights, data analytics is performed on the data where it is cleaned, processed, and presented in the dashboard, which in this sense is known as learning analytics since the data is from the mobile learning environment and the learning context.

Learning analytics was first published in 2010, and publications in this field have been increasing since then. The highest number of publications occurred in 2019, accounting for 22% of the total publications that year [5]. Learning analytics involves the measurement, collection, analysis, and reporting of data in the learner's context to understand and optimize the learning environment that facilitates decision-making [6], [7]. Among the functionalities of learning analytics are “prediction,” “assessment,” “performance,” and "feedback" [8]. It is used in areas such as "citation analysis," "social network analysis," "user modelling," "education/cognitive modelling," "knowledge discovery," "adaptive media," and "e-learning." Learners' interactions while using the learning management system (LMS), such as "navigation patterns," "clicks," "time taken to perform a task," "participation in social networks," "information flow," and "participation in discussions," can be tracked and analyzed. Other than that, data from the completion of assignments activity, attempts on quizzes, extracurricular activities and social interactions, postings in discussion forums, and data from other non-educational activities are collected for those purposes. Learning analytics can also be applied in the context of assessments, whereby the data is derived from assessment psychometrics data, with the outcomes used to provide feedback to learners. For instance, the Hijaiyah m-learning application provides a comprehensive audio assessment and users who use the application can read Hijaiyah letters with correct Makhraj pronunciation [9]. In another example, learning analytics is used for predicting students' academic achievement based on "Total login frequency in LMS," "(Ir) regularity of learning interval in LMS," and "total assignments and assessment composite" [10].

Learning analytics can also facilitate teaching and learning by providing hints, recommendations, and feedback. Kuhnel *et al.* [11] emphasized the importance of incorporating feedback and recommendations into mobile learning platforms to attract more users. The artificial intelligence tutoring system (AITS) provide tutors on the student's knowledge level and performance while offering recommendations, advice, and actions for students to improve their learning [12]. In another study, feedback in the form of hints and learning recommendation were provided to students after they had taken their diagnostic test [13]. Feedback on the analytics results and recommendations are provided to various stakeholders so that the users' knowledge, behaviour, and experience can be modelled, profiles of the users can be created, the users' knowledge domain can be determined, the usage trend can be identified, and users can personalize and adapt the learning environment to their needs and requirements. Through learning analytics, it is possible to address drawbacks in e-learning platforms, such as high dropout rates and the lack of verified users who have completed courses, as mentioned by [14].

In today's competitive job market, companies are increasingly seeking employees with specific competencies. Although there is high employability, the industry is still facing the problem of a shortage of skilled workers. Graduates can find employment faster than non-graduates, but they still face the problem of job mismatch for a long period after leaving education. Amirul *et al.* [15] found that the transition from education to work is challenging for young people in Malaysia and has resulted in skill mismatches and low starting salaries. Therefore, the ability to assess and evaluate these competencies becomes crucial. Jerez *et al.* [16] discussed competence assessments in the context of mobile learning, which includes evaluating knowledge, attitudes, values, and competency behaviour using learning analytics. Besides, it is also crucial to allow employers to be able to perform the assessment and evaluation conveniently anywhere without being constrained to a specific physical location in particular for assessments during scientific trips, clinical assessments for medical students, and for individuals who are constantly on the move. Alrfooh [17] highlighted the advantages of mobile-based assessments (MBA) compared to paper-based or computer-based assessments whereby MBA was found to be able to eliminate such barriers. There is no doubt about the importance of assessments and, learners and teachers are aware with regards to this in ensuring quality learning outcomes [18]. Additionally, according to Rasila *et al.* [19], assessment systems must classify and diagnose students' answers while providing customized feedback. Ibrahim *et al.* [20] "attention, relevance, confidence, and satisfaction (ARSC)" model is used to assess the students' motivation. The large amount of assessment data generated from computer-based and mobile-based assessments can be utilized to track and optimize the learning process, facilitating the improvement and evaluation of conceptual understanding [13], [19]. However, there is a lack of research on the use of learning analytics in mobile learning and assessments that utilize those data to identify the "knowledge vs confidence" quadrant of the learners. A person who possesses the knowledge but lacks confidence may struggle to perform assigned tasks, while an overly confident person with limited knowledge is likely to make errors in their job, and this is crucial in eliminating the problem of job mismatches.

This paper reviews the use of learning analytics in providing insights based on data within the realm of mobile learning and assessments. The conducted reviews will identify research gaps and recommend new research areas such as providing a better understanding of how learning analytics can facilitate in identifying the knowledge-confidence quadrants of students. The objective of this paper is to:
- identify the applications of learning analytics in online learning and assessment.
- investigate the existing frameworks that incorporate learning analytics.
- identify the features provided by assessment analytics.
- investigate how timely feedback can be provided to learners through learning analytics.

The rest of this paper is organized as follows. In section 2, it explains the method used in this study. In section 3, it discusses on the findings from the literature reviews and proposes a taxonomy based on the findings. In section 4, it discusses the challenges and future directions. Lastly, section 5 concludes this review.

2. METHOD

This research utilized a systematic literature review to identify the usages and features of learning analytics about mobile learning and assessment. A systematic literature review involves the use of a systematic and rigorous standard to identify, select, and critically appraise relevant research. It's purpose is to identify research questions, research gaps, and provide justifications for future research [21]. The methodology employed in conducting the systematic literature review for this research is illustrated in the flowchart shown in Figure 1. The main pillar of this study consists of three (3) key elements, namely learning platforms, learning assessment, and analytics. So, the keywords used in the search query were derived from these elements and are presented in Table 1.

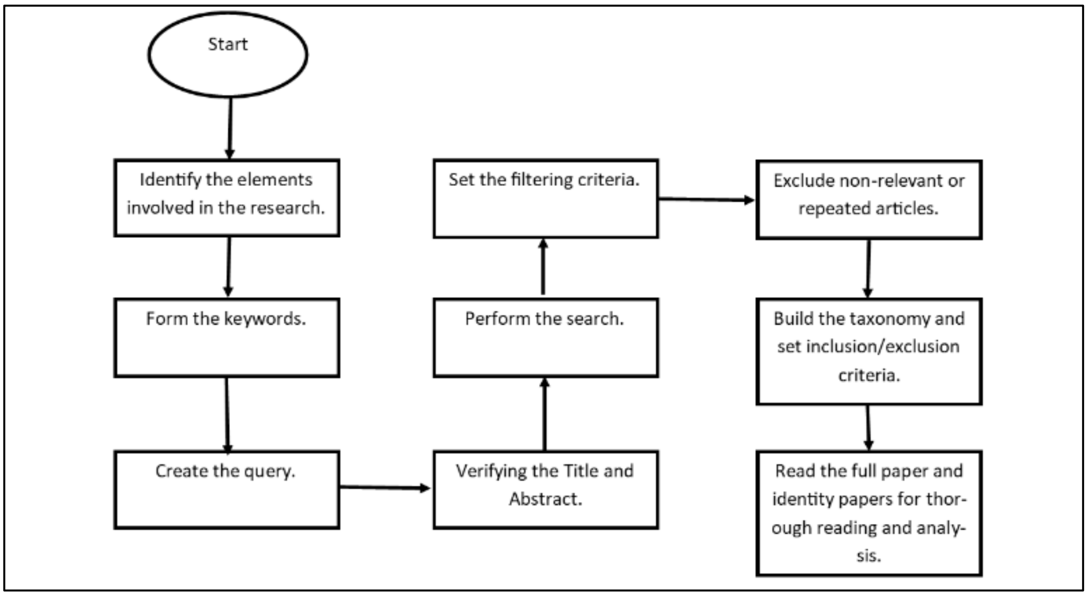

Figure 1. The flow of literature review

Table 1. Research elements

Learning platforms	Learning assessments	Analytics
E-learning	Formative assessment	Learning analytics
Mobile learning	Summative assessment	Assessment analytics
Mobile learning framework		
m-learning framework		

2.1. Information sources

The articles used in this study were obtained from three top-ranked databases namely "Web of Science," "IEEE Xplore," and "Science Direct," as shown in Table 2. IEEE Xplore is a comprehensive source, housing over 4.7 million research articles in the fields of electrical engineering, computer science, and electronics. Given that learning analytics (LA) draws upon data science, artificial intelligence, practices of recommender systems, online marketing, and business intelligence (all falling under computer science), IEEE Xplore serves as a suitable information source. Additionally, the "IEEE International Conference on Advanced Learning Technologies" is recognized as a significant contributor to learning analytics publications [5]. On the other hand, Web of Science provides a rich collection of citation indexes, offering strong coverage in computer science and ensuring access to high-quality scientific information based on evidence [22] while Science Direct enables researchers to stay updated with the latest developments in their respective research areas.

Table 2. Distribution of articles collected from top-ranked databases

Database	Frequency
Web of Science	82
IEEE Explore	37
Science Direct	275
Total	394

2.2. Study selection

Screening was performed to eliminate any duplicate records obtained from various databases and only relevant papers that are crucial for the research are selected. The purpose of this study selection process is to ensure the credibility of the results and their applicability in future research. A search query containing the keywords was created for the three databases: Web of Science, Science Direct, and IEEE Xplore digital library. Figure 2 shows the search query based on the identified keywords. The query utilized the Boolean operator "AND" to ensure that the search results include articles that are related to learning platforms/frameworks, assessment methods, and learning analytics. As the learning platform may be either "e-learning," "mobile learning," "mobile learning framework," or "m-learning framework" the Boolean operator "OR" was used. The same principle was applied to different assessment methods, wherein the Boolean operator "OR" was employed to retrieve papers involving "assessment," "learning assessment," "formative assessment," or "summative assessment". Furthermore, an additional filtering criterion was applied to the search by setting the publication dates ranging from 2009 to 2023. The most recent search was conducted on January 12, 2023. Articles that were not written in the English medium and articles that focused on gamification on online learning platforms were eliminated.

("E-learning" OR "Mobile Learning" OR "Mobile learning framework" OR "m-learning framework") AND ("Assessment" OR "Learning assessment" OR "Formative Assessment" OR "Summative Assessment") AND ("Learning Analytics")

Figure 2. Search query

2.3. Data collection

To identify, select, appraise, and synthesize studies, the researcher followed the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines [23] while conducting and reporting the review work. PRISMA is an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses, which aims to improve the transparency, completeness, and reproducibility of the studies carried out. Figure 3 illustrates the PRISMA flow diagram used to record the flow of information through the various phases of the systematic review.

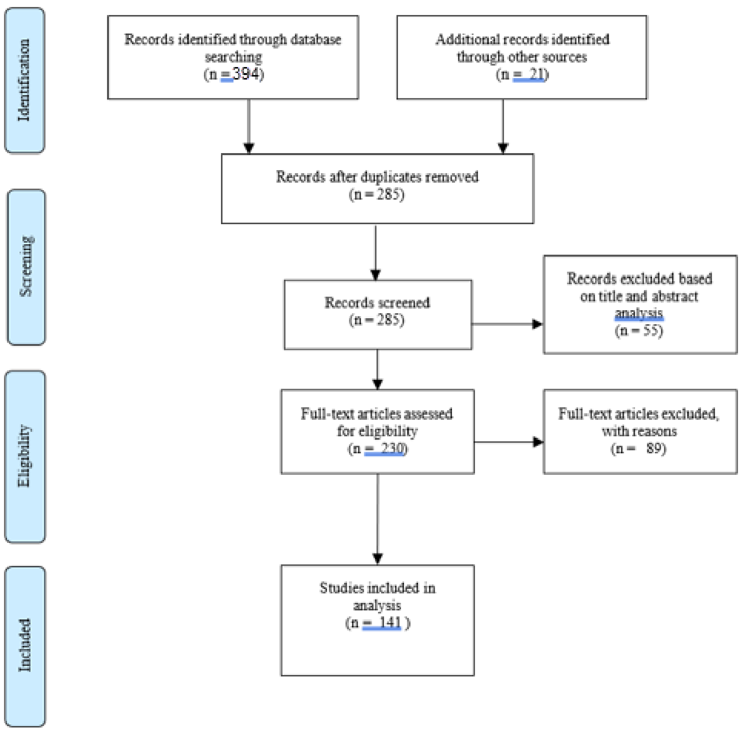

Figure 3. PRISMA flow diagram for the filtering process

3. APPLICATIONS OF LEARNING ANALYTICS IN ONLINE LEARNING

There are many applications of learning analytics in online learning. For instance, learning analytics is used to enhance instruction, promote student learning achievement, and analyze students' mastery levels [24]. To track students' usage patterns in the learning management system, the time spent by students on each activity can be tracked [25]. In a literature review conducted by Aldowah *et al.* [26], it was observed that computer-supported predictive analytics (CSPA) and computer-supported behavioural analytics (CSBA) accounted for a majority of the research studies in the field of data mining and learning analytics. CSPA will be able to suggest how the learning and performance of a student can be improved by suggesting the appropriate learning materials. On the other hand, CSBA involves modelling students' behaviour, actions, and knowledge. A multi-regression analysis model with variables such as "posting messages," "content creation contribution," "quiz efforts," and "the number of files viewed" is effective in predicting students who are likely to fail [27]. Besides using learning analytics to investigate the usage patterns of students in an online learning system, Foung and Chen [28] also used it to predict the student's course grades in which multiple regression analysis based on the activities carried out such as "completion rate of the independent online learning task," "time spent on independent online learning task," "the time when students stopped doing online activities," in the online learning was used for the forecasting. Learning analytics can be categorized into four levels namely, "descriptive analytics," "diagnostic analytics," "predictive analytics," and "prescriptive analytics" [29]. The predictive analytics level makes use of a regression model, wherein the independent variables are derived from the results obtained from "descriptive analytics" and "diagnostic analytics." On the other hand, prescriptive analytics enables teachers to enhance and adapt the course content. For example, an adaptive e-learning algorithm can be used to analyze the learners' success rate in completing e-learning exercises and the results can be utilized to determine the future e-learning exercises that the learners would receive [30], thereby enhancing the effectiveness of the learning process. Learning analytics has proven to be beneficial in enhancing the learning experience of the learners [31]. There have been instances where learning analytics has been utilized in relation to assessments, such as:

- Adapting next quiz items to students' abilities [32].
- Estimating students' emotions such as "boredom," "confusion," "delight," and "frustration" [33]–[35].
- Modelling the time that is spent by the student to think and reflect on the given hint [36].
- Predicting students' learning outcomes based on the scores from the student's assessment and usage in the learning management system [28].
- Predicting students' performances with online activities as early as possible [37].

Learning analytics is also utilized to offer timely feedback to learners, aiming to enhance their engagement in the learning process [38]. Several studies have explored the use of learning analytics for providing feedback, including:

- The automation of personalized assessment task delivery to examinees [39].
- The ability of students to manage their learning [40].
- The impact on the students' emotional state and their ability to perform while facing challenges [41].

Cavalcanti *et al.* [42] conducted a systematic literature review on papers published between January 2009 and December 2018. The literature review revealed that 65.07% of the analyzed literature demonstrated that automatic feedback improves student performance. Feedback can be tailored to learners to assist them in enhancing their learning outcomes. Lim *et al.* [40] investigated the influence of learning analytics-based feedback on self-regulated learning (SRL) using a quasi-experimental design. The findings indicated that the feedback had a positive impact on students' learning. The learning-analytic feedback included three feedback points throughout the course duration, providing opportunities for students to evaluate their progress and make necessary adaptations to improve their academic performance. In mastery learning, learners are required to achieve a high percentage of correct items, usually above 70% of the assessment items in formative mastery assessments to ensure their proficiency before advancing to the next level. There are two types of feedback strategies, namely self-referenced feedback, and reward-based feedback, in formative mastery assessments. Self-referenced feedback can provide detailed feedback messages that guide learners towards materials they can review, while reward-based feedback can be used to provide point rewards for correct responses. Although self-referenced feedback messages can direct learners towards relearning materials, it does not significantly impact their performance in subsequent assessments, particularly for learners who are struggling with the course. On the other hand, reward-based feedback will motivate learners to repeat the tests [43].

Table 3 in APPENDIX presents additional studies on the utilization of learning analytics in online learning. The usages are categorized into nine categories: "recommending resources for learning," "modeling students' behaviour," "improving feedback and assessment services," "predicting performance," "improving teaching," "improving academic integrity," "predicting dropout," "supporting collaborative learning," and "analyzing discussion forums." These studies explore various aspects of learning analytics and their application in enhancing online learning experiences.

"Course improvement"
- Using behavioural analytics to provide insights into learners' behaviour in a virtual class to improve the instructional design [44].

"Improving academic integrity"
- Applying a machine-learning-based framework to identify student identities and student-produced content [45].
- Determining the degree of coherence in discussion threads by measuring the semantic similarity between texts exchanged [46].

"Improving feedback and assessment services"
- Improving the learning analytics model such as the xAPI data model for tracking and modeling assessment data [47].
- Assessing the user interface and user experience of the learning management system [48].
- Adapting assessment components such as assessment model, assessment activity and assessment question [49].
- Analyzing cognitive and social interactions for providing effective and constructive feedback to learners [50].

"Improving teaching"
- Linking various components and technologies in the LMS platform to allow educators to work effectively [51].

"Improving the security of e-assessment"
- Ensuring that security is in place for the online assessment [52].

"Modelling students' behaviour"
- Identifying students' behavioural patterns in their learning [53].

"Predicting dropout and retention rate"
- Predict the potential a student may fail or drop the course based on students' online activities [54].

"Predicting performance"
- Classifying students into "Failed" or "Passed" the course based on students' activities in the LMS [27], [54].

"Recommending resources for learning"
- To recommend a suitable course based on learners' preferences, a fuzzy rule-based method is employed [55].

3.1. Existing frameworks that incorporate learning analytics

Table 4 presents a summary of studies and research on frameworks, models, and tools for mobile-based assessment. These studies utilized various machine learning techniques, including "decision tree", "hierarchical linear modelling", "multilevel regression model", and "univariate regression analysis" for analysis, prediction, and recommendation purposes. For instance, Matzavela and Alepis [59] employed a decision tree to predict students' knowledge levels and determine the appropriate difficulty level of exercises. Chen *et al.* [60] utilized hierarchical linear modelling (HLM) to predict changes in student performance on formative assessments, considering both time-varying predictors (such as academic achievement based on mid-term and final mathematics test scores) and time-invariant predictors (such as gender and goal orientation). HLM is a statistical analysis technique suitable for hierarchical data analysis. Faber and Visscher [61] examined the effects of the digital formative assessment tool called "Snappet", on students' learning achievement by considering predictors such as gender, pretest scores, student motivation, and total assignments.

According to Nikou and Economides [62], the successful implementation of mobile-based assessment relies on user acceptance. The factors influencing students' acceptance of mobile-based assessment include "perceived ubiquity," "content," "mobile self-efficacy," "perceived feedback," "perceived interactivity," "perceived collaboration," "perceived autonomy," "perceived competence," "perceived relatedness," "perceived usefulness," "perceived ease," and "behavioural intention to use" [62]. Nikou and Economides [63] identified several factors influencing students' intention to use mobile technologies for assessment purposes. These factors include "perceived ease of use and perceived usefulness (original TAM)," "facilitating conditions and social influence (environment)," "mobile device anxiety," "personal innovativeness," "mobile self-efficacy," "perceived trust (user profile)," "content and cognitive feedback (educational material)," "user interface," and "perceived ubiquity value (mobile device features)." Students are more motivated when mobile devices are used as mediums for assessment delivery, and this will lead to an increase in learning achievement especially among low-achieving students [64]. An example is the use of smartphones for the assessment of the performance of trainees in clinical practice. The use of smartphones for the assessment allows trainee performance data to be shared with faculty in real-time and the trainees benefit from getting individualized training [65]. The types of assessments that can be performed with smartphones are "workplace-based assessments" to evaluate the trainee's performance, "simulation-based assessments" to evaluate the skills, "oral and written examinations" to assess the applied knowledge and "multiple-choice questions" to evaluate the knowledge.

Table 4. Summary of the studies and research on frameworks, models, and tools for mobile-based assessment

No.	Study	Article title	Summary of study	Proposed framework/Model/Tool/Analysis
1.	[59]	Decision tree learning through a predictive model for student academic performance in intelligent m-learning environments	To create adaptive dynamic tests for assessing student academic performance and to formulate a predictive model for students' knowledge level.	Decision tree
2.	[62]	Mobile-based assessment: integrating acceptance and motivational factors into a combined model of self-determination theory and technology acceptance	To explain and predict behavioral intention to use mobile-based assessment based on the theoretical framework of the self-determination theory (SDT) of motivation and the technology acceptance model (TAM).	Mobile-based assessment - motivational and acceptance model (MBA-MAM)
3.	[63]	MBA: investigating the factors that influence behavioural intention to use	To provide empirical evidence on the acceptance of MBA for assessment delivered using mobile technologies.	Mobile-based assessment acceptance model (MBAAM) that is based on the TAM
4.	[64]	The impact of paper-based, computer-based and mobile-based self-assessment on students' science motivation and achievement	To investigate the effect of paper-based, computer-based, and mobile-based self-assessment on students' motivation and achievement. The study demonstrated that students are more motivated when taking computer and mobile-based assessments and there is an increase in learning achievement among low-achieving students.	Quasi-experimental pre-post-test research design, One-way analysis of variance for revealing the differences among the groups, Cronbach's alpha was used to examine the internal consistencies of the subscales.
5.	[60]	Formative assessment with interactive whiteboards: a one-year longitudinal study of primary students' mathematical performance	The study employed formative assessment (FA) within an interactive white board (IWB) FA system to track changes in mathematical performance among primary school students. The system incorporated various elements such as "feedback," "social learning through discussions," "agentive learning through personalized options," and "game-based learning".	Hierarchical linear modelling (HLM) was utilized to analyze data from the IWB system
6.	[65]	Using smartphones for trainee performance assessment: a SIMPL case study	To describe the motivations and implications of workplace-based assessments that utilize smartphone technology.	SIMPL
7.	[61]	The effects of a digital formative assessment tool on spelling achievement: results of a randomized experiment	To examine the effects of a digital formative assessment tool on the spelling achievement of third-grade students.	Multilevel regression model
8.	[66]	Effects of a computer-assisted formative assessment intervention based on multiple-tier diagnostic items and different feedback types	To investigate if a computer-assisted formative assessment intervention with diagnostic multiple-tier test items improves learning. The study assessed the impact of feedback with different content that takes into consideration the intrinsic motivation and the perception of the use of elaborated feedback on student achievement.	Correlation and univariate regression analysis

3.2. Features provided by assessment analytics

Assessment is an essential component of education, to evaluate learners' knowledge, understanding, and achievements in educational outcomes. It allows educators to gain insights into the effectiveness of their teaching methods and learning activities. Learners can use assessment results to assess their subject knowledge, while parents can utilize them as monitoring tools to track their children's educational progress. According to Curry and Gonzalez-DeJesus [67], assessment is defined as the process of measuring learners' educational outcomes and collecting assessment data.

During the COVID-19 pandemic, various restrictions and lockdown measures were implemented in many places and countries. This had significantly impacted students at different levels, including primary and secondary school students, as well as undergraduate and postgraduate students, who were unable to attend schools or universities for studying and taking exams. Consequently, educational providers have shifted towards e-learning and computer-based or mobile-based assessments. These alternative assessment methods offer the ability to capture various types of assessment data that may not be feasible during traditional pen-and-paper examinations. Analysis of this assessment data can provide valuable insights into students' performance and learning outcomes. Research on the use of learning analytics for predicting students' learning outcomes and providing feedback has gained popularity recently, thanks to the increasing popularity and usefulness of e-learning. Gunness and Singh [51] emphasized the importance of assessing students' metacognitive skills, such as information retrieval and processing through the internet, to develop higher-order thinking skills. Foung and Chen [28] utilized learning analytics to predict students' learning outcomes based on assessment scores and their usage of the learning management system. Howell *et al.* [41] examined the impact of learning analytics messages on students' affect and academic resilience. Other research on learning analytics in the context of assessments includes adapting quiz questions to students' abilities [32], estimating students' emotions during formative learning [33]–[35], implementing formative assessment interventions to improve learning [66], assessing students' metacognitive skills [51], providing self-assessment and learning recommendations [68], using feedback systems for students' SRL [40], providing adaptive e-learning based on learning outcomes [30], and tracking students' performance through formative assessment [60].

Table 5 in APPENDIX shows the features offered by assessment analytics such as "adaptively selecting the next questions," "predicting performance," and "estimating the students' emotions (e.g., boredom, confusion, delight, or frustration)". In predicting students' performance, factors that are analyzed include "response time and idle time while answering questions," "demographic characteristics," "grades (in pre-requisite courses, during assessment quizzes and their final scores)," "students' portfolios," "students' participation, enrollment and engagement in activities such as total number of discussion messages posted, total time online, and number of web links visited," and "students' mood and affective states such as boredom, engaged concentration, confusion, and frustration". To adaptively select questions, a two-step process is employed. Firstly, questions are chosen based on their appropriateness to the course syllabus. The item response theory (IRT) method is utilized to quantify students' knowledge and further refine the question selection. Finally, the question selection process take into consideration the usage history of the questions [32]. Barla *et al.* [32] discovered that adaptive question selection has enhanced the learning experience for students.

In a study conducted by Papamitsiou *et al.* [69], it was found that temporal learning analytics can predict learners' performance, and the use of an "hourglass" visualization can provide learners with an indication of their progress. Monroy *et al.* [70] discussed the use of visualization to help teachers better understand their students' needs, enabling them to provide appropriate resources for acceleration and interventions. Another approach to personalized feedback is understanding the learner's emotional state. D'Mello and Graesser [34] explored the use of sensors to better understand learners' emotions, such as frustration, while Moridis and Economides [33] demonstrated how a learner's mood can be predicted during online self-assessment. However, [33] required learners to manually record their moods.

Based on the literature review conducted, it was found that learning analytics are primarily used for "modelling students' behaviour," and "predicting students' performance" which account for 29.76% of the studies that involved the usage of learning analytics for assessment, as illustrated in Figure 4. The lowest usage categories are "predicting dropout and retention rate" and "improving academic integrity and security of e-assessment" which account for 5.95% of the studies. The median usage in learning analytics for assessments is "increasing the instructors' awareness and course improvements." One or more than one usage category may appear in the same study.

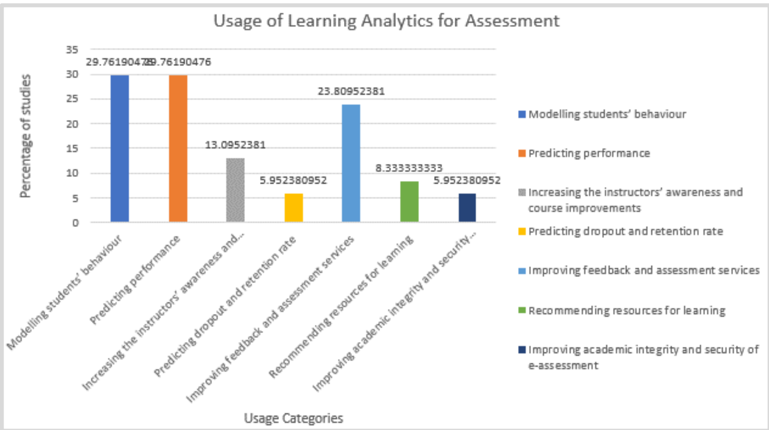

Figure 4. Percentage of usage of learning analytics for assessment

3.3. Taxonomy

Based on the literature reviewed, a taxonomy was developed, as depicted in Figure 5. Online learning consists of two main components: e-learning and m-learning. E-learning refers to courses delivered through the Internet, allowing interaction between learners and educators. In e-learning, educators may conduct live lessons or provide pre-recorded lessons. On the other hand, m-learning enables learners to engage in learning using mobile devices across various contexts, fostering social and content interactions. Both e-learning and m-learning have expanded to include massively open online courses (MOOCs), which attract a large number of learners from around the world. Within MOOCs, participants can create, share, and join discussions using readily available social media tools. While connectivist massive open online courses (cMOOCs) emphasize the connectivist philosophy, mobile massive open online courses (mMOOCs) combine mobile learning with MOOCs, allowing learners to access learning content using their electronic devices. Both cMOOCs and mMOOCs focus on pedagogical aspects such as “networked learning”, “collaborative peer learning”, “lifelong learning”, “authentic learning”, and “self-regulated learning”.

Despite the abundance of studies on m-learning, mobile-based assessment is still in its early stages, particularly in terms of understanding its value and potential [79]. Existing studies on m-learning can be categorized into areas such as “pedagogies and learning environment design,” “platform/system design,” “technology acceptance,” “evaluation of mobile learning,” and “psychological constructs.” For instance, in a study under the category of “pedagogies and learning environment design,” Mohamad *et al.* [80] described the challenges and opportunities in developing a mobile application to promote reading habits among kindergarten children in the Malaysian context.

Assessment plays a crucial role in the teaching and learning processes as it provides a feedback loop for both education providers and learners to enhance the effectiveness of education. Both cMOOCs and mMOOCs incorporate assessment features, with two common forms of assessments found in MOOCs being “formative assessment” and “summative assessment”. The importance of assessment lies in its ability to facilitate both education providers and students the following:
For education providers:
- Improve teaching.
- Identify strengths and weaknesses in teaching.
- Review, assess, and enhance the effectiveness of different teaching strategies.
- Review, assess, and improve the effectiveness of curricular programs.
- Enhance teaching effectiveness.
- Provide valuable analytics for decision-making.

For students:
- Identify strengths and weaknesses in their learning.
- Review, assess, and improve the effectiveness of their learning strategies.
- Utilize valuable assessment analysis for decision-making.
- Improve their learning outcomes.

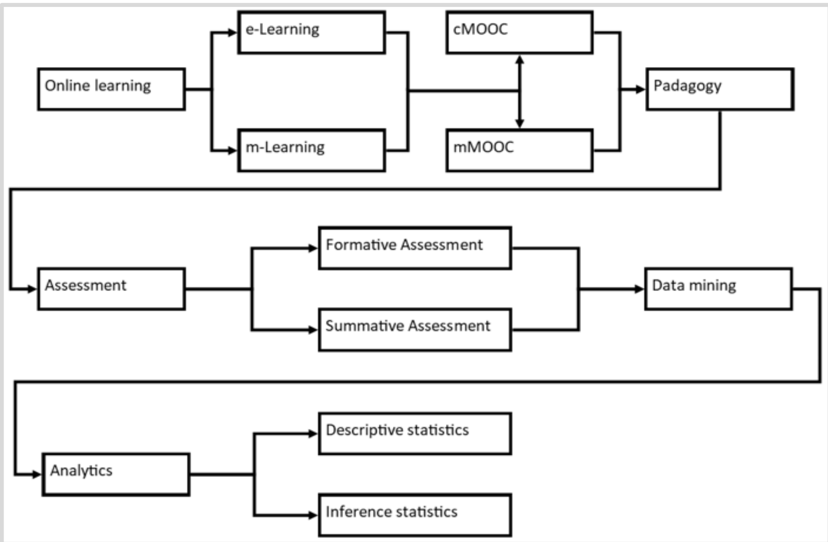

Figure 5. Taxonomy

In the study by Andrews *et al.* [81], a mobile assessment tool was developed to assess visual literacy in cultural education. The study aimed to enhance learners' motivation and visual literacy by providing insights into instructional design. The assessment tool collected various data from participants, including eye-tracking data, which could differentiate between novices and experts in terms of visual literacy. Another example of adaptive learning is the complex event processing (CEP) framework for an adaptive language learning system [82]. This framework incorporates event subsystems to process inputs from voice, video, text, and other interaction events, providing support for learner adaptation and learner visual analytics.

In a study conducted by Chirumamilla and Sindre [83] on e-exam systems, it was identified that teachers desire features that allow them to author exam questions, upload documents, and grade, explain, and analyze exam outcomes. Conversely, students require features that enable them to answer exam questions, upload documents, receive grades, seek explanations, and appeal their grades at the end of the exam. By incorporating learning analytics, mobile-based assessments can offer test questions that are adapted to individual learners. Louhab *et al.* [84] discussed adaptive learning and adaptive assessment in the context of mobile learning and proposed the "adaptive formative assessment in context-aware mobile learning (AFA-CAML)" model. In this model, the "adaptive assessment engine" defined rules for selecting the first test question, subsequent questions, and conditions for test completion. The goal of the model was to provide learners with an adapted and consistent learning process.

However, online assessment introduces new opportunities for students to engage in academic dishonesty. In a literature review conducted by Garg and Goel [85], it was discovered that students engage in online academic dishonesty through actions such as impersonation (sharing access credentials with unauthorized individuals), searching for answers on the internet, collusion (collaborating with other students or sharing answers), plagiarism (using someone else's work without proper attribution), and exploiting the features of the learning management system. Messaging apps like WhatsApp, WeChat, Telegram, and email provide means for students to easily collaborate during online assessments. Consequently, there is a need to prevent cheating, and assessment analytics can be employed to detect dishonesty by analyzing factors such as response time to questions, time spent on individual questions, overall assessment completion time, and submission time [85].

4. CHALLENGES

In their study, Mathrani *et al.* [86] identified three challenges that arise when deploying learning analytics systems: transferability or generalizability, model transparency, and ethical challenges. The challenge of generalization concerns the predictive power of the model. This challenge can arise when the training dataset and the live dataset are obtained from different cohorts of students. For example, the training data may come from final-year undergraduate students, while the live data comes from first-year undergraduate students. Another scenario involves the model's dependency on the features of the assessment. As the course evolves and the assessment features change, the accuracy of the predictive model may be compromised, leading to the phenomenon of concept drift. Concept drift occurs when the training data becomes disconnected from the live data, which can impact the predictive power of the model.

The second challenge identified by Mathrani relates to the transparency of the model. Model transparency involves making the inner workings of the algorithm verifiable. This requires the implementation of "interpretable machine learning," "explainable artificial intelligence (XAI)," "global model interpretability," and "model prediction explainability." Research in these areas is still relatively new.

Ethical considerations are also crucial in analytics activities. Learners should be informed about the use of their assessment and learning data, and consent must be obtained for the use of this data. Ensuring ethical practices in learning analytics involves respecting the privacy and rights of learners. Overall, these challenges highlight the importance of addressing transferability, model transparency, and ethical considerations when deploying learning analytics systems.

When it comes to online assessment, a significant challenge lies in maintaining and upholding the security and integrity of the assessment [85]. Garg and Goel found that students engage in dishonest practices because they seek to achieve their goals with minimal effort. Weak identity control systems further encourage dishonesty, such as cheating and collaborating with others. Additionally, the lack of physical monitoring in online assessments allows students to refer to books or other materials. The study also revealed that collusion and "copying answers using multiple existences online" (CAMEO) occur more frequently in assessments with objective questions, while assessments with subjective questions are more susceptible to plagiarism. In CAMEO, a user utilizes multiple accounts, with one account serving as the "master" account and the others as "harvester" accounts. The "harvester" accounts are used to gather correct answers, which are then entered using the "master" account. Garg and Goel also discussed how technology can be employed to prevent and detect dishonest behaviour, but they noted that these strategies can be compromised once their inner workings and loopholes are exposed. Ensuring the security and reliability of e-exam systems is crucial, as redoing exams can be challenging and costly [83].

While the use of feedback in educational settings has been extensively reviewed by Jensen *et al.* [87], the effectiveness of feedback remains a significant concern. Despite the numerous affordances of educational technologies, feedback often lacks quality or sufficient information. The study identified six conceptual metaphors regarding feedback: “feedback is a treatment,” “feedback is a costly commodity,” “feedback is coaching,” “feedback is a command,” “feedback is a learner tool,” and “feedback is a dialogue.” Therefore, the challenge lies in effectively applying learning analytics to address these various aspects of feedback.

Another challenge in online assessment is the lack of interoperability among different platforms. As mentioned by Chirumamilla and Sindre [83], there is a need for standardization and open interfaces to facilitate easier integration among platforms. However, achieving interoperability and integration with third-party tools remains a challenge. The study found that Norwegian higher education institutions utilize LMS from various vendors, such as BlackBoard, Canvas, and a custom-developed student information system called felles studentsystem (FS). While BlackBoard and Canvas are used for course management, some universities use inspera assessment (IA) for exams and graded coursework, while others use WISEflow (WF).

The study conducted interviews with 12 participants, including vendors, process managers, and system managers at universities. The research identified security challenges during integrations for content sharing between e-exam systems, LMS, and student information systems. Additionally, the study found that most users prefer to utilize external text editors to create exam questions and then upload them to the e-exam system rather than using the system's built-in editor. Problems can arise if the e-exam system does not support the required question types, as each system typically has its own supported question types. Another challenge highlighted by Chirumamilla and Sindre is the lack of a common standard for question types, particularly between WISEflow (WF) and inspera assessment (IA), making the exchange of instructional management systems' (IMS) questions and test interoperability (QTI) specification between them complicated. The study further emphasized that both e-exam systems and supporting systems have their own set of APIs, making it difficult to integrate APIs from different systems.

4.1. Recommendations

In terms of practical contributions, research on the application of learning analytics, specifically assessment analytics for knowledge-confidence analysis, brings benefits to multiple stakeholders:

Government and policy makers:
- Policy makers and government can enforce the capturing of learners' confidence levels in answering assessment questions among education institutions and use the evaluation results as one of the graduation criteria. This ensures that graduates are well-trained and prepared in their fields.

University/Course director/Program director:
- Universities can produce graduates who are highly sought-after by the industry.

Employers:
- Employers can have greater confidence that their employees are well-trained and prepared for their jobs and assignments.
- Employees will also have increased confidence in performing their duties.

Lecturers:
- It enhances teaching methods and teaching materials.
- It facilitates the estimation of students’ performance.
- It improves the detection of students who are at risk of failing the subject.
- It enhances the identification of misconceptions and gaps in students' understanding.
- It helps identify students' guessing or cheating behaviour.

Students:
- It aids in better preparation for their studies.
- It supports self-awareness, self-reflection, and self-regulation.
- It triggers emotional changes, challenges their preparation, and motivates them in their studies.
- It promotes engagement in assessment and learning activities.

Learning analytics allows educators, learners, and employers to have a better understanding of the learners’ emotions during the learning process or assessment and this will allow learners to adapt their learning styles and strategies to have better achievement in the learning outcomes [2], [33]–[35]. Overall, the application of learning analytics, specifically assessment analytics for knowledge-confidence analysis, has practical benefits for government and policymakers, universities, employers, lecturers, and students.

5. CONCLUSION

By incorporating learning analytics and assessment analytics into mobile learning, it is possible to bring education to the next frontier. With assessment analytics gaining in popularity and its usage is expected to continue to increase, learners, educators and employers stand to gain valuable advantages from it since it facilitates the modelling of students' behaviour, predicting performance, increasing instructors' awareness, and improving courses, predicting dropout and retention rates, enhancing feedback and assessment services, recommending learning resources, and improving academic integrity and the security of e-assessment. The literature review conducted has revealed a research gap in learning analytics, particularly in assessment analytics, which is still in its infancy stage, especially in terms of mobile assessment analytics. The insights provided by assessment analytics are beneficial to various stakeholders in different ways. Universities and higher education providers can produce graduates who are in high demand by the industry, and employers can have confidence that their employees are well-trained and prepared for their jobs and assignments. Employers can also rely on the insights generated from assessment analytics as a guide during the employee selection process. For lecturers, the insights on students' performance and understanding can be used to enhance teaching materials and methodologies, while students can use the insights to better prepare for their studies.

APPENDIX

Table 3. Existing studies on the use of learning analytics

No.	Study	Purpose of study/Assessment type/Factors examined	Sample size/Method	Category
1.	[55]	To recommend a suitable course based on learners' preferences. Factor(s) examined: – User overall interest – Knowledge of Instructor – Value of information – Clarity of explanation – Engaging delivery of information – Accuracy of course description – Helpfulness of practice activities Learning platform(s): – MOOC, udemy Technique(s): – Machine learning – Latent dirichlet allocation (LDA), – Decision trees, self-organizing map (SOM) and fuzzy rule-based system	Data collected from MOOC (Udemy)	Recommending resources for learning
2.	[53]	To investigate the relationship between learner's engagement in video-based online learning and learning achievement. Factor(s) examined: – Browsing – Social interaction – Environment configuration – Information seeking Learning platform(s): – Video-based online learning Technique(s): – Factor analysis – Principle component analysis (PCA) – Partitioning around medoids (PAM)	72 undergraduate students	Modelling students' behaviour
3.	[56]	To introduce the approach to analyse students' feedback written in natural language using opinion mining (OM) techniques. A mathematical formalisation of the OM process is presented in the paper to compute the positive, negative, or neutral sentiments of the students. Factor(s) examined: – Students' opinions toward courses and instructors Technique(s): – Preprocessing, feature extraction, polarity detection, and polarity aggregation.	566	Improving feedback and assessment services
4.	[27]	To predict students who are likely to perform poorly. Factor(s) examined: – LMS usage variables such as "reading and posting messages," "content creation contribution," "quiz efforts," and "Number of files viewed" Learning platform(s): – Moodle LMS Technique(s): – Multivariate regression	134	Predicting performance
5.	[57]	To provide guidelines for upholding security in online activities. Assessment(s): – Formative assessment Factor(s) examined: – Online collaborative activities Learning platform(s): – Mobile learning Technique(s): – Neural network-based approaches	12	Improving the security of e-assessment
6.	[44]	To assist teachers in changing from traditional to online teaching methods. Factors examined: – Browsing pattern of instructional videos Learning platform(s): – E-learning	72	Improving teaching

Table 3. Existing studies on the use of learning analytics (*Continued*)

No.	Study	Purpose of study/Assessment type/Factors examined	Sample size/Method	Category
7.	[51]	To link learning various components in the LMS platform to improve the interface and to allow metacognitive skills to be appraised. Factor(s) examined: – Students' marks Learning platform(s): – Moodle Technique(s): – Classification, clustering, regression, artificial intelligence, neural networks, association rules, decision trees, genetic algorithm, and nearest neighbour	survey of literatures	Improving teaching
8.	[47]	To investigate and compare the various learning analytics models. Factors examined: – Assessment data Learning platform(s): – MOOC	survey of literatures	Improving feedback and assessment services
9.	[48]	To assess the user interface and user experience of a learning management system. Factor(s) examined: – Log-files of learners' activities Learning platform(s): – Moodle LMS	Examined more than 30 users of moodle who used both the desktop and mobile interfaces	Improving feedback and assessment services
10.	[45]	To evaluate the computational-based approach to academic integrity. Assessment(s): – Written assignments Factor(s) examined: – Students' writings Technique(s): – Machine learning	20	Improving academic integrity
11.	[54]	To examine the correlation between students' online activities and their exam performance, and to predict students who may fail or drop the course. Factor(s) examined: – Online activity data such as login attempts, viewing of materials, participation in the forums, usage duration, results of formative assessment, and communicating with other users. Learning platform(s): – Moodle LMS Technique(s): – Regression models – Automatic linear modelling (ALM) – Binary logistic regression (BLR)	133	Predicting performance Predicting dropout and retention rate
12.	[49]	To integrate the various components and processes in the online assessment. Assessment(s): – Continuous assessment and final exam Factor(s) examined: – Assessment activities Technique(s): – Bayesian – Fuzzy	Students taking the "computer fundamentals" subject.	Improving feedback and assessment services
13.	[50]	To produce an efficient platform for collaborative activity with personalization features and feedback. Assessment(s): – Cognitive and social assessment Factor(s) examined: – Cognitive assessment data – Social network analysis data Learning platform(s): – Virtualized collaborative session Technique(s): – Statistics	185	Improving feedback and assessment services
14.	[52]	To design, implement and evaluate a holistic security model. Assessment(s): – Continuous assessment Factor(s) examined: – Type of subjects – Specific evaluation model – Evaluation application – Agents involved in the evaluation processes. Learning platform(s): – e-learning Technique(s): – Statistics	59	Improving the security of e-assessment
15.	[58]	To analyze the development of MOOC/SPOC and the learning process. Factor(s) examined: – Learning data Learning platform(s): – MOOC/SPOC Technique(s): – Classifications	7960	Course improvement
16.	[46]	To allow the understanding of knowledge construction among the participants. Factor(s) examined: – Learning activity data Learning platform(s): – Moodle LMS Technique(s): – Path length algorithm – Resnik similarity algorithm – Lin similarity – Jiang-Conrath distance – Wu and palmer measure	Users in Moodle. The number of users was not mentioned.	Improving academic integrity

Table 3. Existing studies on the use of learning analytics (*Continued*)

No.	Study	Purpose of study/Assessment type/Factors examined	Sample size/Method	Category
17.	[10]	To improve learners learning achievement. Factor(s) examined: – Total login frequency in LMS – Total studying time in LMS – (Ir)regularity of learning interval in LMS – Interactions with content – Interactions with peers Interactions – Interactions with the instructor – Total assignments and assessment composite Learning platform(s): – LMS Technique(s): – Multiple linear regression analysis	41	Predicting performance

Table 5. Features provided by assessment analytics

No.	Study	Purpose of the study/Features	Result
1.	[32]	This study combined the following three (3) methods shown below to produce a method that adaptively selects test questions according to the individual needs of students: i) Selecting the most appropriate topic based on a course structure. ii) Selecting the k-best questions based on IRT. iii) Selecting questions based on the questions' usage history. Feature(s): – Adapting the next quiz item to students' abilities. – Selecting the k-bast questions with the most appropriate difficulty for a user. – Selecting not recently asked questions.	Adaptively selecting test questions increased the overall learning outcome, especially for lower-than-average performing students.
2.	[69]	This study explored the predictive capabilities of the time spent on answering the multiple-choice question and the final assessment score in predicting student's performance. Feature(s): – Predicting students' performance based on students' response times to the submitted answers and the amount of idle time.	A more Computer Based Assessment (CBA) that utilizes the temporal behaviour of their users can be developed to improve the users' performance.
3.	[70]	This study incorporated heat maps and timelines as features to aid teachers and administrators in comprehending the data: Feature(s): – Implementation of data visualization techniques, including the utilization of heat maps, to interpret and visualize the data.	There is a need to examine the various dimensions of use and time.
4.	[34]	This study explored the reliability of detecting learners' gross body language: Feature(s): – Estimating the students' emotions (e.g., delight, boredom, frustration, or confusion) during formative assessment by analyzing sensor data.	Learners did not readily display frustration on their faces as opposed to the bodies that showed otherwise. The contextual information obtained by mining the log files can help detect students' frustration.
5.	[33]	This study explored the prediction of a learner's mood through the mood recognition method. Feature(s): – Utilizing sensor data to estimate students' emotions (e.g., boredom, confusion, delight, or frustration) during formative assessment.	Personalized feedback can be more effective when affect recognition is implemented in the system.
6.	[71]–[76]	This study predicted student academic performance using various methods and data sources. Feature(s): – Predicting students' performance based on "demographic characteristics," "grades (in pre-requisite courses, during assessment quizzes and their final scores)," "students' portfolios," "multimodal skills," "students' participation," "enrollment and engagement in activity," and "students' mood and affective states."	Learning analytics platforms can leverage the learning data to provide alert triggers.
7.	[37]	This study predicted students' performance based on online activities using a neural network (NN) architecture: Feature(s): – Early prediction of student performance by analyzing online activity data.	A more accurate prediction of students' performance in blended learning can be achieved as more data are obtained in the later months of the course.
8.	[73]	This study investigated the prediction of academic achievements based on students' online activities: Feature(s): – Utilizing metrics such as the "total number of discussion messages posted," "total time online," and "number of web links visited" to predict performance.	"Interactions with peers" is a good indicator in determining learning success.

Table 5. Features provided by assessment analytics (*Continued*)

No.	Study	Purpose of the study/Features	Result
9.	[75]	This study investigated the relationships between affective states (such as “engaged concentration,” “confusion,” “boredom,” and “frustration”) and estimated the probability of performing tasks that are not related to learning (such as playing games) with learning outcomes: Feature(s): – Predicting performance based on students' affective states, such as “boredom,” “engaged concentration,” “confusion,” and “frustration.”	Students were more likely to perform poorly if they were feeling bored or confused while answering test questions. However, off-task behaviour was not consistently associated with poorer learning.
10.	[77]	This study assessed the learner’s learning performance based on the learning portfolios. Feature(s): – Investigating the use of six computational intelligence theories, based on the web-based learning portfolios of individual learners, to measure students' satisfaction during mobile formative assessment.	Feedback in formative assessment has a positive impact on the learners’ interest and helps to improve their learning performances.
11.	[78]	This study investigated the impact of computer-assisted formative assessment on improving student performance. Feature(s): – Predicting course grades based on the student characteristics, such as “gender,” “age,” “prior knowledge,” “motivation,” and “assessment scores from online quizzes, the midterm exam, and the final exam”.	Multiple-choice computer-assisted formative assessment can enhance student learning and retention.

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