



Running head: A Study on The Correlation Between Online Learning Behaviour and Academic Achievement Based on Learning Analytics A Case Study of Animation Major Courses in Higher Vocational Colleges

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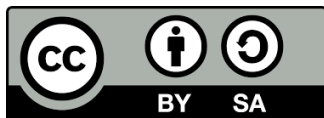
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online learning behaviour;
learning analytics; student
engagement; academic
achievement; intelligent LMS.

Abstract

This study investigated the correlation between online learning behavior and academic achievement among students enrolled in animation major courses at higher vocational colleges. The researchers conducted a qualitative secondary study based on a systematic review of 30 selected studies. Academic databases were searched to identify relevant articles published within the past ten years, which were subsequently analyzed to identify common findings related to online learning, learning analytics, student engagement, and academic achievement. Four major themes emerged from the review: online learning behavior and student engagement, predictive learning analytics, personalized learning and student support, and intelligent learning management systems (LMSs) and technology-supported learning. The findings indicated that regular participation, learning discipline, and active engagement were generally associated with better academic achievement. LMS data could also be used to identify learning patterns, while learning analytics could facilitate performance prediction and identify students who might require early intervention. Personalized learning could assist educators in providing appropriate learning activities and feedback based on students' diverse needs. Academic development and learning could be further supported through intelligent LMSs and emerging digital technologies. Overall, the findings indicate that learning analytics can help educators better understand students' online learning behavior and provide appropriate support to enhance their academic achievement.



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INTRODUCTION

Online learning has become a significant component of higher education. Students can access learning materials and activities, submit assignments, and communicate with instructors through online platforms. This is particularly relevant in higher vocational colleges offering animation courses, as these courses involve digital tools, creative assignments, and regular practice. Online learning platforms also generate digital records of students' learning activities (Lam & Dongol, 2022). These records can provide information about the frequency of students' participation, their study patterns, and their engagement with course activities. Such learning patterns can be examined through learning analytics to determine their relationship with academic achievement. Previous studies have demonstrated that learning records can provide valuable information about students' self-regulated learning, engagement, and academic performance.

This study aims to investigate the relationship between online learning behavior and the academic performance of students majoring in animation at higher vocational colleges, particularly through the application of learning analytics. It focuses on examining the relationship between online learning behavior and student engagement, as well as how learning

analytics can be used to predict academic performance. The study also explores the contribution of personalized learning and student support to improving students' academic achievement.

In addition, the study examines the role of intelligent learning management systems (LMSs) and technology-supported learning in improving student performance. It also investigates how artificial intelligence (AI) and feedback can support students' learning processes and academic success. Overall, the study seeks to understand how learning analytics, personalized support, intelligent LMSs, AI, and feedback can be integrated to enhance learning outcomes among animation students in higher vocational education.

Although online learning has become common in higher education institutions, providing students with online learning materials does not automatically result in improved academic performance. Students differ in their learning habits, levels of participation, and engagement. Some students may consistently engage with online learning platforms, whereas others may participate less frequently or experience difficulties maintaining regular learning routines. These differences may not be easily identified through conventional classroom observation alone. Existing literature indicates that learning analytics can be used to identify learning behaviors, predict academic performance, and provide targeted student support (Chung et al., 2022). However, numerous studies have focused on higher education in general or on specific disciplines and learning environments, with limited attention given to the online learning behaviors of animation students in higher vocational colleges. Therefore, this study examines the relationship between online learning behavior and academic achievement through the application of learning analytics. Student engagement, performance prediction, personalized support, and intelligent learning systems are also considered to provide a broader understanding of online learning among animation students. Previous studies have examined online learning behavior and academic achievement in general higher education contexts, but relatively few have focused specifically on animation major courses in higher vocational colleges. This gap highlights the need for a more comprehensive investigation of the correlation between online learning behavior and academic achievement within this specific educational context, particularly through the application of learning analytics.

This study aims to investigate the relationship between online learning behavior and the academic performance of students majoring in animation at higher vocational colleges, particularly through the application of learning analytics. Specifically, the study examines the relationship between online learning behavior and student engagement, the use of learning analytics to predict academic performance, the contribution of personalized learning and student support to improving academic achievement, and the role of intelligent LMSs and technology-supported learning in enhancing student performance. It also investigates how AI and feedback can support students' learning processes and academic success. The theoretical contribution of this research is to extend the literature on learning analytics in vocational education, particularly within the context of animation major courses. Its practical contribution is to provide recommendations for educators and institutions regarding the development of more effective online learning strategies and student support systems to enhance academic achievement. The contribution of this research further lies in integrating learning analytics, personalized learning, and intelligent LMSs within a single analytical framework, an approach

that has received limited attention in previous studies, particularly in the context of animation major courses in higher vocational colleges.

METHOD

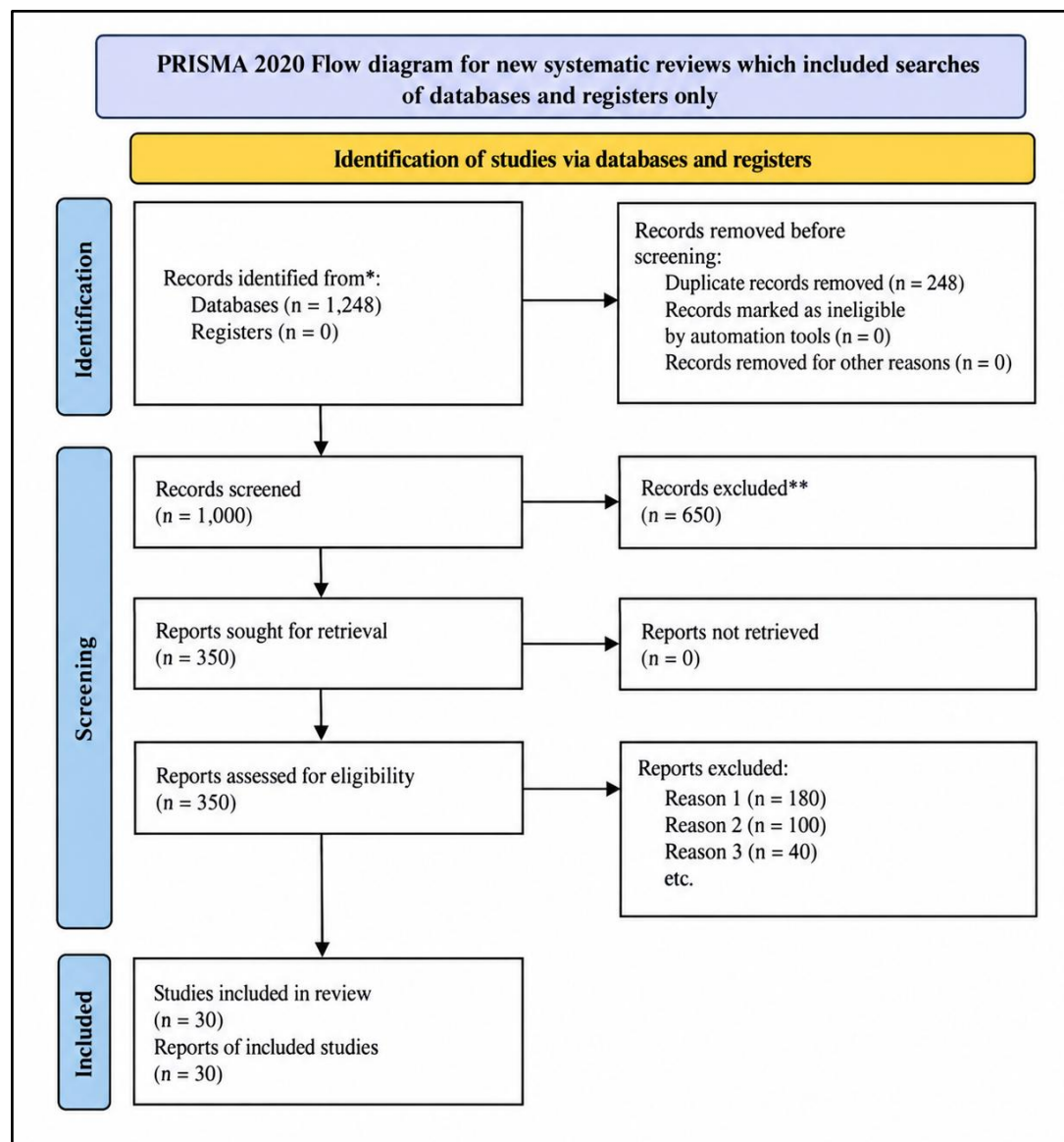


Figure 1: PRISMA Framework
(Source: Self-Created)

This study adopted a secondary qualitative research approach to examine the correlation between online learning behavior and academic achievement. Rather than collecting primary data, the study used previously published research on online learning, learning analytics, student engagement, and academic performance. Relevant studies were identified and analyzed through a systematic literature review (Slack & Priestley, 2023). Scopus, Web of Science, ScienceDirect, and Google Scholar were searched for relevant research articles using terms related to online learning behavior, learning management systems (LMSs), learning analytics, student engagement, academic achievement, and predictive learning techniques. The identified

studies were screened systematically. Duplicate records were removed, after which the remaining studies were screened based on their titles, keywords, and abstracts (Yildirim & Usluel, 2022). Studies that were not relevant to the research topic were excluded. The remaining full-text articles were assessed for relevance and methodological quality, resulting in 30 articles being included in the final review.

The selected articles were analyzed qualitatively and organized into five major themes: learning behavior and engagement, predictive learning analytics, adaptive and personalized learning, intelligent LMSs and behavioral analytics, and AI, feedback, and student success (Christou, 2022). The findings of the selected studies were compared to identify common patterns, differences, and research gaps. This thematic analysis provided a structured basis for examining the relationship between online learning behavior and academic achievement and for evaluating the role of learning analytics in understanding learning patterns and supporting student academic performance.

RESULTS AND DISCUSSION

Results Review

Literature Review Matrix

Table 1: Literature Review Matrix

Author and date of publication	Study design setting	Population/sample size	Methods	Findings	Key strengths and limitations
Ye & Pennisi (2022)	Higher education; online learning	NA	Learning trace-data analysis	Trace data can support students' self-regulation.	Strength: uses real learning data. Limitation: context-specific.
Perez Sanchez <i>et al.</i> (2022)	Higher education; collaborative learning platform	NA	Predictive learning analytics	LMS data helped predict student performance.	Strength: practical predictive model. Limitation: platform-specific.
Krishnan <i>et al.</i> (2022)	Higher education	NA	Learning analytics case study	Analytics supported academic progression monitoring.	Strength: progression focus. Limitation: case-study setting.
Hadisoebroto & Subandoro (2022)	Vocational higher education; Moodle	NA	Moodle data and prediction	LMS activity helped predict final scores.	Strength: uses actual LMS data. Limitation: limited institutional context.
Hellings & Haelermans (2022)	Higher education; programming	NA	Randomised controlled experiment	Learning analytics influenced student behaviour and performance.	Strength: experimental design. Limitation: programming-specific.
Le <i>et al.</i> (2022)	STEM blended learning	STEM	Self-report survey	Digital literacy perceptions varied among students.	Strength: focuses on digital literacy. Limitation: self-reported data.

Author and date of publication	Study design setting	Population/sample size	Methods	Findings	Key strengths and limitations
Sahni (2023)	Online higher education	NA	Learning analytics analysis	Analytics was associated with engagement and performance.	Strength: online-learning focus. Limitation: limited generalisability.
Han & Ellis (2023)	Blended computer science education	CS students;	Self-report and digital-trace comparison	Digital traces provided useful evidence of self-regulated learning.	Strength: compares measures. Limitation: discipline-specific.
Le <i>et al.</i> (2026)	LMS-based higher education	NA	Early-warning prediction	Leakage-excluded models improve trust in early predictions.	Strength: addresses prediction leakage. Limitation: preprint.
Santos & Henriques (2023)	Higher education; LMS	NA	Course-agnostic prediction	LMS logs enabled accurate and timely performance prediction.	Strength: portable approach. Limitation: dependent on LMS data quality.
Shilpa & Suresha (2026)	Higher education	Academic learners;	Data mining	Real-time analytics supported proactive academic decisions.	Strength: real-time focus. Limitation: limited reported context.
Amiri (2026)	Online learning	Online students;	Predictive learning analytics	Analytics can predict student performance.	Strength: current focus. Limitation: preprint evidence.
Hernández-García <i>et al.</i> (2024)	Higher education; LMS	NA	LMS interaction analysis	LMS interactions were related to academic performance.	Strength: examines learning cycles. Limitation: observational design.
Liu <i>et al.</i> (2025)	Higher education	Empirical studies	Meta-analysis	Learning analytics interventions generally improved learning outcomes.	Strength: broad evidence base. Limitation: study heterogeneity.
Alalawi <i>et al.</i> (2025)	Higher education	NA	Intervention study	Learning analytics interventions supported performance improvement.	Strength: evaluates action after prediction. Limitation: intervention context may limit generalisation.
Deng <i>et al.</i> (2025)	Higher education; online learning	NA	CRNN and sequential-data analysis	Identified and optimised student learning paths.	Strength: advanced modelling. Limitation: model complexity.
Yang <i>et al.</i> (2026)	Chinese primary schools	Primary students	Longitudinal analysis	Anxiety and engagement showed asymmetric links; peer relationships mattered.	Strength: longitudinal design. Limitation: primary-school context.

Author and date of publication	Study design setting	Population/ sample size	Methods	Findings	Key strengths and limitations
Lu <i>et al.</i> (2025)	Technology-enhanced learning	NA	Engagement and outcome analysis	Engagement was linked with academic outcomes.	Strength: technology focus. Limitation: contextual factors may differ.
Duch <i>et al.</i> (2024)	Higher education; LMS	LMS students;	Attribute identification and predictive algorithms	Key LMS attributes supported performance prediction.	Strength: predictive approach. Limitation: conference study.
Rebelo Marcolino <i>et al.</i> (2025)	Higher education; Moodle	NA	Machine-learning optimisation	Moodle logs successfully supported dropout prediction.	Strength: practical ML application. Limitation: Moodle-specific data.
Çakiroğlu <i>et al.</i> (2024)	Online higher education; LMS	Online learners;	Profiling analysis	LMS interactions revealed different self-regulated learning profiles.	Strength: learner profiling. Limitation: profile generalisation.
Goh (2026)	Higher education; LMS	NA	Log-data analytics	Persistent and consistent engagement supported academic success.	Strength: examines engagement patterns. Limitation: LMS dependence.
Wahyudi <i>et al.</i> (2026)	Online courses	NA	LMS-use and performance analysis	LMS usage was associated with academic performance.	Strength: direct relationship focusses. Limitation: limited context.
Darbyshire & Beitsayadeh (2025)	Higher education	NA	GAI and predictive analytics	GAI and analytics can support student success.	Strength: current technology focus. Limitation: emerging evidence.
Angeioplastis <i>et al.</i> (2025)	Higher education	NA	Educational data mining	Data mining improved prediction of student performance.	Strength: data-driven approach. Limitation: model-dependent.
Peach <i>et al.</i> (2021)	Online courses	Online learners	Bayesian modelling and time-series analysis	Learner behaviour changed over time and followed identifiable patterns.	Strength: temporal analysis. Limitation: older study.
Lipnickas <i>et al.</i> (2025)	Higher education; online courses	NA	Behavioural analysis	Student behaviour changed across the degree lifecycle.	Strength: lifecycle perspective. Limitation: longitudinal complexity.
Yin <i>et al.</i> (2025)	CSCL; computer science	Student groups;	Visual-GenAI feedback analysis	Analytics feedback was associated with student engagement.	Strength: innovative feedback. Limitation: CSCL-specific.
Acar & Cumaoğlu, (2026)	Online higher education	Online students;	Video-log and	Video-learning behaviour was related to	Strength: specific behavioural data.

Author and date of publication	Study design setting	Population/ sample size	Methods	Findings	Key strengths and limitations
Huang & Yue (2026)	Learning analytics; higher education	NA	achievement analysis Learning behaviour and engagement analysis	academic achievement. Learning behaviour and engagement were associated with performance.	Limitation: video context. Strength: integrates key variables. Limitation: contextual generalisation.

(Source: Created by the author)

Literature Coding and theme development

Table 2: Coding and theme development

Source	Categories or Key Phrases	Frequency	Codes	Emergent Sub-themes	Main theme
Ye & Pennisi (2022)	Self-regulation	6	Trace data	Learning behaviour	Theme 1: Learning behaviour and engagement
Perez Sanchez <i>et al.</i> (2022)	Performance	6	Prediction, collaboration	Academic outcomes	
Krishnan <i>et al.</i> (2022)	Academic progression	6	Analytics, monitoring	Student progress	
Hadisoebroto & Subandoro (2022)	LMS performance	6	Moodle, prediction	Performance monitoring	
Hellings & Haelermans (2022)	Student behaviour	6	Analytics, experiment	Behaviour change	
Le <i>et al.</i> (2022)	Digital literacy	6	STEM, self-perception	Digital skills	
Sahni (2023)	Engagement	6	Online learning	Student engagement	
Han & Ellis (2023)	Self-regulation	6	Digital traces	Learning behaviour	
Le <i>et al.</i> (2026)	Early warning	6	LMS logs, prediction	Early prediction	
Santos & Henriques (2023)	Performance prediction	6	LMS logs	Early prediction	
Shilpa & Suresha (2026)	Academic insights	6	Data mining	Proactive decisions	Theme 2: Predictive learning analytics
Amiri (2026)	Student performance	6	Online analytics	Prediction	
Hernández-García <i>et al.</i> (2024)	LMS interaction	6	Learning cycles	Performance links	
Liu <i>et al.</i> (2025)	Analytics intervention	6	Meta-analysis	Learning outcomes	
Alalawi <i>et al.</i> (2025)	Student performance	6	Intervention	Performance improvement	
Deng <i>et al.</i> (2025)	Learning paths	5	CRNN, sequential data	Personalised learning	
Yang <i>et al.</i> (2026)	Learning anxiety	5	Engagement, peers	Engagement factors	
Lu <i>et al.</i> (2025)	Engagement	5	Technology, outcomes	Academic engagement	
Duch <i>et al.</i> (2024)	LMS attributes	5	Predictive algorithm	Performance prediction	
Rebelo Marcolino <i>et al.</i> (2025)	Dropout	5	Moodle, ML	Dropout prediction	

Source	Categories or Key Phrases	Frequency	Codes	Emergent Sub-themes	Main theme
Çakiroğlu <i>et al.</i> (2024)	Self-regulation	5	LMS profiles	Learner profiling	Theme 4: Intelligent LMS and behavioural analytics
Goh (2026)	Engagement behaviour	5	Persistence, consistency	Academic success	
Wahyudi <i>et al.</i> (2026)	LMS usage	5	Usage, performance	Digital behaviour	
Darbyshire & Beitsayadeh (2025)	GAI	5	Predictive analytics	AI-supported learning	
Angeioplastis <i>et al.</i> (2025)	Data mining	5	Prediction	Learning outcomes	
Peach <i>et al.</i> (2021)	Learner behaviour	5	Bayesian, time series	Behaviour patterns	
Lipnickas <i>et al.</i> (2025)	Behaviour change	5	Course lifecycle	Adaptive design	
Yin <i>et al.</i> (2025)	Analytics feedback	5	Visual-GenAI, CSCL	Interactive feedback	Theme 5: AI, feedback and student success
Acar & Cumaoglu (2026)	Video logs	5	Video, achievement	Learning behaviour	
Huang & Yue (2026)	Learning behaviour	5	Engagement, performance	Academic success	

(Source: Created by the author)

Thematic Analysis

Theme 1: Learning behaviour and engagement

In the first theme, students' learning behaviours and engagement are learnt aspects of online learning. Ye & Pennisi (2022) identified that learning records could give an insight into students' own learning management. There are several studies which reported that students' activity, participation, self-regulation and engagement could be related to the students' learning results. Additionally, Han & Ellis (2023) demonstrated that Digital Learning Records can provide valuable insights into student learning behaviour.

Better learning outcomes also used to be correlated to increased student engagement. Sahni (2023) discovered a correlation between participation with the platform and academic success. Similarly, Lu *et al.* (2025) found that engagement has an impact on academic outcomes. In a subsequent study. This means that students who take part more actively in learning activities are more likely to achieve better academic results. Yang *et al.* (2026) demonstrated how anxiety and peer relationships could impact student engagement. So, learning behaviour is not simply how frequently students use an online system, but also the frequency and level of engagement achieved in students' learning activities.

Theme 2: Predictive learning analytics

The second theme is prediction of future academic outcomes, with a focus on student data. A lot of the studies relied on LMS data to identify the students who may be facing issues in the study. Perez Sanchez *et al.*, (2022) predicted student performance by using Data learning. On the other hand, Hadisoebroto and Subandoro (2022) predicted the final score based on data in Moodle. Commonly, there have been studies also looking at early prediction, more recently. Santos and Henriques (2023) demonstrated LMS records in order to make predictions about early performance. This can help teachers identify students who may need extra support at an early stage.

Le et al. (2026) addressed the issue of avoiding data leakage and improving the reliability of predictions for early warning systems. This helps ensure that the results are accurate and useful for identifying students who may need support early. According to Rebelo Marcolino et al. (2025), records of events in Moodle are used for prediction of student dropouts. This means that teachers are alerted earlier to these problems by prediction that allows them to serve students before they fail or drop out, by offering interventions for help. This indicates that predicting problems allows teachers to intervene before student failures or drop-off by offering interventions for assistance.

Theme 3: Adaptive and personalised learning

The equality theme is the third theme that deals with adapting learning tasks to meet student needs. Deng et al. (2025) analyzed students' learning trajectories and presented ways to enhance these trajectories using learning data. This can help teachers understand how students' progress and provide support when needed. Similarly, Çakiroğlu et al. (2024) have largely attributed student characteristics to their learning environments. Lipnickas et al. (2025) also determined that attitudes of students may vary in their academic levels. This implies that the kind of learning support may be different for a student at various stages of their studies. Personalised strategies can then help to offer more appropriate learning activities and assistance.

Theme 4: Intelligent LMS and behavioural analytics

The fourth theme is related to the broader use of technology to develop an understanding of students' behaviour. A study by Goh (2026) indicates persistence and regular engagement as key elements to academic success. This shows that students who stay active and consistent in their learning are more likely to achieve better academic results. Hernandez Garcia et al. (2024) also related LMS interactions to academic performance. Other studies ventured forward to more in-depth tools. Shilpa & Suresha (2026) discussed Real-time Academic Information through Data Mining. Angioplasty et al. (2025) demonstrated support for predicting performance through the use of educational data mining. The findings of these studies indicate that LMS information can be helpful as evidence of student progress.

Theme 5: AI, feedback and student success

In the final theme, learners explore how students are being supported using feedback and AI tools, which are becoming more common with the use of technology. Darbyshire & Beitsayadeh (2025) investigated how generative AI and predictive analytics predict student achievement. In the era of education 4.0, the integration of artificial intelligence into learning processes has left no doubt about its impact. Education 4.0 has seen the addition of artificial intelligence in learning processes without a shadow of doubt.

Liu et al. (2025) found that the learning analytics interventions have the potential to enhance learning outcomes. This means that using student data can help teachers understand learning needs and provide better support. Alalawi et al. (2025) reviewed how analytics can be coupled with interventions to move in terms of engaging students to achieve student performance. Overall, the five themes presented above, are that the focus of learning analytics is progressing from data collection for students to an understanding of behaviour, student problem prediction and appropriate support to promote student achievement.

Interpretation of results

The outcomes indicate that learning analytics has great potential for enhancing students' learning. Among 30 studies, the majority demonstrate how information gathered from online learning systems can support the teacher in understanding what is happening on the ground and the level of learning taking place. There are two key findings: first, student behaviour and engagement are important. Those students who participate consistently, engage in learning, and control their learning are more likely to show improvement (Tedeschi et al., 2023). This will allow students' activity to provide useful information regarding their progress. The second type is extensive prediction as shown. A lot of studies predicted marks, performance and drop-out based on the learning records. This is helpful because it is possible that teachers can detect that pupils are experiencing difficulties at an early stage (Rahmah & Lubis, 2024). Support given can be constructive ahead of problems getting in the way.

There is the third one that emphasises on Personalised learning. There are different ways for students to learn. The studies indicate that learning records can reveal a variety of learner differences and learning styles. This can assist teachers to engage in more appropriate activity and support. An additional key finding is the increasing adoption of sophisticated digital tools. A better understanding of student behaviour through LMS data, data mining, machine learning and newer tools based on AI techniques (Koshiry et al., 2022). These tools can cut through the crap comparing vast quantities of information faster than human manipulation. The upshot of all this is that feedback and action must be considered very significant. Just taking data of students doesn't suffice. The information must be used to provide feedback, to change learning activities or to provide support. Research into learning analytics interventions such as these can yield better learning outcomes.

Overall, the findings illustrate that learning analytics is not just about gathering student data; it is essentially a method for carrying out analytics. It can guide understanding of pupils' behaviours, proactively detect issues, offer appropriate support and enhance pupil learning. The results also indicate, however, that the system for learning can affect the results as well as the grouping in the classroom and the type of learning environment. Thus, learning analytics must be used in a careful manner and in line with the students' learning needs.

Findings from the Literature Review

The literature review of 30 studies shows that learning analytics is a tool that can be utilised in studying and understanding student learning. From the results of the literature review, it is found that learning analytics can be used to study and improve student learning (Johar et al., 2023). The studies mainly focused on information collected from learning management systems (LMS), such as student logins, learning activities, video use, task completion and other online behaviour. It ran that the engagement of students is important to academic success was the first major finding. Better results were seen in those pupils who demonstrated regular participation in lessons, perseverance and continued to learn well across all areas (DiNapoli, 2023). There also were some studies suggesting a correlation between self-regulation and student's achievement.

The second finding was that there is an ability to predict student performance based on LMS data. The student activity records were used to predict marks and to classify students at risk and to predict possible drop-out. This indicates that responsive information about learning

is available to teachers as insight into early warning of issues (Nolan & Roberts, 2024). Another finding was that students have different learning behaviours. There are some students who are more active and independent, whilst others require more support. However, the one size-fits-all strategy might not work with all learners.

The review also identified that behaviour may change across the course of learning. Continuous monitoring can provide greater insight than having a single point in time look at students' activity (Das, Chakraborty & Mitra, 2022). Last, it was found that the studies had more and more reported usage of machine learning, data mining, feedback done by Artificial Intelligence (AI) and Learning Analytics. These products can capture patterns from lots of student data, helping with improved decisions. Overall, the literature reveals learning analytics as a potential tool to enable early identification and effective support with better academic performance.

Findings from the thematic analysis

The results of the thematic analysis of 30 selected studies reveal that learning analytics can be used to enhance students' learning and academic performance. Five major themes were identified: Learning behaviour and engagement, Prediction of performance, Personalised learning, Behavioural analysis and Use of new digital tools and feedback.

The first that can be said is that there is a high correlation between student engagement and learning success. The regular use of learning systems, the completion of activities and students' involvement in their studying positively affects the learning results (Furqon et al., 2023). This implies the teacher will have enough insight into a student's activity to see if they are working on their assignments. The number of students' logins, however, is not sufficient to assess engagement. The second one is that learning records can anticipate students' performance. Several studies have leveraged the LMS data to look for patterns associated with successful or unsuccessful outcomes (Arizmendi et al., 2023). This may be advantageous for early warning systems. For instance, students who have a low level of activity or minimal participation might require assistance. Early intervention can minimise the risk of poor outcomes or attrition.

Personalised learning is also key, as per the third finding. It is illustrated in the studies that pupils have varying learning styles and needs. Learning records may aid identification of these differences (Heikkinen et al., 2023). Then, teachers can offer various activities and support or feedback to students as needed. This can offer more value for the individual learner through the online learning experience. The fourth finding is that students' behavior may differ from one time to another. The concept of persistence, consistency, self-regulation and uniform participation was found important in the various studies. That is, a single observation taken at one moment may not provide a full picture of a student. The temporal dimension of learning behaviour can help in the insight of progress.

Finally, it can be stated that the increasing use of sophisticated digital tools and feedback. With big information from students, the data mining technology or machine learning, as well as newer AI-based technologies, can locate patterns (López-Meneses et al., 2025). Technology, however, is insufficient to enhance learning. The information should be utilized by teachers to provide effective feedback and appropriate assistance. As a whole, the results confirm that learning analytics can drive education from the responses to poor performance to

taking early action. Concurrently, any result needs to be interpreted with caution as it can vary among different courses, students and learning systems.

The results revealed a significant relationship between students' participation and progress. Students are likely to make greater progress if they frequently participate in learning activities. Student activity data can therefore be applied for the understanding of learning problems. One key aspect found in the literature is that LMS data can be utilized prior to obtaining outcomes. Not every teacher necessarily has to suspect that a pupil is suffering if she is having difficulties, unless it is during the actual examination (Nash-Luckenbach & Friedman, 2024). In this matter, when someone's activity, participation, or task completion changes, this could be an early indicator that support is required. The results also suggest that early help is more effective than just forecasting outcomes. Prediction can be of benefit when teaching and learning activities are changed or feedback is provided by teachers based on the information (Sailer et al., 2023). The thematic analysis found five main areas including student engagement, performance prediction, personalised learning, learning behaviour, and digital tools. Overall, the studies show that student learning data can help identify problems early, understand learning needs, provide better support and improve academic performance.

However, when learning is translated into numbers, learning analytics can help rather than just be a by-product. Another area that is becoming more prevalent, as seen in the review, is on the increasing importance of personalised learning. Students' needs and behaviours vary and therefore learning support should not be the same for all students. However, there are some restrictions. The studies were conducted in various courses, with different students, LMS systems, and methods. Thus, the results may not apply to all educational contexts. Other questions include data quality and privacy issues. Overall, the literature and the themes indicate that LA can support education to be more student-centred, timely, and supportive. This is not just looking to gather student data but to understand students and offer support when it is needed.

CONCLUSION

This study explored the relationship between online learning behavior and academic achievement, particularly in animation major courses at higher vocational colleges. The study was based on the premise that students' activities within online learning environments could provide valuable information about their learning progress and academic achievement. As the use of digital learning platforms has increased, these platforms have generated various forms of learning records, including students' access to learning materials, participation in learning activities, completion of assignments, and engagement with online course content. Learning analytics can be applied to these records to understand how students learn and how their online learning behaviors are associated with academic outcomes. Overall, the findings of the reviewed studies indicate that online learning behavior and student engagement are significantly associated with academic achievement. Students who regularly participate in online learning activities and demonstrate consistent learning behaviors tend to achieve more favorable academic outcomes. However, the amount of time students spend online should not be considered the sole indicator of learning behavior.

The quality and consistency of students' engagement are also important. The reviewed literature indicates that digital learning records can provide valuable evidence regarding self-regulated learning, student engagement, and learning progress. Another important finding is that learning analytics can be useful for identifying students who may be at risk of experiencing academic difficulties. Previous studies have used data from learning management systems (LMSs) to predict student performance, monitor learning progress, and identify students at academic risk at an early stage. Such early identification can enable educators to provide timely interventions and appropriate academic support before students experience more substantial academic difficulties

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CONFLICT OF INTEREST

The author(s) confirm that no personal, commercial, or financial interests exist that could have compromised the impartiality of this study's findings.

AUTHOR CONTRIBUTIONS

Each author played an equal role throughout the research, participating jointly in developing the idea and concept, gathering and analyzing data, and writing and revising the final manuscript.

GENERATIVE ARTIFICIAL INTELLIGENCE USAGE STATEMENT

Artificial Intelligence (AI) tools were employed on a limited basis during manuscript preparation, used only to check grammar and improve language quality. No AI involvement occurred in collecting data, conducting substantive analysis, or formulating the study's conclusions.

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