sustainability

MDPI

Systematic Review

Learning Analytics on Student Engagement to Enhance Students' Learning Performance: A Systematic Review

Nurul Atiqah Johar [1], Si Na Kew [2,3,*], Zaidatun Tasir [1] and Elizabeth Koh [3]

1 School of Education, Universiti Teknologi Malaysia, Skudai 81310, Malaysia
2 Language Academy, Universiti Teknologi Malaysia, Skudai 81310, Malaysia
3 National Institute of Education, Nanyang Technological University, Singapore 639798, Singapore; elizabeth.koh@nie.edu.sg
* Correspondence: snkew@utm.my

Abstract: The study of learning analytics provides statistical analysis and extract insights from data, particularly in education. Various studies regarding student engagement in online learning have been conducted at tertiary institutions to verify its effects on students' learning performance. However, there exists a knowledge gap whereby the types of student-engagement issues derived from learning analytics have not been collectively studied thus far. In order to bridge the knowledge gap, this paper engages a new systematic literature review (SLR) that analysed 42 articles using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The existing research on student engagement in online learning does not extensively integrate the five types of online engagement proposed by Redmond et al., and the use of learning analytics on the subject matter is also limited. Thus, this review sheds light on the types of student engagement indicated by using learning analytics, hoping to enhance students' learning performance in online learning. As revealed in the findings, some studies measured multifaceted engagement to enhance students' learning performance, but they are limited in number. Thus, it is recommended that future research incorporate multifaceted engagement such as social, cognitive, collaborative, behavioural, and emotional engagement in online learning and utilise learning analytics to improve students' learning performance. This review could serve as the basis for future research in online higher education.

Keywords: student engagement; learning analytics; online learning; PRISMA; systematic review

check for updates

Citation: Johar, N.A.; Kew, S.N.; Tasir, Z.; Koh, E. Learning Analytics on Student Engagement to Enhance Students' Learning Performance: A Systematic Review. *Sustainability* **2023**, *15*, 7849. https://doi.org/10.3390/su15107849

Academic Editors: Luis Espejo-Antúnez and Sergio Hernández Sánchez

Received: 31 December 2022
Revised: 26 April 2023
Accepted: 4 May 2023
Published: 10 May 2023

1. Introduction

Online learning is ubiquitous in 21st-century educational contexts. After the outbreak of COVID-19 in December 2019, remote and distance learning became a pressing need in all higher-education institutions, as face-to-face classes could not be conducted. With that, online learning has become the primary option for most courses in higher education, which aligns with Sustainable Development Goal 4 (especially target 4.3) to ensure that all learners have access to education [1]. Student engagement is an essential aspect of online learning [2–4]. Student engagement is a form of student involvement in activities and conditions likely to generate high-quality learning [5]. Students who are highly engaged in online learning tend to have better conceptual understanding and achieve better learning outcomes [3]. Over the past decade, studies have identified various types and characteristics of student engagement—behavioural, cognitive, and emotional [6,7]. One pivotal study of engagement is by Redmond et al. [2] and proposes a conceptual framework of online engagement incorporating five elements: (i) social, (ii) cognitive, (iii) collaborative, (iv) behavioural, and (v) emotional. However, these five types of engagement have yet to be addressed as a whole. Furthermore, learning issues such as the lack of focus and motivation commonly surfaces among students in remote or distance online learning [8]. These are related to engagement, and it is therefore important to examine student engagement in online settings.

The online-learning tools brought about by technological advancement, such as Learning Management Systems (LMSs), allow educators to connect and design interactive student activities. As much as they can make online learning more dynamic and flexible, they have significant added value that can assist the virtual-teaching–learning process. According to Joksimovic et al. [9], ensuring that a course is well designed with engaging content and collaborative activities in online learning is crucial. The instructor should be given the authority to decide the learning materials that can best promote student engagement [9]. Many tools have incorporated learning analytics to provide feedback, such as various statistical indicators of students' online-learning progress. Through learning analytics, the online data can be captured and collected directly. It also produces evidence and data that are more authentic and relevant to be used in an online academic setting as compared to traditional surveys [3,10]. For example, the data interpretation of students' log files in an LMS can solve learning problems such as dropouts and poor learning performance [3]. Fan et al. [11] added that this data-science-driven approach helps reveal student-engagement patterns in a broader context. Learning analytics possesses the potential to enhance student's learning in the online setting. Therefore, this paper intends to establish a systematic literature review that could provide researchers with novel information concerning the utilisation of learning analytics for student engagement and learning performance in online-learning settings. As shown below, Table 1 presents the formulated research questions of this study.

Table 1. The formulated research questions and their respective purpose.

No.	Research Question	Purpose
1	What types of student engagement in online learning have been studied using learning analytics?	This question aims to discover the types of student engagement in online learning that were studied in past research using the application of learning analytics.
2	What is the purpose of using learning analytics on student engagement in online learning?	This question aims to explore the objective of using learning analytics to determine student engagement in online learning through past research.
3	What is the effect of the use of learning analytics for student engagement in online learning?	This question aims to discover whether the utilisation of learning analytics for student engagement could enhance students' learning performance in online learning and the role of learning analytics.

2. Literature Review

2.1. The Engagement and Learning Performance in Online Learning

Engagement in learning is a vital factor that determines students' understanding, learning experience, and performance at the end of a lesson [3]. In an online-learning setting, students' participation can be monitored to determine their engagement [4]. Students who are engaged in learning will not only spend time online actively, but they also put in effort and energy to involve themselves in the learning activities to acquire knowledge. For instance, instructors can track the data of students' log files in an LMS. Artheton et al. [12] pointed out that the more frequently students' access and engage with the learning materials, the better their academic performance. Hence, students' engagement in online learning should be studied further to determine its effects on students' learning [13].

Student engagement and academic achievement are essential in an online-learning environment [14]. Similarly, previous studies have also confirmed that there is a significant relationship between student engagement in online-learning environments and their academic achievement [15]. In this respect, an engaging online-learning environment should be developed to enhance students' learning performance. Crampton et al. [16] reported that there is a correlation between students' performance and the resources accessed in online learning, as well as the emotional and intellectual effort expended by students when involved in online learning [17]. Thus, more studies regarding student engagement in online learning are needed, as they can provide valuable insights for instructors to design engaging online-learning courses. As a result, the education quality and students' learning performance can be enhanced.

Instructors should consider students' goals and motivation in online learning when adapting their engagement strategies [18]. They should use suitable and well-designed learning courses to cater to students' needs in an online-learning setting. According to Redmond et al. [2], learning content must be designed in such a way that it scaffolds and prompts students to elicit the specific outcomes desired. In fact, Redmond et al. proposed that students should engage in learning through five elements: (i) social interaction, (ii) cognitive skills, (iii) behavioural engagement, (iv) collaborative learning, and (v) emotional engagement. These engagement elements can provide comprehensive outcomes where the effects on students' learning performance in online learning can be seen.

For example, social engagement refers to a sociable environment such as social forums and open networking channels designed for students to initiate social interaction in an online world. In LMSs, students can participate in social activities such as a discussion forum. This activity requires students to interact with peers and instructors [19]. Redmond et al. believed that students could develop relationships and trust in their social group. The social-interactive activity in LMSs can promote learning progress and stimulate students to engage more in the learning process [20]. Therefore, the combination of a social setting and activity is essential to promoting students' social engagement.

Moreover, in learning, when students can comprehend complex ideas, they are engaged in cognitive engagement (as cited in Fredricks et al. [21]). Cognitive engagement is a mental effort to engage with the learning resources [22]. According to Redmond et al., cognitive engagement is an active learning process—for example, students providing feedback and replying in online discussion forums or asking questions online; these demonstrate cognitive engagement [23]. When a student is able to integrate ideas through community discussions, it positively affects their cognitive ability and thus produces better learning outcomes [24,25]. Hence, it is necessary to have learning activities that can promote students' cognitive engagement, as it can encourage critical thinking in online learning.

Furthermore, in online-learning settings, the collaboration between students and their peers or instructors is active learning that leads to collaborative engagement [2]. Tasks can be designed to stimulate interactions among students and instructors to promote collaborative engagement [26]. Activities such as discussion forums encourage collaborative engagement in online learning, as they likely involve students in groups [27]. Group activities are suitable for collaborative engagement. From group activities, students learn cooperative values for a better learning experience with peers and instructors [28]. Other than that, activities such as ice breakers and collaborative writing can also promote students' collaborative engagement [26]. Regardless of the type of collaborative activity, it needs to be well planned, and the execution must achieve the learning goals [18,29]. Therefore, it is crucial to identify a suitable group activity to help students achieve collaborative engagement and enhance their learning.

In addition, in online learning, students with positive behaviour engagement will show interest in learning. There are two types of behavioural engagement in learning: (i) dynamic behaviour and (ii) passive behaviour [30]. Usually, students with behavioural engagement are active, have positive attitudes, and are able to self-regulate their learning, put in a high amount of effort, and participate in every learning task [31]. Students' behaviour engagement can be assessed through their actions or activities in online learning. For example, in LMSs, students' activities indicate their learning behaviours [32]. Instructors can trace students' log-file data to see their participation in learning. By looking at the traces of log data, instructors can measure students' behaviour engagement by analysing how frequently they engage with the learning materials or activities in the LMS [33]. Apart from that, students also need to demonstrate behavioural engagement with peers [28,34] and instructors [35]. The support and encouragement from peers and instructors are determining factors that significantly influence students' participation in online learning [36]. In short, students' behaviour engagement can determine the success of their learning, particularly in an online setting.

In addition, students who demonstrate positive behaviours will have good emotional engagement based on their attitude, enthusiasm, curiosity, anxiety, or pleasure in the learning process [2]. Elements that can promote good emotional engagement include a well-instructed course [24], the instructor's presence [28], and student–instructor interaction [37]. In online learning, it is difficult to tell whether students are emotionally engaged or not. this can be shown in their attitude toward online learning [38]. Cleveland-Innes and Campbell [39] conducted a study to assess students' emotions in online learning and evaluate emotional presence in the online-learning community. They presented two scenarios in which emotional engagement might be present: (i) online discussion and (ii) the learning experience. The study found that emotions can either distract or support thinking and decision-making in online learning. They also emphasised the importance of emotional engagement in an online-learning environment. That said, students should be aware of their emotional states in online learning. To put it succinctly, positive emotional engagement plays an important role in inviting students' involvement in online learning.

On top of that, the previous literature on engagement in online learning addressed the integration of three key areas: (1) behavioural, (2) emotional, and (3) cognitive engagement (as cited in [7,21]). These three types of engagement can help instructors understand how students engage in online learning. Nonetheless, Lawson and Lawson [40] opined that it is essential for a "more nuanced and less formulaic conception of student engagement" (p. 433) so that the student-engagement aspect of online learning can be analysed and understood more comprehensively. Consequently, Redmond et al. [2] came up with a conceptual framework for online engagement consisting of social, cognitive, behaviour, emotional, and collaborative aspects to ease the understanding of various types of engagement that are crucial to students' learning, particularly in higher-education institutions. Therefore, this study focuses on synthesising the literature to support the claim that these five types of student engagement in online learning along with the application of learning analytics can enhance students' online-learning performance.

2.2. Student Engagement and Learning Analytics on Students' Learning Performance

The use of learning analytics in an educational context began decades ago [41]. Learning analytics enables "measurement, collection, analysis and reporting of data about learners and their contexts, for understanding and optimising in which environments it occurs" (as cited in Chatti et al. [42]). Its application has assisted learning and teaching especially in higher education. Following that, a reference model proposed by Chatti et al. [42] illustrated four dimensions of learning analytics: (i) what (e.g., data, environments, and context), (ii) why (e.g., objectives), (iii) how (e.g., techniques/methods), and (iv) whom (e.g., stakeholders) to provide an overview of the concept (please refer to Table A3 in Appendix B).

The online data of learning–teaching activities can improve the process of learning, academic progress, and teaching practice [35]. Learning analytics can provide support for educators by indicating the interventions that can be implemented in learning. It can also support the improvement of the learning and teaching environments in higher-education institutions [43]. For instance, instructors can design suitable curricula based on students' behavioural data retrieved from learning analytics [24]. Hence, learning analytics can help instructors to create effective course designs focusing on student engagement to enhance learning performance [44]. Moreover, student engagement can also be traced by using learning analytics. Nizam Ismail et al. [45] highlighted that learning analytics can address students with low engagement in the LMS through interaction data such as student log files. Caspari-Sadeghi [46] found that learning analytics can track students' data without interrupting the learning and that instructors can address online issues such as dropouts and failures by giving prior warnings to students. In short, educators can utilise learning analytics to address student-engagement issues in online learning, which can in turn lead to better learning quality and performance.

Moreover, learning analytics can be used to forecast students' learning performance. For instance, Brozina et al. [47] examined the usage of LMSs on first-year engineering students' grades and discovered that it is feasible to predict students' grades by tracking the timing and frequency of their usage of LMS tools. They also suggested that through learning analytics, instructors can utilise LMSs to influence students' engagement and learning outcomes. In addition, recent studies unveiled that the factors affecting students' success in online learning comprise social interaction among peers [48], course design [19], and collaborative or teamwork tasks [49,50]. Thus, these factors are practical in enhancing students learning performance in online learning.

Other than that, in light of the accessibility of LMSs at higher-education institutions and the potential of learning analytics in handling large data sets, Fan et al. [11] recommended for more relevant studies on students' behaviour and engagement to be carried out. Moreover, learning analytics can be used to examine students' engagement from different aspects, such as behavioural, cognitive, and emotional [51,52]. As mentioned by Redmond et al. [2], future studies on student engagement need to include the five types of student engagement in online learning, which are social, cognitive, behavioural, collaborative, and emotional engagement, as multifaceted engagement to present comprehensive findings that can enhance students' learning performance. Therefore, it is important to investigate learning-analytic studies of engagement and various student-engagement aspects in online-learning environments. Moreover, a systematic process is recommended for this exploratory topic, and a systematic literature review was conducted.

3. Methodology

This study followed the procedure and recommendations of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), a popular and widely accepted guideline for systematic reviews across multiple disciplines. PRISMA suggests a guideline in conducting a comprehensive literature review by (1) determining relevant studies through inclusion/exclusion criteria, (2) carrying out a search strategy, (3) screening and searching to distinguish potential studies, (4) describing and evaluating included studies for review purposes, and (5) analysing and synthesising the findings.

3.1. Inclusion and Exclusion Criteria

This study established specific inclusion and exclusion criteria to classify the reviewed articles in the scope based on the research questions generated. Table 2 outlines the inclusion and exclusion criteria for this systematic literature review.

Table 2. Inclusion and exclusion criteria.

Inclusion	Exclusion
Empirical studies	Non-empirical studies such as reviews
Studies that were written in English	Studies that were not written in English
Studies or publications that intended to use learning analytics on student engagement in online learning	Studies that were not conducted in universities, such as schools and other institutions
Studies or publications that were published from 2011 to 2021	

For the exclusion criteria, this review excluded non-empirical studies by virtue of the fact that the research methodologies employed needed to be taken into consideration. Studies that were not written in English were also excluded because English is the primary language used in this study. Moreover, we excluded studies that were conducted in the K1–12 educational setting, as they do not fall into the scope of this study, which is higher education. The following sections explained more about the literature search and data screening.

3.2. Literature Search

Several databases, such as Scopus, Emerald, SAGE, Science Direct Journal, and Taylor & Francis, were used as data sources, as they cover multiple publishers and are indexing bodies that are well known and widely used worldwide. From the total of 595 articles found from databases, based on the logic proposed by Boolean operators, specific and highly exclusive keywords and search terms were used to ensure that only relevant articles were included in this systematic literature review. Keywords such as "student engagement", "learning analytics", and "online learning" were used in the first stage of this study. This resulted in the search for information (TITLE-ABS-KEY ("student engagement") AND TITLE-ABS-KEY ("online learning") and AND TITLE-ABS-KEY ("learning analytics")). Based on the searches, this study found a total of 595 articles published on student engagement in online learning and learning analytics in the context of higher-education institutions.

Later, the researchers downloaded the database-generated article information for further investigation. After comparing the data, 436 similar articles were identified and these duplicated articles were eliminated, reducing the number of articles for screening to 159. After screening the articles, 59 articles were excluded due to the lack of relevance in the study scope, which further reduced the number of papers for retrieval to 100. A total of 23 articles could not be retrieved due to the inability to find the full text. The remaining 77 articles were downloaded for further analysis.

The analysis based on the predetermined inclusion and exclusion criteria further excluded 15 articles due to methodological relevance, 12 articles due to unknown or vague engagement being focused on the studies, and 8 articles due to topic relevance. After considering the inclusion and exclusion criteria, 42 articles were included in the final review for the study. Figure 1 depicts the research flow based on the guidelines and procedures of PRISMA.

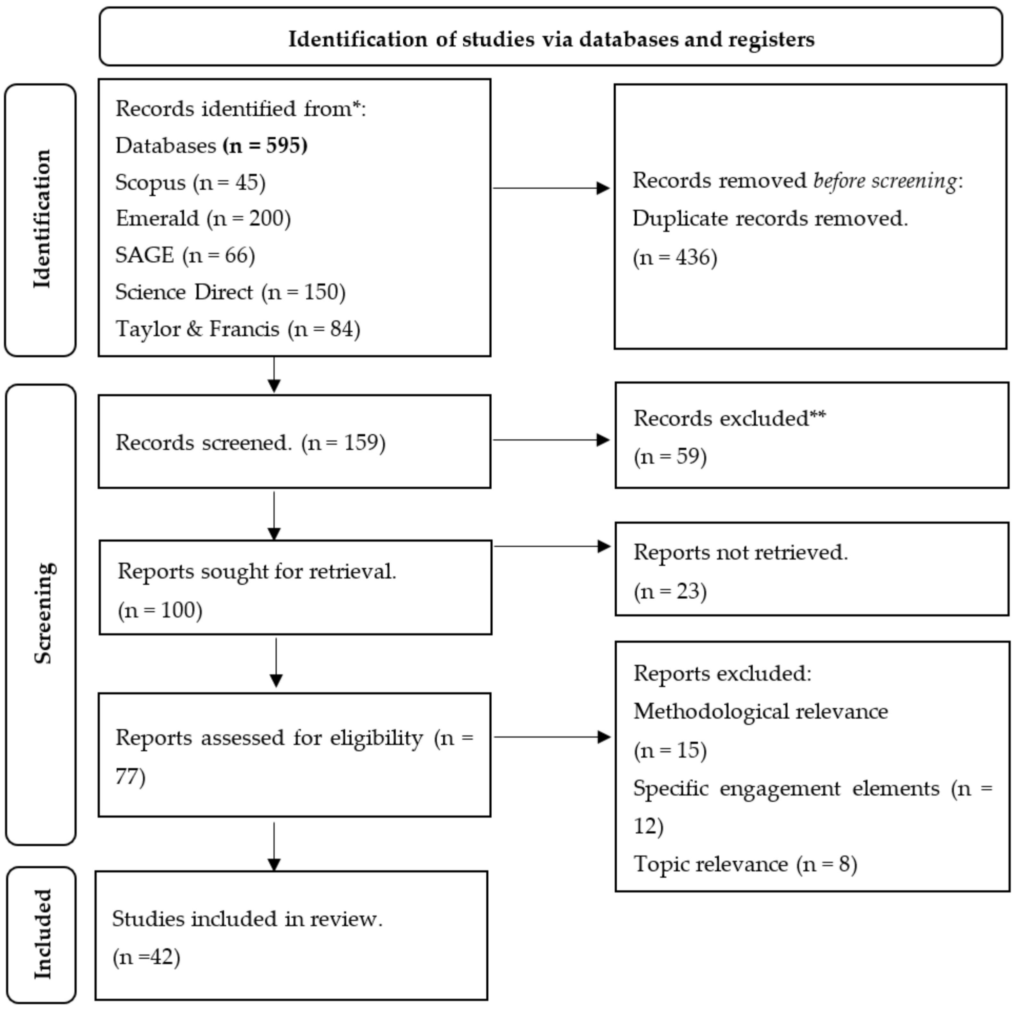

Figure 1. Flowchart outlining the protocol adopted in this study based on Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA).

4. Analysis of the Articles

The 42 articles underwent the identification, screening, and inclusion process recommended by PRISMA [53] to answer the formulated research questions (see Supplementary Materials). They were analysed critically and analytically to determine the trends and direction of learning analytics and student engagement in online learning. Table A1 (see Appendix A) shows the 42 articles reviewed and included in this systematic review.

4.1. Year of Publication

This study analysed articles published within 10 years starting from the emergence of learning analytics in educational contexts in 2011. Even though online learning and student engagement have been a topic of debate for decades, the application of learning analytics on student engagement to enhance students' learning performance remains questionable [54]. Figure 2 shows the publication years and the number of papers selected in this SLR paper.

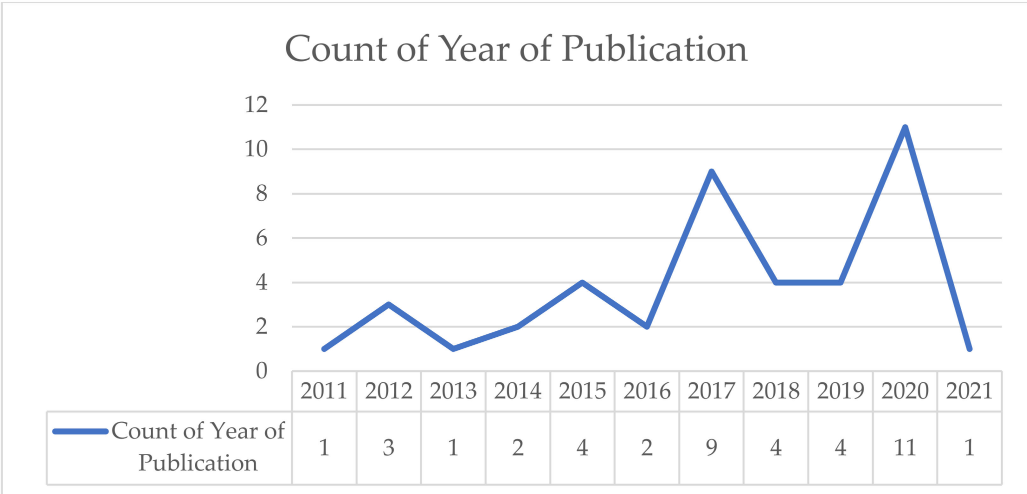

Figure 2. Years of publication of the selected articles.

Figure 2 visualises the total number of articles based on the year of publication retrieved for this study between 2011 and 2021. From 2011 to 2016, the number of published articles fluctuated, as learning analytics was just beginning to enter the picture. However, in 2017, there was a spike in the published articles as a result of the change in the technological trends in learning, probably due to the utilisation of LMSs in higher education. In 2020, the number of studies regarding learning analytics and student engagement in online learning was at a record high. It is assumed that the drastic increase happened due to the world being affected by COVID-19 at that time, and that teaching and learning worldwide was almost entirely switched to online learning. As reported by Leitner et al. [55], the learning-analytics trend will only become more and more popular in the future, as it offers many advantages—for example, instructors can assess data for self-reflection purposes or as a measure to prevent dropouts and promote academic success. Therefore, it is necessary for future researchers to explore and seek solutions to online-learning issues through analytics and measure students' engagement to enhance their learning performance.

4.2. Geographical Locations

In this study, the included articles originated from a total of 15 countries that identified student-engagement elements and used learning analytics to measure students' engagement. Studies concerning learning analytics, student engagement, and online learning had been conducted multiple times in Western countries such as the US, the UK, and Canada. On the other hand, Asian countries such as Malaysia, China, and Indonesia also showed interest in investigating the application of learning analytics and student engagement in online learning. In line with that, it is crucial for future studies to ensure diversity of demographic backgrounds, as it presents manifold outcomes on student-engagement issues in online learning and the application of learning analytics in enhancing students' learning performance. By doing so, students and educators can implement the methods and tools suggested in the studies that feature various types of sampling and demographic backgrounds to enhance the learning–teaching quality and students' learning performance in online-learning settings. Figure 3 shows the geographical distributions of the articles included in this review.

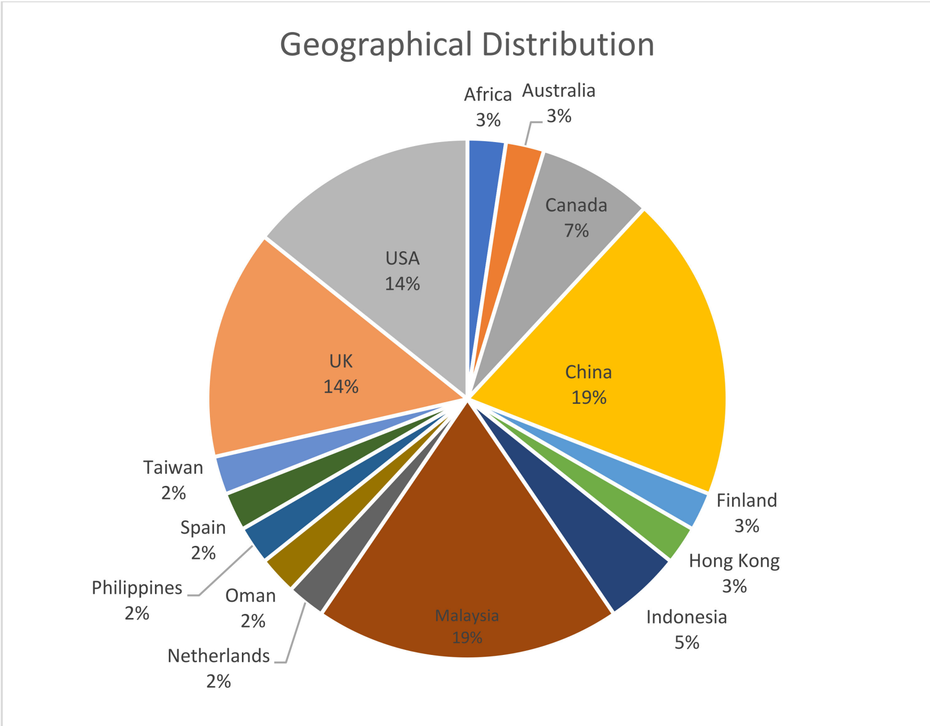

Figure 3. Geographical distribution.

4.3. Methodology of the Included Articles

Based on the included articles, the two main categories of methodology used were (i) the qualitative approach and (ii) the quantitative approach. The majority of them were conducted using the quantitative approach, except for [22], which used the qualitative method. The pie chart (Figure 4) below visualises the types of methodology used in the included articles.

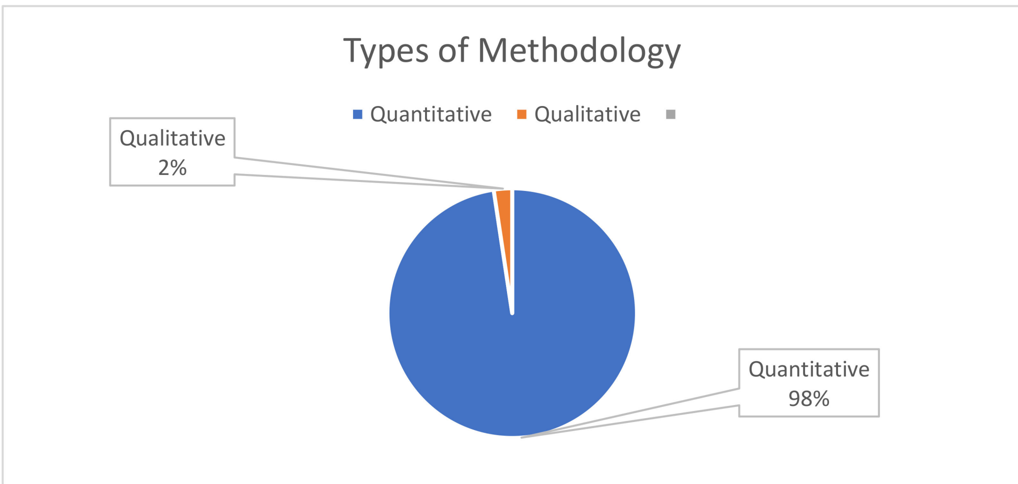

Figure 4. Methodology of the included articles.

As learning analytics generally requires statistical analysis, the quantitative approach would be more common. However, the qualitative approach can also be applied, as it may provide extensive explanations, such as student perceptions of learning analytics.

5. Results

5.1. Research Question 1 (RQ1): The Types of Student Engagement in Online Learning

It is crucial to identify the types of student engagement involved in the study. According to Redmond et al. [2], the concept of online engagement should consist of (i) social, (ii) cognitive, (iii) behavioural, (iv) collaborative, and (v) emotional engagement. Thus, the included articles were classified according to those types of student engagement, as shown in Table 3.

Table 3. The types of student engagement in online learning.

Student Engagement	Article	Count	Percentage (%)
Social engagement	[27,56,57]	3	11.54
Cognitive engagement	[3,58–61]	5	19.23
Behavioural engagement	[48,62]	2	7.69
Collaborative engagement	[14,22,63,64]	4	15.38
Emotional engagement	[39,65–68]	5	19.23
Cognitive, emotional, and behavioural engagement	[25,69–72]	5	19.23
Social, cognitive, and behavioural engagement	[73]	1	3.84
Behavioural and emotional engagement	[74]	1	3.84
Total		26	100%

Each element of student engagement is significant in enhancing students' learning performance. For instance, Lotz et al. [56] identified six themes branching out from social engagement and interaction with peers in the online studio. Students' social engagement was determine based on their time spent on tasks, listening to lectures, quick social interaction, commenting on posts, networking, and their spectrum of engagement. Cognitive and critical thinking are crucial in learning. Seckman [59] pinpointed that to promote cognitive engagement, learning should include feedback and interaction with peers and instructors. The community in online learning can help students achieve engagement and improve their learning performance. Redmond et al. [2] asserted that the act of sharing information on online-learning platforms can reflect students' cognitive engagement. Similarly, Waheed [61] stated that student feedback is crucial in online learning. In his study, he implemented a discussion forum that was geared toward students' cognitive engagement in learning and their feelings about being involved in the learning process. Collaborative activities such as discussion forums often require students to work in a group and promote a sense of community. These activities allow students to collaborate actively and give them the autonomy to participate in their own learning, such as exchanging information with the lecturer. In a way, they develop a sense of belonging in the learning process, and this indicates students' engagement [2]. In other words, active participation helps instructors to be better aware of students' engagement in learning.

In online learning, the record of log-data files stems from students' activities. The more frequently a student visits the online-learning platform, the more actively engaged he/she is in learning. Besides, it is also crucial for students to ensure that their emotions and behaviours are connected. Students who are competent academically and emotionally engaged will find success in their learning [66]. Students who can maintain positive emotions and behaviours in online learning are prone to achieving better learning outcomes than those who fail to maintain an emotional equilibrium. Past studies on student engagement provide insights for instructors to find ways to encourage student engagement and increase learning satisfaction even in distance learning.

On top of that, studies that addressed multifaceted engagement that incorporates more than one type of engagement were usually able to propose measures that are more comprehensive [21]. The common elements of engagement clustered together are emotional, cognitive, and behavioural. [25,69–74]. Through multifaceted engagement, instructors can tackle students' issues from various perspectives. For instance, Pilotti et al. [71] and Tseng [25] identified the influence of instructor's guidance and feedback on students' emotional, cognitive, and behavioural engagement, which determines their learning performance in online learning. In conjunction with the study, instructors can take immediate measures to help students attain better experience with and expectations in learning.

It is possible to carry out a study that includes five types of student engagement, as proven by Redmond et al. The engagement clusters found in this study are (1) behavioural and emotional, and (2) social, cognitive, and behavioural. According to Fredricks et al. [21], there is an increasing trend of carrying out studies on student engagement among educational practitioners because they contribute to learning and academic success. Integrating more than one engagement element in a study can help educators to find better measures to overcome students' learning issues, especially in the setting of online learning.

5.2. Research Question 2 (RQ2): The Purpose of Using Learning Analytics on Student Engagement

To analyse learning data, learning analytics is purposefully adapted to suit educational contexts [42]. The intervention of learning analytics supports the learning–teaching process by providing insightful educational datasets [42]. Therefore, in their study, Chatti and colleagues presented a reference model for learning analytics for future research, including the objectives of the learning analytics. Table 4 illustrates the purpose of using learning analytics to measure student-learning databases in online settings.

Table 4. The purposes of using learning analytics.

Article	Purpose	Description
[19,20,24,41,66,75–78]	Predict	The aim is to develop a model to predict the knowledge absorption and future performance of students, which can be used for intervention purposes. An example of intervention includes suggesting actions that should be taken to help students who need additional assistance.
[66]	Analyse	It tracks students' activities and generates reports to support decision-making. It is also related to teacher's evaluation of the learning process, which can help improve the learning environment. Examining and analysing the ways students use a learning system can assist teachers in detecting patterns and making decisions in terms of future learning activities.
[13,32,50,79,80]		To examine the necessary conditions geared toward engagement in online-learning environments based on the learning-analytics approach.

Table 4. *Cont.*

Article	Purpose	Description
[19,20,24,41,66,75–78]	Predict	The aim is to develop a model to predict the knowledge absorption and future performance of students, which can be used for intervention purposes. An example of intervention includes suggesting actions that should be taken to help students who need additional assistance.
[58]	Feedback	To provide feedback to both students and teachers based on the analysis outcome of the efficiency of the learning process.
[63]		
[49]	Others	To study the potentials and pitfalls of learning analytics as a tool for promoting students' well-being in online learning.
[47]		To study the engagement in LMSs and students' performance through learning analytics.
[65]		To validate a theorised model of engagement in learning analytics.
[48]		To study learning analytics in collaborative learning.

Learning analytics is used to examine students' online activities. It outweighs the traditional survey and data-collection methods by providing timely evidence for practical observation [10]. For instance, it can identify learners' performance, which helps educators to understand their students better [81], and most importantly, to determine student engagement by tracking log-file data. Students' engagement can be tracked when students actively participate and engage in online-learning activities [51,82]. Learning analytics has the potential to provide an overall understanding of student engagement by forming a model or framework that can enhance students' learning performance [83]. Based on Table 4, half of the articles used learning analytics to predict students' learning process in online learning [19,20,41,75–77]. By predicting students' engagement and learning, actions can be taken to assist students in need. Students' learning behaviour can predict academic success [41,47,50]. For example, Brozina et al. [47] suggested that the clarity of learning instructions can influence students' behaviour in learning. In parallel to this claim, Ma et al. [50] believed that instructors should design courses with clear objectives, as it is one of the factors that lays the foundation of students' academic performance.

According to Chatti et al. [42], learning analytics allows instructors to explore the data traces in online learning. Future researchers can refer to the learning-analytics reference model proposed by Chatti et al. to determine the objectives and the types of student engagement to help the students at risk in an online-learning setting. This study scrutinised different purposes and methods involved in the application of learning analytics on student engagement in order to shed light on how to enhance students' learning performance.

5.3. Research Question 3 (RQ3): The Effect of the Use of Learning Analytics on Student Engagement in Online-Learning Settings

The articles used learning analytics to track students' engagement in online learning. Based on Table 5, four types of engagement (i.e., cognitive, collaborative, and behavioural) surfaced in the reviewed articles. The type of engagement was, however, unknown in some articles. The most popular type of engagement that utilises the assistance of analytics was behavioural engagement, followed by cognitive, collaborative, and social engagement. Table 5 presents the use of the learning-analytics intervention on students' learning in online settings.

Table 5. The use of learning analytics for student engagement.

Article	Type of Engagement	Online-Learning Platform/Tool	LA Role	LA Intervention	Findings
[58]	Cognitive	Discussion forum	LA discovered that students' cognitive engagement can be promoted by providing feedback through quality responses and discussion questions.	Yes (feedback)	Students' cognitive engagement was promoted due to feedback given.
[63]	Collaborative	Online discussion using Blackboard	LA suggested that feedback aids students' engagement and assists their learning.	Yes (feedback)	Students' engagement and learning was strengthened by feedback given.
[36]	Collaborative	VLE tools: OpenDesignStudio (ODS) to post forums, live chat, etc.	The visualisation from LA gave students a chance to reflect on their writing process to promote engagement and learning performance.	No	Students learning was improved and supported due to visualisation.
[84]	Behavioural	Moodle LMS	LA predicted students' performance by analysing students' grade performance in the LMS based on their learning traces.	No	Students' final grades were increased with prediction but only slightly.
[76]	Behavioural	MOOC courses	LA was used to predict students' performance through participation in online tasks.	No	Students' final exam grades were harder to predict than final grades due to different assignments during the course.
[29]	Behavioural	Video learning and datamining through a student-information system (SIS), student online activities from the LMS Moodle and student video-interaction data from eDify (mobile application)	LA predicted students' performance through online behaviour.	No	Students' performances and interaction were improved.
[77]	Behavioural and Social	Case-analysis report through Slack	LA predicted students' performance based on task participation and interaction among students.	No	Students' teamwork engagement was promoted and positively influenced students' success.
[47]	Behavioural	Student data on the LMS	LA predicted that high learning performance can be achieved with clear learning objectives from instructors.	No	Students' performance was predicted to be influenced by good learning engagement.
[50]	Behavioural	Instructors teaching through an LMS, Tsinghua Educational Online (THEOL)	LA analysed that course design and instructor's guidance are the keys to students' positive behaviours in task completion, which leads to improved learning performance.	No	Students' actions in online learning was reported.
[41]	Behavioural	Online platform	LA predicted students' performance through the CPT+ model based on their behavioural engagement in learning.	No	Students' performance behaviour was significantly predicted.
[24]	Behavioural	Interaction in an LMS	LA predicted students' academic performance through their online behaviour of self-regulated learning and interactions.	No	Students' engagement and performance was positively influenced with better learning approaches.
[78]	Behavioural	Clickstream and answer quiz on the MOOC platform	LA predicted students' grades based on students' online behaviour and involvement.	No	Students' behaviour was predicted to not correlated with performance.
[75]	Behavioural	Activity on MOOC	LA analysed students' grades based on participation and academic-oriented behaviour.	No	Students' grades coincided with positive participation and learning behaviour.
[13]	Behavioural	Posts and discussion on Canvas	LA was used to assess students' learning experience and performance based on their behavioural engagement through self-directed learning and collaborative learning.	No	Students' performance was predicted to not be associated with their engagement.
[79]	Behavioural	Activity in VLE	LA was used to identify the study materials and the causes that affect students' academic achievement.	No	Students' interaction was identified to influence engagement in learning.
[80]	Behavioural	Daily trace data in VLE	LA was used to monitor student engagement considering factors affecting engagement, learning experience, and performance.	No	A comparison of students' grades was carried out.
[85]	Social	Academic data in VLE	LA predicted students' performance based on students' academic data using the AugmentED model.	Yes (visualised feedback)	Students' academic performance was highly predicted, especially for at-risk students.

LA: learning analytics.

Based on these articles, learning analytics has different effects on students' engagement in online learning. In particular, it could be applied to measure students' engagement in online learning and predict students' learning performance [13,41,47]. The results of some studies also found that students' learning performance was enhanced [29,36,58,63,77]. Additionally, the learning-analytics interventions implemented in the studies were also found to serve as a treatment to assist and enhance students' learning. A discussion forum is a medium of learning whereby an instructor assists the learning process and provides feedback as an intervention to ensure that students are motivated and engaged in their learning [58,63]. Learning analytics determined students that needed feedback to enhance their learning participation and performance. For instance, Casimiro and Aderibigbe [58,63] provided feedback on the students' discussion posts to ensure that they participated, and it was shown that their learning and engagement was promoted. Casimiro [58] investigated students' cognitive engagement in discussion forums and discovered five conditions that could determine students' engagement in online learning, namely, students posting discussion questions, the quality of student responses, the learning community, student characteristics, and teacher facilitation. Learning analytics provides quantified evidence on students' engagement, in which three out of five conditions—the type of discussion questions, the quality of student responses, and the learning community—appeared to promote students' cognitive engagement. Aderibigbe [63] utilised learning analytics as part of their methodology to quantify students' experience in online discussion forums and strengthen their engagement in online learning. The study discovered that the discussion forum aided students' engagement in learning. The application of learning analytics was also able to strengthen students' engagement in online discussions and learning by providing constructive feedback, clear guidelines, and reflective questions. Meanwhile, Liu et al. [36] found that the visualisation from learning analytics gave students a chance to reflect on and improve their learning. They used learning analytics to analyse students' writing behaviours in collaborative activities. Hence, collaborative engagement in students' learning was promoted via the visualisation that informed instructor on ways to assist students in their learning.

Behavioural engagement is often measured through learning analytics, and prediction is a forecaster of students' learning performance. Students' data traces in the LMSs were analysed and predicted to inform instructors on what and how to ensure students' learning and performance was improved [86]. For instance, students' behaviours towards the learning task assigned is one of the predictive factors for their learning performance [36,41,47,50,75,78]. The course design must be inviting so students will participate in the learning activity and demonstrate positive behaviours in learning [13,50]. A study conducted by Toro-Troconis et al. [13] investigated the Postgraduate Photography Program to explore students' insights and behaviours in online learning. They used learning analytics as an indicator of students' engagement through low-end cognitive activities (self-directed learning) and high-end cognitive activities (collaborative learning) while assessing students' learning experience and performance. Toro-Troconis et al. ascertained that learning analytics could be used to determine students' engagement in online learning. Similarly, Nguyen et al. [80] expressed that learning analytics is applicable to identifying the study materials and the causes that determine students' learning success. They suggested that the design of an online-learning course needs to be done carefully and considerately, as it affects students' learning experience and performance to a large extent. Hence, prediction of students' learning activity indicates what and how instructors can promote learning engagement and performance in online-learning settings.

Students' behaviour and performance can also be affected by learning instructions [47]. Brozina et al. emphasised the importance of having clear objectives in course delivery via an LMS in students' online-learning performance. They discovered that students perform better in their learning when instructors provide clear instructions on the activity to be conducted. To conclude, course design and clear instructions facilitate students' behavioural engagement in online learning and serve as the prerequisite of academic success.

On the other hand, Hasan et al. [29] observed students' activity in online learning using videos. They tracked and analysed students' interactions in the video recorded to assess their learning outcomes. They discovered that students' learning performance could be predicted by video analysis based on the time spent and the interactions shown in the video. Moreno-Marcos et al. [76] analysed the factors that affect students' performance. They figured that task participation is a significant factor in students' success in online learning. Students who engaged in online tasks were predicted to achieve better performance. These studies proved that students' participation in online learning was associated with their learning performance; however, the types of student engagement were vague.

Even though learning analytics is helpful in determining students' engagement based on their behaviours in online learning, the data can be manipulated. A study by Holmes [79] involving second-year undergraduate Physical Geography students at University of Northampton, UK, investigated the module delivered to students in a virtual learning environment (VLE). There were three modules; one used continuous e-assessment and the other two adopted traditional assessment methods. Holmes monitored students' activity through the number of hours spent in the VLE, the number of logins, and the frequency of interaction with the learning content to determine students' engagement. The findings showed a significant increase in students' engagement with the use of continuous e-assessment in the VLE as compared to that of traditional assessment methods; notwithstanding, the researcher asserted that the interpretation of the data needs to be carried out cautiously. This is because he detected a contradictory finding whereby students who spent fewer hours in the VLE achieved better results in the e-assessment in the same study. All in all, learning analytics is helpful in monitoring student engagement in a VLE. Other factors that could affect students' engagement should not be neglected either, as they can help maintain said engagement and enhance the learning experience [79].

It is suggested that future researchers be specific on the methods and the objectives of learning-analytics interventions used in measuring engagement in online learning to capture the full potential of LA [42]. In the following subsections, the review of the included articles is presented to determine the use of learning analytics on students' engagement to enhance their learning performance.

6. Discussion

This paper aimed to study the effects of utilising learning analytics in the handling of student-engagement issues in online-learning settings to enhance learning performance. Among the 42 articles included, 26 articles were identified with distinctive engagement and multifaceted engagement, and 15 articles were found to utilise learning analytics to enhance students' learning performance. This section discusses the findings based on the research questions to identify the gaps found in the articles.

There were different types of student engagement, such as behavioural engagement, cognitive engagement, emotional engagement, collaborative engagement, and social engagement, as proposed by Redmond et al. [2], which can be used to identify the effects on students' learning performance. Thus, it is interesting to examine the types of engagement that were taken into consideration in the current research studies. There were also studies that incorporated multifaceted engagement (e.g., cognitive engagement, emotional engagement, and behavioural engagement). This study highlighted the importance of multifaceted engagement in learning. As claimed by Fredricks et al. [21], multifaceted engagement allows educators to understand and encourage students to learn and achieve better learning outcomes, as it caters to different aspects of students' learning needs.

There were studies on multifaceted engagement that integrated cognitive, behavioural, and emotional engagement together [25,69–72]. For instance, Adams et al. [69] discovered that demographic factors such as age, gender, etc. are closely related to students' engagement (cognitive, behavioural, and emotional) in online-learning activities. In addition, Tze et al. [72] investigated how the length of time spent on MOOC can affect students' behavioural, cognitive, and emotional engagement, to which end they discovered that each type of engagement varies from person to person. Alshuaibi et al. [70] suggested that social media has the potential to engage students in learning; however, it only promotes cognitive engagement and not behavioural and emotional engagement. They found that students are in charge of their learning on online platforms and are the ones who decide the ways in which they engage with the learning content.

Moreover, multifaceted engagement can enhance students' learning performance. For instance, Pilotti et al. [71] examined the relationship between student engagement and the presence of instructors on academic performance. On the other hand, Tseng [25] investigated the influence of teacher assistance on students' learning engagement. Pilotti et al. examined how classroom size can affect teacher instruction and student engagement. The findings showed that bigger classrooms yield low cognitive and behavioural engagement, and that emotional engagement helps to improve students' learning performance. Meanwhile, Tseng [25] proposed that teachers' instructions fostered cognitive and behavioural engagement, but this was not the case for their emotional engagement. This is because students' emotional state was disturbed by the overlapping of instructions; hence, their emotional engagement was promoted less. It is appropriate to consider cognitive, behavioural, and emotional engagement together, as they collectively reflect students' online learning and academic performance. In line with that, Sinha et al. [73] studied behavioural and social engagement, as they believed that each engagement co-affects every other. To explain further, students' positive learning behaviours encourage them to be socially engaged. In summary, a study that features multifaceted engagement can produce more comprehensive measures to overcome online-learning issues and achieve academic success.

Nevertheless, based on the articles reviewed, none of the studies integrated the five types of engagement, namely, (i) social, (ii) behavioural, (iii) collaborative, (iv) cognitive, and (v) emotional. The author believes that by integrating more than one type of engagement in a study, more efficient measures can be taken to solve online-learning issues among students. Therefore, more extensive research needs to be carried out to look into different types of student engagement or collective engagement in online learning. That way, various outcomes on how different combinations of engagement affect both students and educators can be obtained, especially in the context of higher education.

Furthermore, learning analytics refers to the process of presenting and analysing data so that actions can be taken [42]. Through learning analytics, students' academic performance can be enhanced, as it helps educators to understand their students better [81]. Based on the articles reviewed in this study, it was found that behavioural engagement was commonly measured through learning analytics (please refer to Table 5). Learning analytics was proven to be effective in predicting students' behaviours in online learning to achieve better learning performance [24,41,75,85]. For instance, Zhao et al. [85] developed an academic-prediction model by analysing students' behavioural patterns in online learning. They found that learning analytics has the potential to provide data on students' learning and thus predict their academic performance. Pardo et al. [24] explored the data of self-regulated learning and students' participation in online activities and confirmed that they could predict students' learning performance. Data that reflect students' behaviours in online learning can be used by instructors to improve the task design of their teaching. Lotz et al. [56], on the other hand, found that there is a positive correlation between engagement and interaction in online learning that leads to students' success. In online learning, students are encouraged to form a community to share their thoughts and engage in social networking.

Learning analytics can provide information on factors related to students' academic success. It was suggested that the instructor's presence and guidance in online learning are instrumental to students' learning performance [47,50]. In addition, learning analytics was used to identify the factors affecting students' success in online learning and it was found that social interaction [77], course design [13,50,84], and collaborative or teamwork tasks [49,76] are effective in enhancing students' online-learning performance. In addition, Moreno-Marcos et al. [76] predicted students' learning performance through several features of LMSs, such as clickstream data, course duration, the exercises given, and students' previous grades. They found that the best predictor for students' success was participation in exercises. Students who completed the exercises achieved better learning performance. Similarly, Fincham et al. [75] echoed that students' behaviours and tendency to participate in learning tasks were associated with good academic grades. This shows that students' positive behaviours in online learning encourage them to engage in learning and hence lead to better learning performance [78]. In short, students' data traces, which reflect their behaviours and participation in online learning, can be interpreted by learning analytics to uncover the iceberg of their academic performance.

Previously, Chatti et al. [42] stated that intelligent tutoring and adaptations are the primary purposes for researchers to use learning analytics in their studies. However, based on the articles reviewed, learning analytics is commonly used to predict students' engagement to enhance their learning performance. To add to that, the consideration of other factors affecting students' learning [79], such as the design of courses materials [80], can also improve students' learning experience and performance [13]. Thus, more studies need to be conducted to further explore the potentials of student engagement in online learning by utilising learning analytics. Future researchers can refer to the learning-analytics reference model configured by Chatti et al. to determine the objectives and types of student engagement to support students at risk in online learning.

Learning analytics is undeniably helpful in the online-learning context. Its capability to provide statistical evidence on students' learning progress in online learning is beyond doubt. Learning analytics is also adapted to the online learning context in that it measures student engagement to enhance their learning performance. This can improve online teaching–learning. Therefore, it is crucial to incorporate learning analytics into studies that revolve around student engagement so that it can help both educators and students, respectively, in their teaching and learning in an online setting. Future researchers are encouraged to sail into the uncharted territory of using learning analytics for different objectives, such as monitoring and analysis or assessment and feedback, to aid educators in finding innovative solutions to counter engagement issues in online learning.

7. Conclusions

This study identified a gap in the application of learning analytics on student engagement to enhance students' learning performance. The review of the articles found that none of the studies integrated the five types of student engagement together for comprehensive findings. By applying learning analytics to measure student engagement in online learning, instructors and students will benefit in their teaching and learning process, respectively, to achieve academic success. Lee [44] emphasised that the implementation of learning analytics on student engagement can enhance learning performance. Through learning analytics, students' log files and participation in online learning activities can be traced [47]. This keeps the instructors informed so they can give timely warnings and prevent dropouts.

Moreover, in this pandemic era, higher-education institutions frequently employ online instruction. Hence, it is crucial to have more research relating to student engagement to improve the quality of online learning. Salas-Pilco et al. [87] asserted that the quality of online learning can be ameliorated by paying attention to the technological aspect such as social networking platform [88] and teaching approach, which are capable of promoting engagement in learning. In addition, multifaceted engagement in online learning can provide multidimensional solutions to dealing with online-learning issues in a thorough manner. The idea of combining all five elements of student engagement as a comprehensive measure with clear definitions and guidelines for future researchers to further explore student engagement in online learning needs to be taken seriously. Recent studies have also indicated that multifaceted engagement can provide factual findings on how these elements of student engagement can help educators to improve students' learning experience and performance in the online-learning setting [70,71].

Furthermore, past studies have also shown the potential for learning analytics to predict student dropout and provide targeted intervention [89] to encourage school completion [90], thereby allowing for a more sustainable education [91]. Therefore, this study is expected to add value to the future application of learning analytics to measure multifaceted engagement in online learning to enhance students' learning performance, which can enable a more sustainable education.

8. Limitations and Recommendations

The findings of this review paper provide insight into one of the most discussed online-learning issues, namely, student engagement. In addition, valuable recommendations regarding the potential of learning analytics on student engagement to enhance students' learning performance are provided. However, there are limitations that need to be addressed by future researchers so that they can study the issue in a more comprehensive manner. The main limitation of this paper is the limited number of studies reviewed (42 studies from 2011 to 2021). Due to this limitation, prominent pedagogical approaches such as blended learning, flipped classrooms, etc., are absent in this review. Future researchers are recommended to expand their research to include more studies that have integrated these engagement elements and to look for more studies that involve multi-layered engagement to see how the engagement influences students' learning outcomes, as many educational institutions these days are using the online setting as a medium of instruction. These limitations should be taken into consideration by future researchers so that they are able to conduct more extensive and comprehensive studies on the utilisation of learning analytics on student engagement in different online-learning settings. In particular, future studies can examine student engagement in online settings and how the engagement-analysis outcome can be used to inform the development of interventions to overcome learning problems such as dropouts and poor learning performance. In addition, future researchers can develop a learning platform that incorporates multifaceted engagement, such as social, cognitive, collaborative, behavioural, and emotional engagement in online learning.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15107849/s1, PRISMA 2020 Checklist.

Author Contributions: Conceptualisation, N.A.J., S.N.K. and Z.T.; methodology, N.A.J. and S.N.K.; formal analysis, N.A.J., S.N.K. and Z.T.; writing—original draft preparation, N.A.J., S.N.K. and Z.T.; writing—review and editing, N.A.J., S.N.K., Z.T. and E.K.; funding acquisition, S.N.K. and Z.T. All authors have read and agreed to the published version of the manuscript.

Funding: The authors would like to thank the Ministry of Higher Education (MOHE) and Universiti Teknologi Malaysia (UTM) for their support in making this project possible and those who helped with this research. This research was supported by the Research University Grant (RUG) Program: [Q.J130000.3853.19J71] initiated by UTM and the Postdoctoral Program Scholarship by the Malaysian Ministry of Higher Education.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The authors would like to thank the Malaysia Ministry of Higher Education and Universiti Teknologi Malaysia for providing the opportunity to conduct this research.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Table A1. List of articles included.

Label	Paper	Year of Publication	Origin	Methodology	Types of Engagement	Purpose of Research	Findings
A1	[67]	2011	Canada	Quantitative	Emotional	To investigate and analyse student engagement in enhancing students' learning performance.	Emotions related meaningfully to students' learning and performance.
A2	[57]	2012	Hong Kong	Quantitative	Social	To promote students' interaction and social networking in online learning.	Social interaction appeared to enhance social engagement but had a limited impact on cognitive engagement.
A3	[90]	2012	Malaysia	Quantitative	Collaborative	To promote students' interaction and social networking in online learning.	Students participated actively in the online forum even with minimal intervention from the lecturer.
A4	[39]	2012	Canada	Quantitative	Emotional	To develop a sense of community in online learning.	Students' emotions were present (1) when they were involved in discussion (2) in engaging experiences in online learning.
A5	[62]	2013	Malaysia	Quantitative	Behavioural	To develop learning persistence and engagement among students in online learning.	Students demonstrated positive behaviours in discussions due to the implementation of collaborative learning.
A6	[59]	2014	USA	Quantitative	Cognitive	To investigate and analyse student engagement in enhancing students' learning performance.	There was a positive relationship between cognitive-engagement activities and learning outcomes due to participation in learning tasks.
A7	[60]	2014	Malaysia	Quantitative	Cognitive	To investigate students' cognitive ability.	Students struggled to contribute messages at a high level of cognitive engagement.
A8	[56]	2015	UK	Quantitative	Social	To investigate and analyse student engagement in enhancing students' learning performance.	There was a positive correlation between engagement and interaction in the online studio and students' success.
A9	[27]	2015	Indonesia	Quantitative	Social	To promote students' interaction and social networking in online learning.	Through social-media implementation in learning, students were more concerned with the quality of information, as comprehensive of communication enhanced engagement and promoted an active learning process for better performance.
A10	[73]	2015	USA	Quantitative	Social, cognitive, behavioural	To develop learning persistence and engagement among students in online learning.	The quality of student engagement influenced students' performance in online learning.
A11	[58]	2016	Philippines	Quantitative	Cognitive	To investigate students' cognitive ability.	Students' cognitive engagement was quantified and could be promoted by providing quality responses and discussion questions.
A12	[65]	2016	Indonesia	Quantitative	Behavioural	To develop learning persistence and engagement among students in online learning.	Students showed positive perceptions and behaviours in online learning, and it resulted in good grades.
A13	[61]	2017	Australia	Quantitative	Social, emotional	To investigate and analyse student engagement in enhancing students' learning performance.	Social and cognitive engagement could be fostered through feedback provided in the learning process and involvement in group activities. They helped to promote a sense of community, which in turn allowed students to share and gain more in their learning process.
A14	[48]	2017	China	Quantitative	Behavioural	To develop a sense of community in online learning.	Students' communication behaviours in online courses reflected their sense of community.

Table A1. *Cont.*

Label	Paper	Year of Publication	Origin	Methodology	Types of Engagement	Purpose of Research	Findings
A15	[71]	2017	USA	Quantitative	Cognitive, behavioural, emotional	To investigate and analyse student engagement in enhancing students' learning performance.	Classroom size affected teachers' instruction and students' engagement.
A16	[72]	2017	Canada	Quantitative	Cognitive, behavioural, emotional	To identify how the length of time spent by students on MOOC can affect their behavioural, cognitive, and emotional engagement.	The level of anxiety influenced students' engagement in online learning.
A17	[64]	2018	Africa	Quantitative	Collaborative	To promote students' interaction and social networking in online learning.	The use of social media to promote students' collaboration and engagement was vital, as it lay the foundation for constructive solutions in which social media could help enhance students' learning, competence, and ultimately performance.
A18	[70]	2018	Malaysia	Quantitative	Cognitive, behavioural, emotional	To investigate and analyse student engagement in enhancing students' learning performance.	Social media had the potential to engage students in learning. It only facilitated cognitive engagement, but not behavioural or emotional engagement.
A19	[63]	2020	Malaysia	Quantitative	Collaborative	To develop learning persistence and engagement among students in online learning.	The use of discussion forums as an intervention in online learning aided students' engagement.
A20	[22]	2020	Finland	Qualitative	Collaborative	To promote students' interaction and social networking in online learning.	Positive interaction could be meaningful in the collaborative learning progress.
A21	[66]	2020	USA	Quantitative	Emotional	To investigate and analyse student engagement in enhancing students' learning performance.	Students were emotionally engaged in their learning, and competence was the only predictor of emotional engagement.
A22	[68]	2020	China	Quantitative	Emotional	To develop learning persistence and engagement among students in online learning.	Students' online interaction and emotional engagement were the central determinants of learning persistence.
A23	[69]	2020	Malaysia	Quantitative	Cognitive, behavioural, emotional	To develop learning persistence and engagement among students in online learning.	Demographic factors such as age, gender, etc. were closely related to the level of engagement (cognitive, behavioural, and emotional) in online-learning activities.
A24	[74]	2020	USA	Quantitative	Behavioural, emotional	To promote students' interaction and social networking in online learning.	Student–faculty interactions were positively linked to the effort expended by students and behavioural and emotional engagement.
A25	[3]	2020	Malaysia	Quantitative	Cognitive	To investigate students' cognitive ability.	Students displayed low cognitive engagement due to the lack of cognitive demand and mental effort.
A26	[25]	2021	China	Quantitative	Cognitive, behavioural, emotional	To predict students' performance from LMS data by analysing 17 different courses on Moodle.	Students' performance varied across courses.
A27	[36]	2017	China	Quantitative	Collaborative	To use learning analytics to analyse students' writing behaviours in collaborative writing activities.	The visualisation from learning analytics offered students a chance to reflect on their writing process.
A28	[84]	2017	Netherlands	Quantitative	Unknown	To study the potentials and pitfalls of learning analytics as a tool for supporting students' well-being.	LA was used to assist staff in supporting students' learning.
A29	[49]	2018	UK	Quantitative	Unknown	To analyse factors influencing learner performance with learning analytics.	The online tasks or activities were effective in predicting students' learning performance.
A30	[76]	2020	Spain	Quantitative	Unknown	To predict students' performance in higher-education institutions using video-learning analytics and data-mining techniques.	Students' academic performance could be predicted using learning analytics.

Table A1. *Cont.*

Label	Paper	Year of Publication	Origin	Methodology	Types of Engagement	Purpose of Research	Findings
A31	[29]	2020	Malaysia	Quantitative	Unknown	To study the engagement in LMSs and students' performance through learning analytics.	LA could predict high learning performance in LMSs, and clear objectives from instructors increased students' LMS usage and performance.
A32	[47]	2019	USA	Quantitative	Behavioural	To examine the necessary conditions for engagement in online-learning environments based on a learning-analytics approach.	Course design and instructor guidance were the keys to students' positive behaviours in task completion.
A33	[50]	2015	China	Quantitative	Behavioural	To integrate learning analytics to predict students' performance.	LA could significantly predict students' performance in learning.
A34	[24]	2017	Oman	Quantitative	Behavioural	To study the combination of self-regulated learning indicators and engagement with online-learning events to predict academic performance.	Students' behaviours in online learning indicated noteworthy results on their academic performance in self-regulated learning.
A35	[78]	2017	Taiwan	Quantitative	Behavioural	To predict behaviour-based grades for MOOC via time-series neural networks.	Students' behaviours in online learning influenced their learning performance.
A36	[75]	2017	UK	Quantitative	Behavioural	To validate a theorised model of engagement in learning analytics.	Students' participation and academic-oriented behaviours were positively associated with their grades.
A37	[87]	2019	China	Quantitative	Behavioural	To predict academic performance based on multi-sourced and multi-featured behavioural data.	The augmented model could predict students' performance.
A38	[77]	2020	China	Quantitative	Unknown	To study learning analytics in collaborative learning.	Social influence and teamwork engagement had positive effects on students' success.
A39	[86]	2019	China	Quantitative	Unknown	To predict students' performance from LMS data by analysing 17 different courses on Moodle.	Students' performance varied across courses.
A40	[13]	2018	UK	Quantitative	Behavioural	To use learning analytics to explore students' insights and behaviours in online learning.	Learning analytics could be used to determine students' engagement in online learning, and course design affected students' learning experience and performance.
A41	[82]	2020	UK	Quantitative	Behavioural	To analyse black minority ethnicities' (BMEs') and white students' behavioural engagement on their attainment differences in online distance learning.	There were gaps between BMEs' and white students' academic attainment based on their behavioural engagement in online learning using learning analytics.
A42	[81]	2018	UK	Quantitative	Behavioural	To investigate the modules delivered and monitor students' behaviours in a virtual learning environment (VLE).	Learning analytics helped to monitor student engagement in the VLE.

Appendix B

Table A2. Types of engagement and purposes of learning analytics.

Label	Author	Description	Types of Engagement
A1	[86]	To predict students' performance from LMS data by analysing 17 different courses in Moodle.	Unknown
A2	[29]	To predict student performance in higher-education institutions using video-learning analytics and data-mining techniques.	
A3	[76]	To analyse factors influencing learners' performance with learning analytics.	
A4	[49]	To study the potentials and pitfalls of learning analytics as a tool for supporting student wellbeing.	
A5	[77]	To study learning analytics in collaborative learning.	

Table A2. *Cont.*

Label	Author	Description	Types of Engagement
A6	[41]	To integrate learning analytics to predict students' performance behaviours.	Behavioural
A7	[24]	To study the combination of self-regulated-learning indicators and engagement with online-learning events to predict academic performance.	
A8	[78]	To predict behaviour-based grades for MOOC via time-series neural networks.	
A9	[36]	To use learning analytics to analyse students' writing behaviours in collaborative writing activities.	
A10	[47]	To study the engagement in LMSs and students' performance through learning analytics.	
A11	[50]	To examine the necessary conditions for engagement in online-learning environments based on a learning-analytics approach.	
A12	[75]	To validate a theorised model of engagement in learning analytics.	
A13	[13]	To explore students' insights and behaviours in online learning.	
A14	[82]	To analyse students' behavioural engagement in terms of their attainment differences in online distance learning.	
A15	[81]	To investigate the modules delivered and monitor students' behaviours in a virtual learning environment (VLE).	
A16	[87]	To predict academic performance based on multi-sourced and multi-featured behavioural data.	Social
A17	[58]	To investigate students' cognitive engagement in the discussion forum.	Cognitive
A18	[63]	Student engagement in online discussions.	Collaborative

Table A3. Objectives of learning analytics in the Learning Analytics Reference Model [42].

Objectives	Description
Monitoring/analysis	To track students' activities and generate reports to support decision-making. It is also related to teachers' evaluations of the learning process to improve the learning environment. Moreover, it examines and analyses the ways students use a learning system that can assist teachers in detecting patterns and making decisions on the future design of learning activities.
Prediction/intervention	The aim is to develop a model that can predict the knowledge absorption and future performance of students, which can be used for intervention purposes. An example of intervention includes suggesting actions that should be taken to help students who need additional assistance.
Tutoring/mentoring	Tutoring focuses on the teaching process (control of the tutor), whereas mentoring focuses on the learning process of students.
Assessment/feedback	To provide feedback to both students and teachers based on the assessment of the efficacy and efficiency of the learning process.
Adaptation	Adaptation is to be carried out by the teacher/tutoring system or educational institution. It is concerned with guiding students with the next move by organising and establishing instructional activities and learning resources based on individual needs.
Personalisation/recommendation	Personalisation refers to assisting students in making decisions about their own learning and continuously shaping their PLEs to achieve learning goals. Meanwhile, the recommender system plays a role in fostering self-directed learning by recommending explicit and tacit knowledge nodes based on individual preferences and activities of other learners with similar preferences.

References

1. The Global Goals. 4 Quality Education. 2023. Available online: https://www.globalgoals.org/goals/4-quality-education/ (accessed on 1 May 2023).
2. Redmond, P.; Heffernan, A.; Abawi, L.; Brown, A.; Henderson, R. An Online Engagement Framework for Higher Education. *OLJ* **2018**, *22*. [CrossRef]
3. Kew, S.N.; Tasir, Z. Analysing Students' Cognitive Engagement in e-Learning Discussion Forums through Content Analysis. *Knowl. Manag. E-Learn. Int. J.* **2021**, *13*, 39–57. [CrossRef]

4. Picciano, A.G. Beyond Student Perceptions: Issues of Interaction, Presence, and Performance in An Online Course. *OLJ* **2019**, *6*. [CrossRef]
5. Ball, I.; Perry, C. Differences in Student Engagement: Investigating the Role of the Dominant Cognitive Processes Preferred by Engineering and Education Students. *Educ. Res. Int.* **2011**, *2011*, 414068. [CrossRef]
6. Fredricks, J.A.; Blumenfeld, P.C.; Paris, A.H. School Engagement: Potential of the Concept, State of the Evidence. *Rev. Educ. Res.* **2004**, *74*, 59–109. [CrossRef]
7. Reeve, J.; Tseng, C.-M. Agency as a Fourth Aspect of Students' Engagement during Learning Activities. *Contemp. Educ. Psychol.* **2011**, *36*, 257–267. [CrossRef]
8. Mamun, M.A.A.; Lawrie, G. *Factors Affecting Student Behavioural Engagement in an Inquiry-Based Online Learning Environment*; Research Square: Durham, NC, USA, 2021.
9. Joksimovic, S.; Kovanovic, V.; Gasevic, D.; Dawson, S.; Siemens, G. The History and State of Online Learning. In *Preparing for the Digital University: A Review of the History and Current State of Distance, Blended, and Online Learning*; Athabasca University: Athabasca, AB, Canada, 2015; pp. 93–132.
10. Lockyer, L.; Heathcote, E.; Dawson, S. Informing Pedagogical Action: Aligning Learning Analytics with Learning Design. *Am. Behav. Sci.* **2013**, *57*, 1439–1459. [CrossRef]
11. Fan, S.; Chen, L.; Nair, M.; Garg, S.; Yeom, S.; Kregor, G.; Yang, Y.; Wang, Y. Revealing Impact Factors on Student Engagement: Learning Analytics Adoption in Online and Blended Courses in Higher Education. *Educ. Sci.* **2021**, *11*, 608. [CrossRef]
12. Atherton, M.; Shah, M.; Vazquez, J.; Griffiths, Z.; Jackson, B.; Burgess, C. Using Learning Analytics to Assess Student Engagement and Academic Outcomes in Open Access Enabling Programmes. *Open Learn. J. Open Distance e-Learn.* **2017**, *32*, 119–136. [CrossRef]
13. Toro-Troconis, M.; Alexander, J.; Frutos-Perez, M. Assessing Student Engagement in Online Programmes: Using Learning Design and Learning Analytics. *IJHE* **2019**, *8*, 171. [CrossRef]
14. Berman, N.B.; Artino, A.R. Development and Initial Validation of an Online Engagement Metric Using Virtual Patients. *BMC Med. Educ.* **2018**, *18*, 213. [CrossRef] [PubMed]
15. Macfadyen, L.P.; Dawson, S. Numbers Are Not Enough. Why e-Learning Analytics Failed to Inform an Institutional Strategic Plan. *J. Educ. Technol. Soc.* **2012**, *15*, 149–163.
16. Crampton, A.; Ragusa, T.A.; Cavanagh, H. Cross-Discipline Investigation of the Relationship between Academic Performance and Online Resource Access by Distance Education Students. *Res. Learn. Technol.* **2012**, *20*, 14430. [CrossRef]
17. Pittaway, S.M.; Moss, T. "Initially, We Were Just Names on a Computer Screen": Designing Engagement in Online Teacher Education. *AJTE* **2014**, *39*, 140–156. [CrossRef]
18. Abou-Khalil, V.; Helou, S.; Khalifé, E.; Chen, M.A.; Majumdar, R.; Ogata, H. Emergency Online Learning in Low-Resource Settings: Effective Student Engagement Strategies. *Educ. Sci.* **2021**, *11*, 24. [CrossRef]
19. Conduit, J.; Karpen, I.; Farrelly, F. Student Engagement: A Multiple Layer Phenomenon. In *Making a Difference through Marketing*; Springer: Singapore, 2016; pp. 229–245. ISBN 978-981-10-0462-9.
20. Wang, F.H. On the Relationships between Behaviors and Achievement in Technology-Mediated Flipped Classrooms: A Two-Phase Online Behavioral PLS-SEM Model. *Comput. Educ.* **2019**, *142*, 103653. [CrossRef]
21. Fredricks, J.A.; Filsecker, M.; Lawson, M.A. Student Engagement, Context, and Adjustment: Addressing Definitional, Measurement, and Methodological Issues. *Learn. Instr.* **2016**, *43*, 1–4. [CrossRef]
22. Isohätälä, J.; Näykki, P.; Järvelä, S. Convergences of Joint, Positive Interactions and Regulation in Collaborative Learning. *Small Group Res.* **2020**, *51*, 229–264. [CrossRef]
23. Guo, W.; Chen, Y.; Lei, J.; Wen, Y. The Effects of Facilitating Feedback on Online Learners' Cognitive Engagement: Evidence from the Asynchronous Online Discussion. *Educ. Sci.* **2014**, *4*, 193–208. [CrossRef]
24. Pardo, A.; Han, F.; Ellis, R.A. Combining University Student Self-Regulated Learning Indicators and Engagement with Online Learning Events to Predict Academic Performance. *IEEE Trans. Learn. Technol.* **2017**, *10*, 82–92. [CrossRef]
25. Tseng, S.-S. The Influence of Teacher Annotations on Student Learning Engagement and Video Watching Behaviors. *Int. J. Educ. Technol. High Educ.* **2021**, *18*, 7. [CrossRef]
26. Martin, F.; Bolliger, D.U. Engagement Matters: Student Perceptions on the Importance of Engagement Strategies in the Online Learning Environment. *OLJ* **2018**, *22*. [CrossRef]
27. Meyliana, M.; Hidayanto, A.N.; Budiardjo, E.K. Evaluation of Social Media Channel Preference for Student Engagement Improvement in Universities Using Entropy and TOPSIS Method. *JIEM* **2015**, *8*, 1676–1697. [CrossRef]
28. Gray, J.A.; DiLoreto, M. *The Effects of Student Engagement, Student Satisfaction, and Perceived Learning in Online Learning Environments*; National Council of Professors of Educational Administration: Madison, WI, USA, 2016; p. 20.
29. Hasan, R.; Palaniappan, S.; Mahmood, S.; Abbas, A.; Sarker, K.U.; Sattar, M.U. Predicting Student Performance in Higher Educational Institutions Using Video Learning Analytics and Data Mining Techniques. *Appl. Sci.* **2020**, *10*, 3894. [CrossRef]
30. Hospel, V.; Galand, B.; Janosz, M. Multidimensionality of Behavioural Engagement: Empirical Support and Implications. *Int. J. Educ. Res.* **2016**, *77*, 37–49. [CrossRef]
31. Young, M.R. The Art and Science of Fostering Engaged Learning. *Acad. Educ. Leadersh. J.* **2010**, *14*, 1–18.
32. Lowes, S.; Lin, P.; Kinghorn, B. Exploring the Link between Online Behaviours and Course Performance in Asynchronous Online High School Courses. *Learn. Anal.* **2015**, *2*, 169–194. [CrossRef]

33. Dixson, M.D. Measuring Student Engagement in the Online Course: The Online Student Engagement Scale (OSE). *OLJ* **2015**, *19*. [CrossRef]
34. Lashari, T.A.; Alias, M.; Kesot, M.J.; Akasah, Z.A. An Affective-Cognitive Teaching and Learning Approach for Enhanced Behavioural Engagements among Engineering Students. *Eng. Educ.* **2013**, *8*, 65–78. [CrossRef]
35. Wright, R.; Jones, G.; D', A.; Alba, N.A. Online Students' Attitudes towards Rapport-Building Traits and Practices. *IJIL* **2015**, *17*, 36–58. [CrossRef]
36. Liu, M.; Pardo, A.; Liu, L. Using Learning Analytics to Support Engagement in Collaborative Writing. *Int. J. Distance Educ. Technol.* **2017**, *15*, 79–98. [CrossRef]
37. Hewett, S.; Becker, K.; Bish, A. Blended Workplace Learning: The Value of Human Interaction. *ET* **2019**, *61*, 2–16. [CrossRef]
38. Webb, S. Online Tutoring and Emotional Labour in the Private Sector. *J. Workplace Learn.* **2012**, *24*, 365–388. [CrossRef]
39. Cleveland-Innes, M.; Campbell, P. Emotional Presence, Learning, and the Online Learning Environment. *IRRODL* **2012**, *13*, 269. [CrossRef]
40. Lawson, M.A.; Lawson, H.A. New Conceptual Frameworks for Student Engagement Research, Policy, and Practice. *Rev. Educ. Res.* **2013**, *83*, 432–479. [CrossRef]
41. Abdulwahhab, R.S.; Abdulwahab, S.S. Integrating Learning Analytics to Predict Student Performance Behavior. In Proceedings of the 2017 6th International Conference on Information and Communication Technology and Accessibility (ICTA), Muscat, Oman, 19–21 December 2017; pp. 1–6.
42. Chatti, M.A.; Lukarov, V.; Thüs, H.; Muslim, A.; Mohamed, A.; Yousef, F.; Wahid, U.; Greven, C.; Chakrabarti, A.; Schroeder, U. Learning Analytics: Challenges and Future Research Directions. *eleed* **2011**, *10*, 1.
43. Viberg, O.; Hatakka, M.; Bälter, O.; Mavroudi, A. The Current Landscape of Learning Analytics in Higher Education. *Comput. Hum. Behav.* **2018**, *89*, 98–110. [CrossRef]
44. Lee, J.-S. The Relationship Between Student Engagement and Academic Performance: Is It a Myth or Reality? *J. Educ. Res.* **2014**, *107*, 177–185. [CrossRef]
45. Nizam Ismail, S.; Hamid, S.; Chiroma, H. The Utilization of Learning Analytics to Develop Student Engagement Model in Learning Management System. *J. Phys. Conf. Ser.* **2019**, *1339*, 012096. [CrossRef]
46. Caspari-Sadeghi, S. Applying Learning Analytics in Online Environments: Measuring Learners' Engagement Unobtrusively. *Front. Educ.* **2022**, *7*, 840947. [CrossRef]
47. Brozina, C.; Knight, D.B.; Kinoshita, T.; Johri, A. Engaged to Succeed: Understanding First-Year Engineering Students' Course Engagement and Performance Through Analytics. *IEEE Access* **2019**, *7*, 163686–163699. [CrossRef]
48. Wu, W.; Chen, L.; Yang, Q. Inferring Students' Sense of Community from Their Communication Behavior in Online Courses. In Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization, Bratislava, Slovakia, 9–12 July 2017; ACM: New York, NY, USA, 2017; pp. 238–246.
49. Ahern, S.J. The Potential and Pitfalls of Learning Analytics as a Tool for Supporting Student Wellbeing. *JLTHE* **2018**, *1*, 165–172. [CrossRef]
50. Ma, J.; Han, X.; Yang, J.; Cheng, J. Examining the Necessary Condition for Engagement in an Online Learning Environment Based on Learning Analytics Approach: The Role of the Instructor. *Internet High. Educ.* **2015**, *24*, 26–34. [CrossRef]
51. Ben-Eliyahu, A.; Moore, D.; Dorph, R.; Schunn, C.D. Investigating the Multidimensionality of Engagement: Affective, Behavioral, and Cognitive Engagement across Science Activities and Contexts. *Contemp. Educ. Psychol.* **2018**, *53*, 87–105. [CrossRef]
52. Schindler, L.A.; Burkholder, G.J.; Morad, O.A.; Marsh, C. Computer-Based Technology and Student Engagement: A Critical Review of the Literature. *Int. J. Educ. Technol. High. Educ.* **2017**, *14*, 25. [CrossRef]
53. Page, M.J.; McKenzie, J.; Bossuyt, P.; Boutron, I.; Hoffmann, T.; Mulrow, C.; Shamseer, L.; Tetzlaff, J.; Akl, E.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n71. [CrossRef]
54. De Freitas, S.I.; Morgan, J.; Gibson, D. Will MOOCs Transform Learning and Teaching in Higher Education? Engagement and Course Retention in Online Learning Provision: Engagement and Course Retention in Online Learning Provision. *Br. J. Educ. Technol.* **2015**, *46*, 455–471. [CrossRef]
55. Leitner, P.; Khalil, M.; Ebner, M. Learning Analytics in Higher Education—A Literature Review. In *Learning Analytics: Fundaments, Applications, and Trends*; Peña-Ayala, A., Ed.; Studies in Systems, Decision and Control; Springer International Publishing: Cham, Switzerland, 2017; Volume 94, pp. 1–23. ISBN 978-3-319-52976-9.
56. Lotz, N.; Holden, G.; Derek, J. Social Engagement in Online Design Pedagogies. Available online: http://oro.open.ac.uk/43592/1/SocialEngagementLxD2015Lotz.pdf (accessed on 19 April 2021).
57. Lu, J.; Churchill, D. The Effect of Social Interaction on Learning Engagement in a Social Networking Environment. *Interact. Learn. Environ.* **2012**, *22*, 401–417. [CrossRef]
58. Casimiro, L.T. Cognitive Engagement in Online Intercultural Interactions: Beyond Analytics. *IJIET* **2016**, *6*, 441–447. [CrossRef]
59. Seckman, C.A. Perceived Sense of Community, Cognitive Engagement, and Learning Outcomes Among Undergraduate Nursing Students Enrolled in an Internet-Based Learning Course. *CIN Comput. Inform. Nurs.* **2014**, *32*, 482–489. [CrossRef]
60. Shukor, N.A.; Tasir, Z.; Van der Meijden, H.; Harun, J. A Predictive Model to Evaluate Students' Cognitive Engagement in Online Learning. *Procedia Soc. Behav. Sci.* **2014**, *116*, 4844–4853. [CrossRef]
61. Waheed, N. Effects of an Online Discussion Forum on Student Engagement and Learning in a First Year Undergraduate Nursing Unit an Action Research Study. In Proceedings of the Worldwide Nursing Conference, Singapore, 24–25 July 2017; pp. 18–25.

62. Ting, L.; Wan Mansor, W.F.A.; Zakaria, M.H.; Deris, F.D. Online Discussion Behavior within Collaborative Learning via E-Forum. *J. Teknol.* **2013**, *65*. [CrossRef]
63. Aderibigbe, S.A. Online Discussions as an Intervention for Strengthening Students' Engagement in General Education. *JOItmC* **2020**, *6*, 98. [CrossRef]
64. Diraditsile, K.; Samakabadi, G.G. The Effect of Social Media on Student Engagement And Collaboration: The Use of Facebook at The University of Botswana. *JoLT* **2018**, *9*, 15.
65. Fadilah, N. Student Engagement in the E-Learning Process and the Impact on Their Grades in English Language Education. 2016. Available online: http://repository.polnep.ac.id/xmlui/handle/123456789/1206 (accessed on 2 January 2023).
66. Kuchinski-Donnelly, D.; Krouse, A.M. Predictors of Emotional Engagement in Online Graduate Nursing Students. *Nurse Educ.* **2020**, *45*, 214–219. [CrossRef]
67. Pekrun, R.; Goetz, T.; Frenzel, A.C.; Barchfeld, P.; Perry, R.P. Measuring Emotions in Students' Learning and Performance: The Achievement Emotions Questionnaire (AEQ). *Contemp. Educ. Psychol.* **2011**, *36*, 36–48. [CrossRef]
68. Yu, J.; Huang, C.; Wang, X.; Tu, Y. Exploring the Relationships Among Interaction, Emotional Engagement and Learning Persistence in Online Learning Environments. In Proceedings of the 2020 International Symposium on Educational Technology (ISET), Bangkok, Thailand, 24–27 August 2020; pp. 293–297.
69. Adams, D.; Joo, M.T.H.; Sumintono, B.; Pei, O.S. Blended Learning Engagement in Higher Education Institutions: A Differential Item Functioning Analysis of Students' Backgrounds. *MJLI* **2020**, *17*, 133–158. [CrossRef]
70. Alshuaibi, M.S.I.; Alshuaibi, A.S.I.; Shamsudin, F.M.; Arshad, D.A. Use of Social Media, Student Engagement, and Academic Performance of Business Students in Malaysia. *Int. J. Educ. Manag.* **2018**, *32*, 625–640. [CrossRef]
71. Pilotti, M.; Anderson, S.; Hardy, P.; Murphy, P.; Vincent, P. Factors Related to Cognitive, Emotional, and Behavioral Engagement in the Online Asynchronous Classroom. *Int. J. Teach. Learn. High. Educ.* **2017**, *29*, 145–153.
72. Tze, V.M.C.; Daniels, L.M.; Buhr, E.; Le, L. Affective Profiles in a Massive Open Online Course and Their Relationship with Engagement. *Front. Educ.* **2017**, *2*, 65. [CrossRef]
73. Sinha, S.; Rogat, T.K.; Adams-Wiggins, K.R.; Hmelo-Silver, C.E. Collaborative Group Engagement in a Computer-Supported Inquiry Learning Environment. *Intern. J. Comput.-Support. Collab. Learn* **2015**, *10*, 273–307. [CrossRef]
74. Wilson, D.M.; Summers, L.; Wright, J. Faculty Support and Student Engagement in Undergraduate Engineering. *JRIT* **2020**, *13*, 83–101. [CrossRef]
75. Fincham, E.; Whitelock-Wainwright, A.; Kovanović, V.; Joksimović, S.; van Staalduinen, J.-P.; Gašević, D. Counting Clicks Is Not Enough: Validating a Theorized Model of Engagement in Learning Analytics. In Proceedings of the 9th International Conference on Learning Analytics & Knowledge, Tempe, AZ, USA, 4–8 March 2019; ACM: New York, NY, USA; pp. 501–510.
76. Moreno-Marcos, P.M.; Pong, T.-C.; Munoz-Merino, P.J.; Delgado Kloos, C. Analysis of the Factors Influencing Learners' Performance Prediction With Learning Analytics. *IEEE Access* **2020**, *8*, 5264–5282. [CrossRef]
77. Zhang, X.; Meng, Y.; Ordóñez de Pablos, P.; Sun, Y. Learning Analytics in Collaborative Learning Supported by Slack: From the Perspective of Engagement. *Comput. Hum. Behav.* **2019**, *92*, 625–633. [CrossRef]
78. Yang, T.-Y.; Brinton, C.G.; Joe-Wong, C.; Chiang, M. Behavior-Based Grade Prediction for MOOCs via Time Series Neural Networks. *IEEE J. Sel. Top. Signal Process.* **2017**, *11*, 716–728. [CrossRef]
79. Holmes, N. Engaging with Assessment: Increasing Student Engagement through Continuous Assessment. *Act. Learn. High. Educ.* **2018**, *19*, 23–34. [CrossRef]
80. Nguyen, Q.; Rienties, B.; Richardson, J.T.E. Learning Analytics to Uncover Inequality in Behavioural Engagement and Academic Attainment in a Distance Learning Setting. *Assess. Eval. High. Educ.* **2020**, *45*, 594–606. [CrossRef]
81. Suchitra, R.; Vaidhehi, V.V.; Easwaran Iyer, N. Survey of Learning Analytics Based on Purpose and Techniques for Improving Student Performance. *IJCA* **2015**, *111*, 22–26. [CrossRef]
82. Salomone, J.J. Student Engagement in Online Learning: Understanding and Defining the Infusion of the Social and Academic Shared Experiences. Ph.D. Thesis, University of Drexel, Philadelphia, PA, USA, 2016.
83. Banoor, R.Y.; Issack, S.M.; Frank, R. *The Use of Learning Analytics to Improve Online Learning Outcomes: A Systematic Literature Review*; Commonwealth of Learning: Burnaby, Canada, 2019; p. 11.
84. Conijn, R.; Snijders, C.; Kleingeld, A.; Matzat, U. Predicting Student Performance from LMS Data: A Comparison of 17 Blended Courses Using Moodle LMS. *IEEE Trans. Learn. Technol.* **2017**, *10*, 17–29. [CrossRef]
85. Zhao, L.; Chen, K.; Song, J.; Zhu, X.; Sun, J.; Caulfield, B.; Namee, B.M. Academic Performance Prediction Based on Multisource, Multifeature Behavioral Data. *IEEE Access* **2021**, *9*, 5453–5465. [CrossRef]
86. Henrie, C.R.; Halverson, L.R.; Graham, C.R. Measuring Student Engagement in Technology-Mediated Learning: A Review. *Comput. Educ.* **2015**, *90*, 36–53. [CrossRef]
87. Salas-Pilco, S.Z.; Yang, Y.; Zhang, Z. Student engagement in online learning in Latin American higher education during the COVID-19 pandemic: A systematic review. *Br. J. Educ. Technol.* **2022**, *53*, 593–619. [CrossRef] [PubMed]
88. Nor, N.F.M.; Hamat, A.; Embi, M.A. Patterns of Discourse in Online Interaction: Seeking Evidence of the Collaborative Learning Process. *Comput. Assist. Lang. Learn.* **2012**, *25*, 237–256. [CrossRef]
89. Kew, S.N.; Tasir, Z. Developing a learning analytics intervention in e-learning to enhance students' learning performance: A case study. *Educ. Inf. Technol.* **2022**, *27*, 7099–7134. [CrossRef]

90. Tran, T.P.; Jan, T.; Kew, S.N. Learning Analytics for Improved Course Delivery: Applications and Techniques. In Proceedings of the 6th International Conference on Digital Technology in Education, Hangzhou, China, 16–18 September 2022; pp. 100–106.
91. Pardo, A.; Bartimote, K.; Buckingham Shum, S.; Dawson, S.; Gao, J.; Gašević, D.; Leichtweis, S.; Liu, D.; Martínez-Maldonado, R.; Mirriahi, N.; et al. OnTask: Delivering data-informed, personalized learning support actions. *J. Learn. Anal.* **2018**, *5*, 235–249. [CrossRef]