A Systematic Review of Learning Analytics–Incorporated Instructional Interventions on Learning Management Systems

Zilong Pan[1], Lauren Biegley[2], Allen Taylor[3] and Hua Zheng[4]

Abstract

The learning management system (LMS) is widely used in educational settings to support teaching and learning practices. The usage log data, generated by both learners and instructors, enables the development and implementation of learning analytics (LA) interventions aimed at facilitating teaching and learning activities. To examine the current status of the development and empirical impacts of learning analytics–incorporated interventions within LMSs on improving teaching and learning practices, we conducted a systematic review that examined 27 articles published from 2012 through 2023. The outcomes of this review provided valuable insights into the design and development of learning analytics–incorporated interventions implemented on LMSs and empirical evidence of the impacts of these interventions, along with implications to inform future design and applications.

Notes for Practice

- When developing LA instructional interventions on LMSs, interventions with multifunctional features, such as detection systems with corresponding dashboards or prompting systems, can enrich the learning outcomes of the intervention. They also provide designers with more feedback and outcomes to evaluate the effectiveness.

- Given the prominence of dashboards in effective interventions, instructional designers and educators should prioritize incorporating dashboard functionalities into their learning management systems. Dashboards can provide valuable insights into student progress and engagement, facilitating timely interventions and support.

- For the future design of LA interventions on LMSs, researchers and educators can begin to leverage the large amounts of learner-generated qualitative data, in addition to the quantitative usage log data, instead of relying solely on quantitative log data. For example, on a LA dashboard, designers could also incorporate insights from qualitative data, providing teachers with better information about their students' learning status.

- While learner-focused interventions are prevalent, it is important for designers not to neglect teacher-focused interventions. Supporting educators with tools and resources that enhance their effectiveness in utilizing data and implementing interventions is critical for student success.

- Given the evolving landscape of educational technology and interventions, educators and instructional designers should engage in ongoing professional development and collaborate with researchers to stay informed about the latest trends and best practices in intervention design and implementation.

Corresponding author [1]Email: zip322@lehigh.edu Address: Lehigh University, A-107 Iacocca Hall, 111 Research Drive, Bethlehem, PA, USA, 18015. ORCID iD: https://orcid.org/0000-0001-7641-0362
[2]Email: lat307@lehigh.edu Address: Lehigh University, A-107 Iacocca Hall, 111 Research Drive, Bethlehem, PA, USA, 18015. ORCID iD: https://orcid.org/0009-0000-3285-5028
[3]Email: alt313@lehigh.edu Address: Lehigh University, Iacocca Hall, 111 Research Drive, Bethlehem, PA, USA, 18015.
[4]Email: zhenghua503@gmail.com Address: Charles R. Drew University, Office of Academic Affairs, 1731 E 120th St, Los Angeles, CA, USA, 90059.

1. Introduction

A learning management system (LMS) is a digital education platform that enables instructors and learners with an integrated objective to share, collaborate, and conduct educational practices (Prahani et al., 2022). Its affordances, such as the ability to share learning materials and engage in forum discussions, empower instructors to conduct teaching activities across diverse settings, including in-person, hybrid, and synchronous or asynchronous online learning environments (Hariri, 2014; Saroha & Mehta, 2016). The advancement of LMS platforms has expanded their capabilities beyond basic functionalities like assignment submission and access to instructional materials. These platforms now facilitate a diverse range of learning tasks, such as real-time collaboration and personalized learning experiences (Zhang & She, 2021). Moreover, LMSs also offer instructors an alternative approach to comprehend student learning patterns. As indicated by Balkaya and Akkucuk (2021), LMSs have evolved from mere platforms for delivering learning materials to powerful tools that aid instructors in monitoring student progress, thus allowing instructors to adjust their teaching accordingly.

An important reason why the LMS enables instructors to effectively monitor student learning status is its ability to track and document all student activities as back-end log data (Saroha & Mehta, 2016). The collected log data could mirror learner behaviours throughout the whole learning trajectory, thus revealing insights about learning processes (Chanifah et al., 2021). In fact, extensive research has examined LMS usage log data from a learning analytics (LA) perspective due to its fertile data sources (Mwalumbwe & Mtebe, 2017; Poon et al., 2017). By applying LA techniques like clustering or sequential analysis to the log data from LMSs, researchers have gained the ability to delve deeper into learner behavioural patterns. This approach yields objective, in-depth, and highly granular outcomes (Lang et al., 2017). For instance, a strand of studies collected various types of LMS usage logs to conduct clustering analysis to categorize learners based on behavioural patterns (Su et al., 2021; Wintoro & Pratama, 2022) or develop prediction models (Daimari et al., 2021; Santoso, 2020). Moreover, Tan and Samavedham (2022) examined learner sequential behavioural patterns on LMSs and were able to identify study tactics associated with learning performance. In addition to quantitative log data, studies have examined the patterns of qualitative log data collected from learning management systems, such as student posts in discussion forums and assessment writings (Afify, 2019; Wong et al., 2021). These studies were conducted to reveal, depict, or represent the hidden learning patterns generated from refined mining techniques that work on usage log data. While the outcomes have significantly enriched our understanding of learning behaviours, as indicated by these studies, the goal of utilizing LMS usage log data and LA techniques to understand usage patterns is to enable researchers and educators to design and implement interventions that better meet student needs (Ismail et al., 2021).

Researchers have taken the initiative to employ LA techniques on LMSs for designing and implementing instructional interventions (Khiat & Vogel, 2022; Laeeq & Memon, 2021). LA-incorporated interventions refer to instructional methods that utilize tools or systems incorporating learning analytics techniques based on processing student-generated usage data to facilitate educational practices (Knobbout & Van Der Stappen, 2020; Larrabee Sønderlund et al., 2019). Previous studies that developed and evaluated LA-incorporated interventions presented a broad range of intervention types, such as real-time feedback systems (Zheng et al., 2022), detection systems (Atif et al., 2020), and personalized recommendation systems (Karaoglan Yilmaz & Yilmaz, 2022), for facilitating teaching or learning practices. More specifically, one common example of LA-incorporated intervention is the learning analytics dashboard (LAD; Goomas & Czupryn, 2021), which enables researchers to monitor student learning behaviour, performance, and skills (e.g., self-regulated learning) to identify subsequent instructional interventions (Tabuenca et al., 2015). Other types of LA-incorporated interventions on LMSs include prompting or detecting systems (Liu et al., 2015). These empirical studies and their findings provide innovative insights and facilitate further research examining the role of LA in designing and implementing LMS-based interventions. Consequently, an increasing number of researchers are expected to incorporate LA techniques in the design of educational interventions on LMSs, aiming to enhance educational practices. Thus, it is crucial for researchers to gain a comprehensive understanding of the current state of empirical studies concerning LA-incorporated LMS-related interventions. By examining the experiences and challenges presented by pioneering studies, researchers can better prepare for the future development and implementation of LA-incorporated LMS interventions. Therefore, the objective of this study is to conduct a systematic review of instructional interventions that incorporate learning analytics on learning management systems. The outcomes of this review aim to provide future researchers with a comprehensive and in-depth analysis of empirical studies that have integrated LA techniques in LMS interventions. More specifically, this review focuses on addressing two main research questions:

RQ1. What are the key design characteristics exhibited by current LA-incorporated instructional interventions on LMSs?

To answer this first question, this study investigates the characteristics of intervention designs for LMSs, including LMS type, intervention functionality, data used, theoretical frameworks utilized in design, implementation process, and outcomes of usability testing.

RQ2. What are the empirical impacts and implications of current LA-incorporated instructional interventions on LMSs?

To address the second question, this review examines the effects of incorporating LA interventions in LMSs on learners' academic, psychological, and behavioural outcomes. It also explores implications for future intervention design and practices, as well as challenges in the design and implementation processes.

2. Related Work

The design and implementation of LA-incorporated instructional interventions requires accounting for instructional conditions in order to utilize the practice implications uncovered by the analysis (Gašević et al., 2017). Moreover, LA-incorporated interventions, especially by involving usage log data collected from the LMS, provides valuable information to the instructors, learners, and education administrators about in-situ learning progress and the overall learning trajectory. Researchers have conducted literature reviews about educational and LA interventions installed on different platforms and LMSs to evaluate the effects and educational outcomes (see Appendix A).

For example, Mangaroska and Giannakos (2019) focused their systematic literature reviews on empirical studies that utilized LA techniques to enhance the design of learning activities. More specifically, they examined what LA measures inform learning design and how the LA are used. They concluded that the studies that applied LA-incorporated interventions thus far have been heavily empirical and require stronger theoretical underpinnings/frameworks to advance the field. In another literature review, Costa et al. (2020) focused on the relationship between learning analytics and ontologies and how they have been applied concurrently. Additionally, Larrabee Sønderlund et al. (2019) conducted a systematic review focused on the efficacy of learning analytics interventions in predicting and improving student retention and academic success while addressing the challenges of high dropout rates, tracing the evolution of learning analytics models, and advocating for further empirical research to substantiate their effectiveness. This review discussed LA in higher education more broadly, not in the context of LMSs specifically. In sum, although the above reviews provided empirical evidence to prove the effectiveness of LA-incorporated interventions and practical implications about designing future interventions, these reviews did not specifically focus on the interventions within the LMS but instead focused on general learning contexts.

Altinpulluk and Kesim (2021) and Prahani et al. (2022) conducted systematic literature reviews examining the trends in educational interventions implemented on LMSs. They centred their review on descriptive data surrounding LMS usage and did not focus on how LA was utilized in enhancing LMS interventions. Similarly, Alhazmi et al. (2021) examined the specific features of LMSs that determine the success or failure of LMS adoption by teachers and students. Their literature review also included expert analysis of the LMS success and failure aspects, revealing seven features of success and eight of failure. The findings provide useful information to practitioners; however, their review mainly investigated LMS tools and usability of the intervention, and the specific technique of LA was not emphasized.

In addition, Araka et al. (2020) conducted a review that examined the trends and advances in using LA on LMSs to measure self-regulated learning (SRL); however, LA techniques were mainly applied as a tool to monitor the learning activities instead of being used to design for an intervention. They concluded that LA is underutilized to measure SRL and that traditional in-person measures are being used instead in the LMS. The review by Xin et al. (2021) explored LMSs by comparing various platforms in terms of features and usability while highlighting common issues like security concerns and the absence of parental roles, and briefly mentioning a proposed system called Learn-On-Line (LOL). However, this review did not focus on LA's role in designing or implementing interventions. Furthermore, Lima and Isotani (2021) investigated the use of Google Classroom (GC) as an LMS during the COVID-19 pandemic, with a primary focus on the experiences of teachers and students, assessing effectiveness, challenges, and solutions. However, it only examined GC and does not provide an in-depth examination of instructional interventions within the LMS. Nor did it detail how learning analytics could enhance the effectiveness of these interventions or address broader design and impact questions in comparison to LMS interventions in general.

The meta-analysis by García-Murillo et al. (2020) focused on the level of technological satisfaction among users of Moodle in higher education institutions (HEIs), finding high levels of overall satisfaction with higher levels among students than lecturers. This review focused solely on Moodle and specifically technological satisfaction, providing limited insights into the educational benefits of Moodle or LMSs generally. It also did not address LA-incorporated instructional interventions. The review provided in the Miah et al. (2020) editorial note discusses the broader context of big data technologies in higher education and their potential to improve LMS and other relevant processes and practices. However, it did not delve deeply into specific LA-supported LMS interventions nor does it provide insights into the characteristics or impacts of LA interventions. Additionally, the review by Setiadi et al. (2021) provided a comprehensive overview of the state of online learning in Indonesia, covering asynchronous and synchronous approaches, commonly used platforms, teaching strategies, and the role of social media, with an emphasis on the prevalence of blended learning and a focus on the region's trends. It does not explicitly frame specific research questions but rather summarizes findings in these areas and offers a region-specific exploration of online learning trends.

Although prior reviews have been conducted on 1) LA-incorporated interventions or 2) instructional interventions implemented on LMSs, no reviews have examined specifically how LA-incorporated instructional interventions were

designed and implemented on LMSs, and what the empirical effects were. This review intends to examine empirical studies that incorporate LA in instructional interventions on LMSs.

3. Methods

This review intends to examine the implementation of LA-incorporated interventions on LMSs and their empirical effects on enhancing teaching and learning activities. Conducting a literature review allows researchers to identify, evaluate, and interpret relevant research findings (Costa et al., 2020). The outcome of this review presents the current application status of different LA-incorporated LMS interventions and provides further implications for future design and implementation.

3.1. Search protocol

The search process followed the four-step framework proposed by Moher et al. (2009): 1) identify, 2) screening, 3) eligibility, and 4) included.

3.1.1. Identify

To start the search process, targeted databases were first identified by examining those used in previous literature reviews about instructional interventions on LMSs or LA-incorporated instructional interventions. As a result, seven databases were identified: 1) EBSCO's Academic Search Ultimate, 2) ACM Digital Library, 3) APA PsycInfo, 4) Education Source, 5) ERIC, 6) IEEE (IEEE Transactions on Learning Technologies & IEEE Transactions on Education), and 7) Web of Science. The keywords used for searching the databases were generated based on the research questions as well as previous literature reviews about LA interventions and empirical studies about LMSs. More specifically, the search terms consisted of the four components laid out in Table 1.

Table 1. Boolean Search Terms

Included databases: EBSCO's Academic Search Ultimate, ACM Digital Library, APA PsycInfo, Education Source, ERIC, IEEE, Web of Science

Part 1 Intervention	AND	Part 2 Platform	AND	Part 3 Method/Data	AND	Part 4 User/Modifier
"intervention" OR "strategy" OR "system" OR "facilitat*" OR "feedback" OR "assist*" OR "support" OR "adapt*" OR "treatment" OR "evaluation" OR "remediation" OR "dashboard" OR "detect*" OR "visuliz*"		"*learn* management system" OR "*course* management system" OR "*learn* platform" OR "*learn* system" OR "instruction* system" OR "Virtual Learning Environment"		"learning analytics" OR "educational analytics" OR "log data" OR "data mining"		"student" OR "learner" OR "instructor" OR "teacher" OR "faculty"

Note. Given the varying requirements of different databases regarding search string syntax, the syntax provided in this Boolean table, such as quotes or asterisks, may differ.

A. To investigate the terms associated with the intervention component, researchers conducted a search specifically centred around review articles related to learning analytics interventions and found that these literature reviews employed the term "learning analytics intervention" (e.g., Knobbout & Van Der Stappen, 2020; Larrabee Sønderlund et al., 2019). After examining these reviews, researchers identified the terminology employed by the studies to signify LA interventions when they did not explicitly reference the term as "intervention."

B. For the terms about the platform component, researchers discovered that whenever a specific system's name was mentioned, it was often referred to as a "learning management system" (LMS). For articles that didn't explicitly mention "LMS" but did reference specific types such as "Moodle," those authors opted to use interchangeable terms such as "course management system" or "learning platform. Additionally, due to the abundance of LMS options in the field, instead of listing all the LMS names such as "Canvas" or "Blackboard," researchers employed a set of interchangeable terms for LMSs based on previous studies (e.g., Davies et al., 2017; Jayashanka et al., 2022; Willans et al., 2019).

C. For search terms related to data and method components, researchers included "learning analytics," "educational analytics," "log data," and "data mining" as these are critical themes in learning analytics studies.

D. As to the user and modifier component, considering that the contexts of the review was instructional interventions, researchers included following terms: "student," "learner," "instructor," "teacher," and "faculty."

In sum, a total of 1519 articles were retrieved from all the databases via Boolean search in the Identify step. The article number returned from each database is presented in PRISMA in Figure 1.

3.1.2. Screening and Eligibility

For the steps of screening and eligibility, inclusion and exclusion criteria were developed to aid the process (see Table 2).

Table 2. Inclusion and Exclusion Criteria

Inclusion	Exclusion
• Empirical studies that involved the LA-incorporated intervention on the LMS • Empirical studies that reported the outcomes LA-incorporated intervention on the LMS • Peer-reviewed articles • Articles published from 2012–2023 • Published in English	• Literature reviews and meta-analysis without empirical findings • Conceptual and design papers without empirical findings • Books, book chapters, or non-peer reviewed articles • Published before 2012 • Not published in English

In this step, researchers imported all the retrieved articles ($n = 1519$) into Rayyan, a web-based platform for systematic reviews, researchers can work collaboratively by assigning each article into "Include," "Exclude," or "Maybe" categories. Within Rayyan, duplicated items were removed, which led to 1097 unique articles. Then, by examining the titles, keywords, and abstracts from each study, books, book chapters, non-peer reviewed articles, research published in languages other than English, research published before 2012, literature reviews, meta-analysis, conceptual papers, and design papers without empirical findings were identified and subsequently removed by researchers, which left 791 articles for full-text review. Four reviewers were divided into two groups, with each group assigned half of the articles.

The researchers devised a detailed schedule for the review process by assigning a specific number of papers to review each day. They maintained frequent communication to address any potential questions. Reviewers within each group independently assessed the articles against predefined inclusion and exclusion criteria. In this process, 149 articles were assigned to the "Maybe" category, 25 articles to the "Include" category, and 600 articles to the "Exclude" category. In addition, there were 17 conflicts where one reviewer suggested "Exclude" while the other proposed "Include." A third reviewer from the opposite group independently assessed the "Maybe" and "Conflict" articles and resolved any remaining differences through discussion with the two reviewers in the group. Subsequently, all four reviewers thoroughly examined all included articles and engaged in discussions to reach a consensus. As a result, the review of the articles against the inclusion and exclusion criteria yielded 27 articles for analysis in this study.

3.1.3. Included

A total of 27 articles were selected for further detailed analysis. Figure 1 presents the modified PRISMA flow diagram that reflects the four-step article collecting and inclusion process of this study.
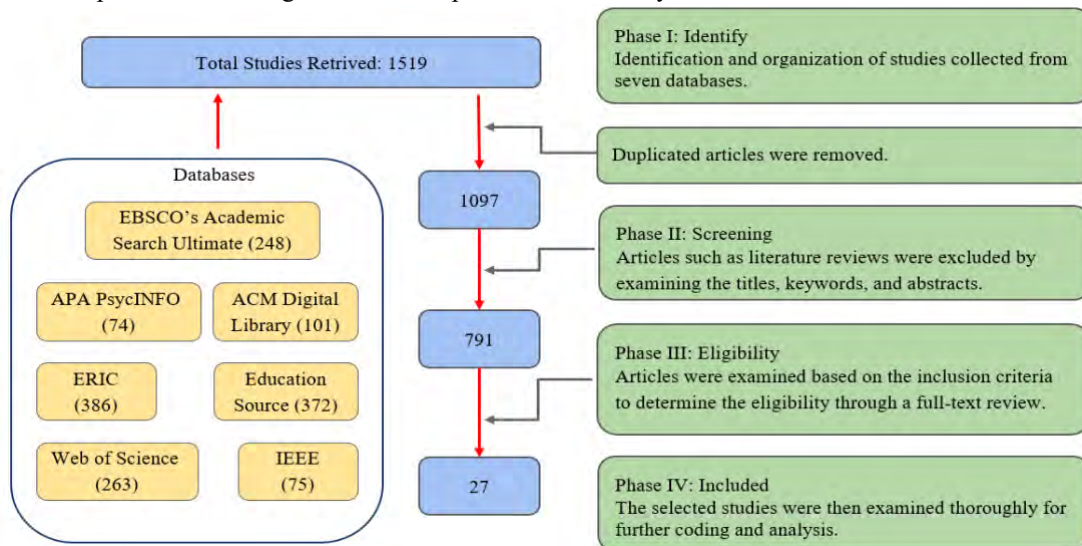

Figure 1. PRISMA flow applied in the study.

3.2. Article Coding

Based on their research questions, researchers discussed potential categories related to each of the questions and created a spreadsheet with information extracted from the final 27 articles. Example categories include LMS type, intervention functions, or the types of log data used in intervention development (see Appendix B). The inductive coding method was applied in categorizing and analyzing the collected studies (Miles et al., 2013). More specifically, two researchers coded the articles independently to generate codes under each category and discussed regularly to compare and triangulate in order to resolve any emerging disagreements. The codes were then reviewed by a third researcher as well. Throughout the process of examining the articles, researchers also adjusted or added categories as needed. Once an agreement was reached to add a new category, researchers would then input the information from the articles related to that category. To ensure trustworthiness, the coding process was performed iteratively using the constant comparative method (Creswell & Creswell, 2017). The researchers reviewed, revised, and refined the codes and themes throughout the process until 100% inter-rater agreement was achieved.

4. Results

The 27 included studies were published between 2012–2023, with the majority (n = 21) published between 2019–2023. These 27 studies were published in 23 different journals, one article per journal, with only *Computers & Education*, *Computers in Human Behaviour*, and *Interactive Learning Environments* publishing two each. The number of authors per article ranged from one to eight with a median authorship of three. The 27 articles represent the work of 82 researchers representing 34 postsecondary institutions from 20 different countries on five continents (Africa, Asia, Australia, Europe, and North America).

4.1. The Key Design Characteristics of Current LA-Incorporated Instructional Interventions on LMSs

The key characteristics of intervention designs encompass the detailed information about intervention functionality, the data employed in interventions, the theoretical frameworks that informed their design, the length of each implementation as well as the outcomes from usability testing.

4.1.1. Intervention Functionality

The studies are organized by their LMS intervention functionality that can be divided into the following categories: dashboards, detecting systems, standalone programs for learning support, standalone programs for facilitation, and chatbots. A standalone program refers to a system that was uniquely developed by researchers for a specific educational intervention within the study's context. Chatbots were coded as learning analytics interventions owing to their ability to capture and process learner usage data. A noteworthy finding is that except for the unifunctional interventions (n = 19), which provide one feature such as prompting systems, there are eight multifunctional interventions (n = 8) such as detecting systems combined with prompts or detecting system-enhanced dashboards (see Figure 2).
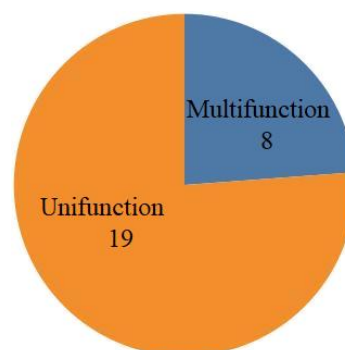

Figure 2. Proportion of unifunction and multifunction interventions.

4.1.1.1. Unifunction LMS Intervention

For the interventions that focused on a single function, eight of the interventions related to dashboards (42%), followed by three chatbots interventions (16%), three standalone programs for learning support (16%), and three standalone programs for facilitating learning activities (16%), as well as two detecting systems (11%; see Figure 3). Dashboards were the most common intervention type. For instance, Abazi-Bexheti et al. (2018) developed a dashboard system incorporated into the LMS to support HEI administrators, academic leaders, or deans. Utilizing users' demographic information, including instructor's name or ethnicity, this dashboard allows users to have a systematic view of the course list taught by faculties

across different departments. Moreover, since the dashboard is linked with real-time behavioural log data generated by users on LMSs, such as course posted date, it provides higher education coordinators, deans, and directors with processed data in the form of reporting diagrams to assist them in gaining a deeper understanding of how the course works.

In another study, instead of focusing on administrative or leadership uses of the dashboard, Al-Shaikhli et al. (2022) developed and validated a student-facing dashboard system called Visualised Weekly Learning Outcomes (VWLO), which collected and processed student-generated usage log data, allowing them to navigate the dashboard and view content by clicking on expandable hyperlinks in the competency tree. Clicking on a tree node displayed its description on the right-hand side of the dashboard. This enhancement fostered learners' cognitive absorption, which is a deeper cognitive engagement in learning activities where users become fully engrossed, losing track of time and their surroundings, during learning activities on the LMS.
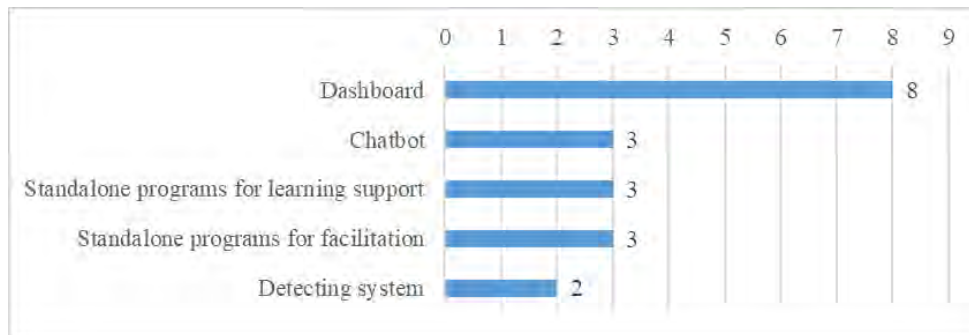

Figure 3. Types of functionalities for unifunctional interventions.

Three studies incorporated chatbots as an LMS intervention; for instance, Laeeq and Memon (2021) developed a virtual assistant that students can interact with either via text or voice. The system processes students' real-time requests, either in text or audio, and conducts searches to fulfill their needs. Internal quizzes address LMS-related requests, while external searches provide the top five resources from predetermined websites. These services enable students to make various requests without using a mouse or keyboard. Other than a chatbot, researchers also developed and installed instructional plugins for students. Chen (2018) incorporated a gamified standalone program on the LMS to support students in reviewing knowledge. One of the plugins, called "Jeopardy Exam Review," consists of six categories of topics with various difficulty levels. By collecting students' real-time answers, the plugin provides feedback either in a textual explanation or an instructional video.

In another study, researchers created a standalone program on Moodle to support pre-service teachers' Regulation of Cognition (RC) skills (Gutman, 2017). The program allowed the researcher to collect usage log data to identify pre-service teachers' help-seeking patterns during the four phases of the RC process. After comparing the frequency of help-seeking patterns for each phase between two groups that performed different RC strategies, the outcomes showed significant differences in the planning and evaluating stages, which yielded practical implications for improving metacognitive instructional methods in technological learning environments. Finally, two studies developed and implemented detecting systems on LMSs. For instance, Atif et al. (2020) developed an early alarm system to monitor student engagement in the LMS using a series of indicators such as assessment submissions or forum interactions. Based on an algorithm that included all indicators, instructors were able to set a threshold that would show which students were below the threshold, meaning those at-risk and needing further support. In sum, the above unifunction LMS interventions presented diverse approaches for collecting student usage data on the LMS to support teaching and learning practices.

4.1.1.2. Multifunction LMS Interventions

Of the eight studies that developed LA-incorporated interventions with multiple functions, all involved the functionality of the dashboard, whereas another five incorporated prompting features. More specifically, Afzaal et al. (2021) developed a data-driven feedback and intelligent action recommendation (DFIAR) system. Student usage log data on the LMS is collected and processed in real-time to provide feedback on the dashboard and prompt students with action recommendations. The dashboard fits the collected log data in a machine learning model that predicts performance probability for whether a student would be a low or high achiever for each quiz and assignment. On the dashboard, students were able to see where they were lacking and how much progress was needed via the graphs based on prediction results. A recommendation box with a list of essential items and their priority levels would be shown on the dashboard to guide students in enhancing their performance. In another study, Tabuenca et al. (2015) applied LearnTracker, a system that detects student usage behaviours and provides learners with notifications to support their self-regulated learning activities. The system monitors individual learner usage patterns and provides comparative data regarding the time spent between the student and their peers in the same classroom,

as well as the time initially estimated by the teacher. The prompting system notifies students in three patterns: 1) morning for planning, 2) evening for summarizing and reflecting, and 3) randomly throughout the day. The contents in the prompts include generic tips for self-regulated learning — such as suggesting that students disconnect instant messaging while studying — and outcomes generated from personal and group usage patterns, which includes indicating a specific chapter that the learner or the whole class spent relatively fewer hours studying. In addition, Şahin & Yurdugül (2019) incorporated three functionalities — detecting system, dashboard, and prompting system — in their intervention. The detection system categorizes learners into six levels based on LMS usage and assessment performance. The dashboard shows red, yellow, and green signals for each task, with red indicating deficiencies and prompting topic contingent feedback. It also displays individual and comparative interaction performance across various categories such as learning content (L-C) and learning assessment (L-A). Additionally, the prompting system sends SMS and email notifications to motivate students who have not logged in for a while.

Given their prevalence in the education sector to support teachers and enhance learning (Liu et al., 2021; Schwendimann et al., 2017), it is unsurprising that dashboarding represents the largest area of functionality and is almost equally present in both unifunction and multifunction systems in LMSs. It is notable that both prompting (multifunction) and chatbot (unifunction) are represented in only one category, perhaps indicating that prompting is only beneficial when associated with another function to improve teaching and learning while chatbots, having evolved into a more robust technological offering over time, can be used by themselves. In summary, both unifunction and multifunction interventions presented a wide range of features that provide a versatile learning support system (see Figure 4).
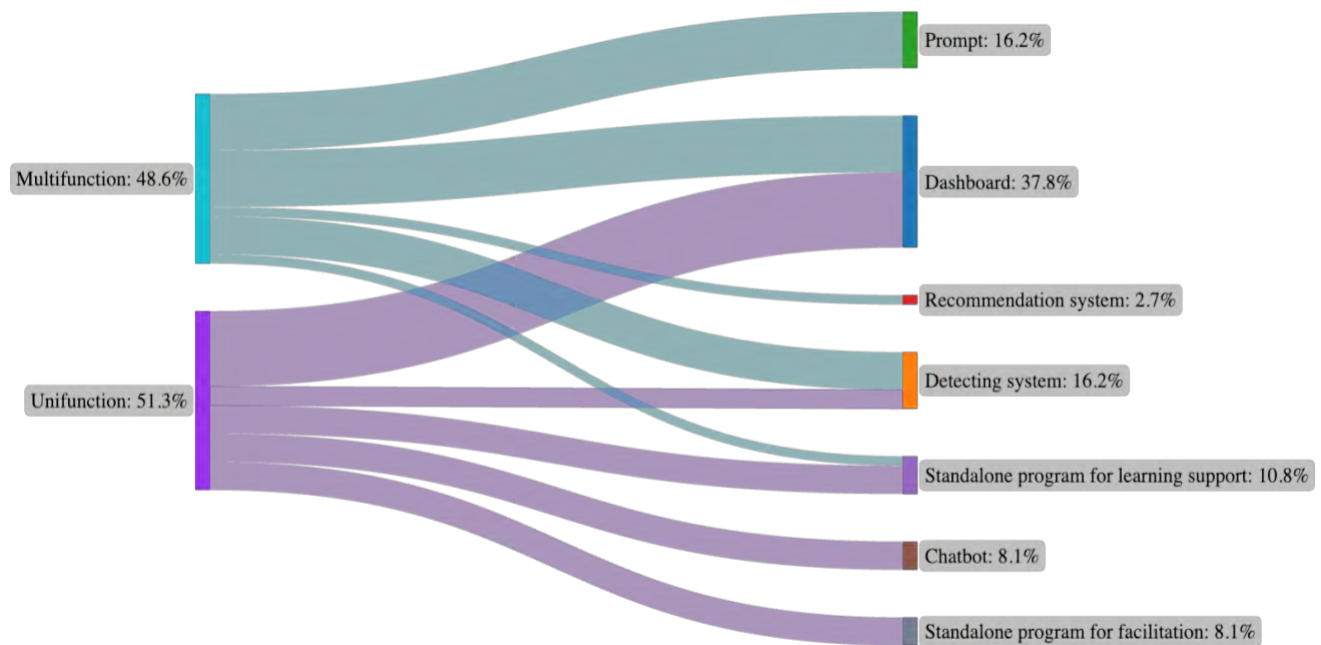

Figure 4. Distribution of functionalities.

4.1.2. The Uses of Data in Intervention Design

4.1.2.1. Quantitative Data

Out of the 27 studies reviewed, 19 discussed the use of quantitative data in the design of their respective interventions. The most commonly used quantitative data ($n = 14$) was trace data from the LMS. Şahin and Yurdugül (2019) employed a variety of trace data in their Intelligent Intervention System (In2S). Metrics including time spent on content, assessment, and discussions, the number of completed assessments, and messages exchanged were used in their instructional, and motivational interventions. In another study utilizing a prompting and dashboard intervention (Karaoglan Yilmaz, 2022a), researchers used LMS log data related to frequency of students' weekly LMS usage and quiz participation in an effort to improve student academic self-efficacy and problem-solving skills. Of the 14 studies employing trace data, seven used the data in the design of their dashboard. Khiat and Vogel (2022) used trace data such as time spent on learning resources and quiz data to display a student's progress in SRL on the learning analytics dashboard (LAD) in their ePSRL Management System while Aljohani et al. (2019) used trace data specified by individual instructors in the development of their Analyze My Blackboard Activities (AMBA) tool designed to empower students with a student-centred LMS engagement LAD.

Karaoglan Yilmaz (2022a) used log and trace data such as the number of views of the course videos and the frequency of interaction in the forum environment in a LAD designed to improve student metacognitive awareness and academic achievement in an online learning environment.

In addition to incorporating quantitative data into the intervention, researchers also utilized the data during its development. Khiat and Vogel (2022) were one of three studies that used an initial assessment or survey data in developing their intervention. Specifically, they used a 33-item self-regulated learning diagnostic survey to develop the personalized study content in ePSRL for each student. Afzaal et al. (2021) also used a combination of LMS trace data (quiz scores, assignment attempts, and number of clicks over a 30-day time period) and an initial student survey about previous programming experiences and motivation in the construction of their machine learning model that supports their DFIAR dashboard intervention.

Finally, the remaining studies used quantitative data unique to the specific intervention under investigation. In their study to explore the effects of time tracking on SRL, Tabuenca et al. (2015) used the duration of time spent on course activities from their LearnTracker system to send timely notification prompts to students, informing them about their peers' study duration, aiming to improve their time management behaviour. Asha and Chellappan (2011) transformed voice samples into mathematical frequencies (Mel-Frequency Cepstral Coefficients) to train their voice activated e-learning system chatbot to enrich the LMS experience for visually impaired students.

4.1.2.2. Qualitative Data

Qualitative data, such as interview transcripts, was used to assist researchers in the development of their interventions. For instance, Liu et al. (2015) developed a detecting system — MEAP+ — following a design-based narrative. To better understand how and when it would be useful for stakeholders to monitor and contact students, researchers conducted a series of interviews including nine academic staff and three student support staff. By analyzing the results, researchers were able to conceptualize any additional information that staff would need, as well as the interfaces through which students could be identified and contacted. In another study, Atif et al. (2020) also collected feedback from target users following an exploratory sequential mixed-method model. The alert system was developed to assist teachers in identifying and providing in-time support to at-risk students. For the qualitative phase, nine-unit convenors were interviewed since their main responsibility was to oversee the academic activities and performance of the enrolled students in a unit. Based on the analysis of the interview transcripts, researchers were able to code several themes related to the participant feedback regarding the features, such as contacting at-risk students or identifying engagement levels.

Overall, the outcomes from all these studies indicated the values of collecting and utilizing quantitative and qualitative data in the development of interventions on LMSs.

4.1.3. The Application of Theoretical Framework in Intervention Design

In 17 of the studies, the uses of theoretical frameworks in designing interventions were examined. Of the studies that provided a theoretical framework, over one-third were for self-regulated learning (SRL) theory ($n = 6$).

For example, Khiat and Vogel (2022) applied SRL in designing their ePSRL LMS intervention. One of the features was the Personalized Study Plan, presented in the form of a calendar. Learners were able to create, plan, and organize learning activities related to course objectives based on correspondent timelines. The design of this feature was informed by the forethought and planning phase in SRL, in which learners were expected to set goals and develop plans to accomplish these goals. ePSRL also provided learners with a dashboard that demonstrates a holistic view of their progress and growth in different domains. This feature was designed to align with the reflection phase in SRL where learners conduct self-evaluations of outcomes to goals. Saadati et al. (2023) integrated SRL into the blockchain-based LMS design, employing the three phases of planning, action, and reflection. Their approach aimed to enhance student self-regulation skills in planning, monitoring, scaffolding, and reflection, thereby improving learning outcomes. In addition, Şahin and Yurdugül (2019) also used SRL as their theoretical framework but only addressed it in their discussion section. There was limited justification for implementing this framework, nor any explanation of how the theory was applied in designing the research.

Al-Shaikhli et al. (2022) applied goal theory, which connects goal setting to task performance, as their theoretical framework. In goal theory, the existence of a goal and the characteristics of the goal affect the level of engagement for the learner. Their research objective was to improve student perceptions of the LMS system to increase student use. They created Visualised Weekly Learning Outcomes (VWLO) to utilize the LMS as an organizing tool. The week-by-week learning outcomes provided by the VWLO functioned as goals for the students. Given that engagement was part of the performance measures, researchers also focused on the perceived utility of VWLO to students since it impacts learner engagement. Additionally, Chung et al. (2022) used the theory of planned behaviour in their research designed to understand patterns of student engagement with an online mindfulness program within the university LMS. This theory emphasizes a learner's behavioural intent and attitude towards the learning as critical factors in determining success. The theory allowed researchers to identify the barriers and motivations for student use of the online mindfulness program. In addition, Gutman (2017) used the IMPROVE framework with the addition of dual teacher and learner perspectives in her research. The IMPROVE framework is a metacognitive learning method that includes a series of instructional strategies: introducing new concepts;

metacognitive questioning; practising; reviewing; obtaining mastery; verification; and enrichment. The model was applied to an online classroom lesson design task for pre-service teachers. The participants responded to each section of the IMPROVE model from both the teacher's and the learner's perspectives. For example, in "practice metacognitive questioning" the participant must develop questions to ask learners within the classroom lesson and then answer those questions as the learner. The participant then moves to "review the expected mistakes and cognitive misconceptions of the learners." While in the review stage, participants formulate multiple responses to the questions and evaluate why some are correct and others incorrect, determining the root of misconceptions within the lesson.

Moreover, it is worth noting that some studies applied more than one theoretical framework in guiding their intervention design. For example, Chen (2018) integrated self-determination theory and gamified learning. The research aim was to evaluate the effectiveness of existing low-cost gamified learning systems and determine perceived learner competence and learning motivation/outcomes. According to gamified learning theory, game elements such as feedback, challenge, rewards, and objectives may improve academic outcomes. The researcher used simple HTML-based games and wikis from within the Blackboard LMS to examine student attitudes (perceived usefulness) towards gamified learning. The researcher used "Concept Review Bingo" and "Jeopardy Exam Review" games in wiki format for integration within the LMS. These games incorporated gamified learning elements of points, leaderboards, progression, status, levels, and rewards to motivate students. Klein et al. (2019) also provided two theoretical frameworks: constructivism and data-frame theory of sensemaking. Data-frame theory explains sensemaking as a process of framing and reframing data in explanatory structures. The researchers used these frameworks to design scenario-based questions, modelled on current and future LAD interventions. Sensemaking is a metacognitive process that students undergo when confronted with new information. Therefore, the future changes proposed in the researcher scenarios would activate student sensemaking.

4.1.4. The Intervention Design Process

For the studies that indicated the number of design iterations ($n = 19$), most researchers went through a three-to-four phase design process ($n = 6$). For instance, in the study by Klein et al. (2019), there were four phases. They conducted an instrumental case study on student sensemaking of learning analytics dashboards (LADs). In phase one, they asked students questions about how they interpret specific features and qualities of LADs. Questions were based on different scenarios related to the colours, graphics and data visualizations used by their school's LAD. They asked students to provide feedback on what LAD components they find helpful and how they would respond to various LAD-based interventions. There was specific focus on how students would interpret predictive suggestions from the LAD based on their individual student data. In phases two and three, researchers used their scenario questions and interviews to analyze how undergraduate students make sense of LADs. The final phase was the analysis of the results. The specific LAD used by the researchers was not named; however, they did describe it as an "open-source LAD" used by their university.

The Ferdiánová (2017) study had two phases in designing their LMS intervention for learning Monge projections in geometry. In phase one, researchers gathered data on Monge projections and student opinions through an academic task and an anonymous questionnaire. They created Monge projection example tasks with construction descriptions, drawings, paper models, and anaglyph versions. These materials were accessible through the LMS using GeoGebra. Students could construct digital models and receive feedback from the teacher. Researchers analyzed the student performance data and questionnaire feedback. Asha and Chellappan (2011) followed a six-phase design process for their voice-activated E-learning system for the visually impaired. They collected speech samples and voice models in the first phase, generated feature vectors in the second phase, trained and tested unique voice models in the third and fourth phases, performed user verification and word recognition in the fifth phase, and evaluated the system in the sixth phase. The system recorded user information, created user-specific thresholds, allowed enrollment in subjects, verified user identity, and enabled audio speed control. Ambiguous silence was addressed through keyboard controls. Afzaal et al. (2021) utilized a nine-phase process to develop an intelligent machine learning system for providing feedback to students. They collected and preprocessed student data from the LMS, eliminated irrelevant information, and linked activities to students. The data was segmented and underwent feature selection and data resampling techniques. Model building and evaluation measures were applied, leading to the selection of the best predictive model through cross-validation. An automatic feedback system and a student dashboard were designed. A structured approach allowed for early issue identification and timely revisions. Overall, the findings suggest that a multi-phase approach to intervention design is an effective strategy for enhancing student learning experiences in the LMS.

4.1.5. Usability Testing

Eight of the articles explicitly noted researcher engagement in usability testing as a part of their studies. Generally, such testing was conducted either using a specialized instrument or through interviews or questionnaires with participants. For example, Tabuenca et al. (2015) used the System Usability Scale, a recognized tool for mobile apps, to affirm the usability of their LearnTracker LMS companion mobile app. Their app achieved a score of 76.8, indicating above-average usability. In another study, Laeeq and Memon (2021) leveraged the ISO/IEC 9126-4 usability standards as the basis for their six task scenarios to test their Scavenge chatbot. Their experimental design revealed that the group using Scavenge boasted an average task effectiveness score of 80.8% and completed 0.328 goals per minute. In contrast, the control group averaged

64.8% and accomplished 0.158 goals per minute. In contrast, Liu et al. (2015) conducted usability testing interviews with staff members and used their feedback — which included the addition of assessment and gradebook indicators and less abstraction of student engagement data — to refine the prototypes of their MEAP+ detecting system. Similarly, Goomas and Czupryn (2021) used a questionnaire to assess the usability of their master LMS template designed for their adult basic education course. From specialized usability testing instruments to participant interviews and questionnaires, various methods are implemented across studies to validate and refine the usability of interventions in LMSs. Usability testing has been shown to be a key tool for learning analytics systems designers, ensuring the intervention itself is adapted to local conditions and provides insight into future design and implementation (Ahn et al., 2019). Therefore, the broad application and versatility of usability testing across these studies exemplifies its fundamental role in optimizing the design and function of LA systems.

4.2. The Empirical Impacts and Implications of Current LA-Incorporated Instructional Interventions

This section will present the empirical impacts of LA-incorporated interventions within the LMS from academic, psychological, and behavioural perspectives. Furthermore, it will demonstrate the implications for future intervention design and practices, as well as the challenges raised in designing and implementing processes.

4.2.1. Academic Outcomes

For the articles that provided empirical evidence about academic outcomes ($n = 12$), the findings yielded mixed results. For instance, Chen (2018) incorporated interventions on Blackboard with gamified features and the results showed that students in the experimental group had significantly higher scores than the control group on their performance in a biostatistics course. This finding was consistent with previous studies about game-based learning. i.e., that it was effective in enhancing student academic achievement. Whereas in a study that applied an SRL-enhanced intervention — ePSRL (Khiat & Vogel, 2022) — the results from Mann–Whitney U test showed that although the completion rate for students who engaged with the intervention was significantly higher than those who did not, no significant difference on assessment results was revealed between the two groups. In another study, researchers implemented an intervention to support geometry learning called Geogebra (Ferdiánová, 2017). Students who used Geogebra were given three tasks to measure their learning growth; the tasks, with different difficulty levels, ranged from finding the steps of a plane to affinity in construction. The outcomes showed that, compared to students who did not engage with Geogebra, these students saw an increase of 3.82% on their geometry achievements. Besides, after implementing a prompting system on the LMS to support student self-regulated learning behaviours, Fung et al. (2019) found that although the repeated ANOVA showed that participants developed significantly more study plans and spent more time studying, their understanding of topics became significantly lower as time went by. This outcome might be because as students' SRL skills grew, they would be willing to invest more time in studying topics that they understood less. In conclusion, the empirical evidence from the articles reviewed presented mixed findings about the impact on academic outcomes, suggesting that the effectiveness of interventions may vary depending on the specific context and intervention design.

4.2.2. Psychological Outcomes

Of the articles that provided psychological outcome data ($n = 21$), motivation and engagement were two psychological measures commonly investigated to evaluate interventions. LMS features that were perceived as useful, efficient, and/or effective were more engaging and motivating for users. Three studies focused specifically on user satisfaction, perceived usefulness, efficiency, and effectiveness. Laeeq and Memon (2021) reported a 78.3% satisfaction rating among their experimental group of users of their Scavenge chatbot. This compares to a 62.8% satisfaction rating with the control group who had only the LMS without the voice-enabled chatbot. Similarly, Odhiambo et al. (2017) reported high rates of user satisfaction. Nearly all their users (92.7%) agreed that the chatbot made learning more enjoyable and 69.5% of users felt their learning was more effective and efficient with the chatbot. Chen (2018) also reported high rates of user satisfaction, enjoyment, and motivation with gamification added into the LMS. Over 80% of students enjoyed using the learning games and would recommend them for other courses. Nearly 70% of students reported higher motivation and 72% reported the gamified LMS as highly useful. However, also within this study were some student reports that they disliked the competitive atmosphere of the games.

For the psychological outcomes of the articles focused on self-regulated learning or self-efficacy outcomes ($n = 3$), the results were also generally positive. For example, Şahin and Yurdugül (2019) reported that users felt the supportive intervention features (interaction and performance data) provided by the In2S system improved their self-regulation and planning skills. Signal lights, used as an instructional intervention, was a favourite feature and the motivational interventions (leaderboards, badges, and notifications) increased learner motivation. Karaoglan Yilmaz (2022b) found that academic self-efficacy increased after the LA intervention. This study also found a statistically significant increase in social status after the intervention with a small effect size.

4.2.3. Behavioral Outcomes

For the articles that measured behavioural outcomes ($n = 25$), a variety of measures were used and presented mixed outcomes. One measure used more frequently was engagement, also described as user interaction ($n = 5$). These findings were mixed, with Chen (2018) finding no difference in engagement levels between groups. Whereas students in the experimental group from Odhiambo et al. (2017) reported that the chatbot increased student-to-instructor and student-to-computer interaction. Liu et al. (2015) focused on LA as a way to identify student engagement indicators using the Moodle (MEAP+) LMS. They identified the following disengagement triggers for students: class attendance, assessment submissions, forum usage, LMS logins, interim grades, the final exam, access to resources, and interactions with the academic staff. To address disengagement triggers related to interactions with the academic staff, pre-written snippets, derived from PassNote, were provided to instructors within the MEAP+ system. The snippets allowed for more individualized communication between staff and students based on the suggested indicators from MEAP+ but had the benefit of reduced load on the instructor's time.

Afzaal et al. (2021), measured student engagement by examining their interactions with learning materials within the LMS for a distance learning computer programming course. They reported that user engagement with student discussion forums, practical videos, and practical articles had the highest predictive value on student performance. Chung et al. (2022) looked at patterns of student engagement with an online mindfulness program using LA. They reported three levels of engagement based on the total number of program weeks accessed: no engagement (zero logins), trial engagement (1–2 logins), and active engagement (3 or more logins). The results were mixed given that the "no engagement" group showed significant score differences in two out of the three measures: well-being and mindfulness. The active engagement group showed significant differences in all three outcome measures of mental well-being, perceived stress, and mindfulness from the baseline. The trial engagement group showed a significant increase in scores on mental well-being and perceived stress but not on mindfulness.

4.2.4. Implications for Future Design

Prior research has produced insightful implications that provide practical and conceptual guidance for informing future studies in the design of interventions. Out of the 23 articles that presented implications, two major themes were identified: 1) the significance of conducting usability testing and 2) the need for adaptive design. First, usability is crucial when designing a new system (Laeeq & Memon, 2021). The more user-friendly a system is, the more effective it will be. This information is invaluable for researchers and developers as they strive to create accessible, intuitive systems. Besides, usability heuristics are also an important tool in evaluating the intervention (Odhiambo et al., 2017). By applying these heuristics during the design and evaluation process, researchers can ensure that their systems are not only easy to use but also meet the needs and expectations of their users. Second, the study outcomes also implied that personalization and user adaptivity are essential for a successful design. To achieve this, it is important to identify learner patterns and develop systems that can make interventions based on these patterns. By determining sequential patterns, interventions can be structured to meet the individual needs of each learner (Khiat & Vogel, 2022). Another way to personalize the learning process is by adding features such as plagiarism detection, cognitive support, strategy training, and customizable learning (Şahin & Yurdugül, 2019). These features can help learners improve their skills and achieve their learning goals in a way that is tailored to their individual needs.

In addition, prior studies also provide a wide range of practice guidance. For instance, Saadati et al. (2023) indicated the importance of scaffolding in designing intervention as it is vital in higher performance and SRL development. In evaluating a LAD designed by Klein et al. (2019), researchers pointed out that predictive data would be viewed as more valid by students if provided by a "trusted source." Besides, in the detecting and prompting system developed by Tabuenca et al. (2015), they found out that pushing notifications randomly throughout the day does not lead to significant improvements in time management. However, sending notifications at fixed times each day may have a positive impact on time management, which provides insights about future notification design. In all, previous studies have offered valuable implications that have enriched our understanding of how to design interventions for learning management systems. These implications have practical and conceptual significance and can guide the development of future interventions and can be applied to create interventions tailored to the unique needs of learners, thereby improving their learning outcomes.

4.2.5. Implications for Future Implementation

When considering how to implement LA interventions into LMSs in future studies, 21 articles provided practical advice and guidance. First, seven studies highlighted the importance of obtaining student buy-in and staff support for the intervention. Chen (2018) found that while students generally expressed positive feedback about their gamification intervention, the competitive atmosphere of the game diminished the learning experience for some students. Similarly, Klein et al. (2019) reported that some students felt "turned off" by their dashboard and its predictive data, leading them to ignore or act contrary to the LAD. Two studies using detection systems (Liu et al., 2015; Atif et al., 2020) emphasized the need to train staff on how to best use the system and interpret the results of the detection systems for maximum effectiveness while Chung et al.

(2022) highlighted the complexities of implementing an LA intervention university-wide. Taken together, these studies demonstrate that even well-designed interventions may not produce their intended outcomes without sufficient support from those involved in the study.

In addition, eight studies discussed the impacts of LA interventions in the LMS on student ability to monitor and control their own learning. Prompt systems combined with dashboards were especially effective at providing students with opportunities to monitor their individual performance and compare themselves with the group (Şahin & Yurdugül, 2019), increasing student interest in learning and motivating them to adapt their learning to better meet their needs (Afzaal et al., 2021), and observing their learning deficiencies (Karaoglan Yilmaz, 2022b). Also, standalone programs for facilitation provided an increase in positive attitudes toward learning (García-Martín & García-Sánchez, 2018) and allowed for increased reflection and opportunities for peer-assessment (Saadati et al., 2023). Jointly, these studies highlight the role LA interventions can play in amplifying aspects of SRL and overall student engagement.

4.2.6. Challenges in Design and Implementation

Twenty articles mentioned the challenges and limitations associated with implementing the intervention. One study pointed out that many learning analytics tools primarily rely on static metrics, such as average online session duration or forum post count. This approach may overlook the intricate nature of learner activity, provide a narrow understanding of student engagement and learning, and pose challenges in generating appropriate recommendations and interventions (Liu et al., 2015). Other research has emphasized the importance of assessing the long-term effects of interventions. For instance, Afzaal et al. (2021) indicated their intention of providing evidence regarding the extent to which the dashboard's suggestions could enhance student comprehension of course concepts. A finding worth noting is that a study mentioned the time requirement for instructors to utilize the intervention. Karaoglan Yilmaz (2022b) indicated that although the dashboard provided analytical information on student learning progress, it required teachers to spend more time processing the information, including individual recommendations and guidance based on the reports. Furthermore, the studies have identified generalizability as a primary constraint. Given the various types of LMSs available, an intervention created and executed on a specific LMS, such as Moodle, may not be suitable for other LMSs (Al-Shaikhli et al., 2022). Additionally, the studies have also highlighted limitations such as small sample sizes (Ferdiánová, 2017), interpretability of knowledge tracing models used (Wan et al., 2023), and single disciplinary focus (Afzaal et al., 2021).

5. Discussion

The examination and analysis of the articles led to valuable insights into the key characteristics and design process of the current LA-incorporated interventions implemented within the LMS. Moreover, it revealed the intricate design processes undertaken during the development of these interventions, and critically examined their empirical effects and potential future ramifications, which will be presented in the subsequent sections.

5.1. The Predominance of Multifunction Interventions

Most studies featuring multifunction interventions reported academic outcomes, and conversely, most reports on academic outcomes originated from studies with multifunction interventions. This may indicate that combining different interventions may have a complementary effect, where each intervention addresses different aspects of the learning process, thus leading to improved overall academic outcomes. Furthermore, utilizing multiple interventions may also help enhance student engagement by offering a more interactive and immersive learning experience (Na & Tasir, 2017) and by increasing student engagement, academic outcomes are also improved (Lu et al., 2017).

In addition, six out of eight multifunction interventions integrated a prompt system in their design. Prompt systems can play a pivotal role in fostering SRL as they often encourage specific student behaviours and serve as reminders to take control of their learning process (Lallé et al., 2017). Prompt systems have also been shown to increase overall student engagement with course materials, which is often associated with better academic performance (Karaoglan Yilmaz & Yilmaz, 2022). As most multifunction interventions reported positive academic and psychological outcomes, prompt systems may be a key to designing effective LA interventions in the LMS that impact academic outcomes. Further empirical studies aiming to design and implement LA interventions within the LMS could benefit from utilizing a prompt system that engages students through tailored prompts.

5.2. The Prominence of Dashboards as Functionality

The outcomes of this review echo with Jivet et al. (2018) that dashboards are a commonly used learning analytics option in education. Their immense flexibility and versatility allow them to be easily adapted to fit into various learning contexts and into different LMSs (Bodily & Verbert, 2017). Among all the collected studies, eight deal with dashboards or LADs, whereas six integrated dashboards with other systems like detecting (Lonn et al., 2015) or recommendations (Wan et al., 2023). Primarily, dashboards are used to provide an easy-to-understand visual representation of complex data to help learners and

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64

educators grasp information, identify patterns, and make informed decisions (Arnold & Pistilli, 2012). This idea was present across all of the studies employing dashboards, as they sought to display data related to their intervention in the LMS to students and instructors. In addition, dashboards are often used to display comparisons between learners, but not all learners perceive this to be a positive attribute (Jivet et al., 2018). Specifically, Klein et al. (2019) found this in their intervention, and this should be considered when implementing further such dashboard interventions in LMSs.

Because dashboards offer real-time feedback to students, some interventions utilized it to support self-regulated learning skills (Afzaal et al., 2021; Al-Shaikhli et al., 2022; Şahin & Yurdugül, 2019) or goal setting (Khiat & Vogel, 2022) to engage learners to stay on track (Sedrakyan et al., 2020). The dashboard interventions presented a positive effect on SRL and academic outcomes. In addition, adapting a theoretical framework in dashboard design represents a response to a previous literature review on LA dashboards that identified this as a deficiency (Jivet et al., 2018). However, there are persistent calls for a more extensive exploration of dashboard evaluation methodology (Verbert et al., 2020), including the alignment of dashboard design with teacher inquiries (Pozdniakov et al., 2022). Given the widespread use of LMSs and their potential as rich sources of data for LA, future studies incorporating dashboards should take these additional considerations into account.

5.3. The Reliance of Quantitative Data in Intervention Design

Although qualitative data such as open-ended questions or interviews were utilized to inform the design process of the intervention, the ten articles that presented learner-generated data all used quantitative data. Although student engagement with the LMS usually generates rich textual data such as reflections or posts in discussion forums (de Lima et al., 2019), the qualitative data was not fully employed to benefit the functionality of the interventions. For instance, the dashboards developed by researchers mostly fit with or visualized student quantitative usage log data whereas student interactions or conversational corps data produced in the discussion forum was not demonstrated on the dashboards. In addition, although some interventions were chatbots, the algorithm or models behind were fit with pre-trained data instead of student-generated data on the LMS. As indicated by previous studies that examined the qualitative data on LMSs, there is a potential for researchers to fully utilize and take advantage of the qualitative data. For instance, learner-generated qualitative data in the discussion forum allows researchers and instructors to analyze thematic findings, as well as student engagement and learning outcomes. Moreover, there exists a technical feasibility to efficiently process vast volumes of corporate data and subsequently display them in a real-time manner (Pan et al., 2020). Based on the findings of this review, it is evident that LMS interventions that integrate both quantitative and qualitative data are not only beneficial but also essential for enhancing the overall learning and teaching experiences within the LMS. Furthermore, with the ongoing advancements in natural language processing (NLP) techniques, more LA techniques and approaches will be available for researchers to incorporate learner-generated qualitative data into designing and implementing innovative interventions on LMSs.

5.4. The Priority of Learner-Focused Over Teacher-Focused Interventions

In addition, most interventions targeted learners rather than instructors. Out of 21 studies, 16 were exclusively designed for learners, while only four were focused solely on instructors, and one study targeted both learners and instructors (see Figure 5). The interventions designed for learners included diverse types of interventions including chatbots (Laeeq & Memon, 2021), dashboards (Khiat & Vogel, 2022), detecting systems (Tabuenca et al., 2015), prompting systems (Afzaal et al., 2021), and multiple function interventions (Şahin & Yurdugül, 2019). In contrast, interventions designed for instructors were all unifunctional, consisting only of dashboards (Goomas & Czupryn, 2021) and detecting systems (Liu et al., 2015). This finding suggests that the current trend of integrating interventions into the LMS is aimed at enhancing student learning outcomes. Another possible explanation is the disparity in numbers between learners and instructors. With learners generating larger and more diverse amounts of log data on the LMS than the individual instructor, educational developers were able to collect these rich data sources to develop learning analytics–incorporated interventions such as detecting systems and dashboards, which are targeted towards students. It is important to note that while more interventions are targeted towards students, the value of interventions for instructors should not be overlooked. Additionally, as mentioned earlier, most interventions were dashboards, and the learning outcomes generated by these interventions could also be leveraged by instructors. Therefore, more empirical studies are needed to assess how interventions in the LMS can be applied to support instructors in facilitating their teaching practices.
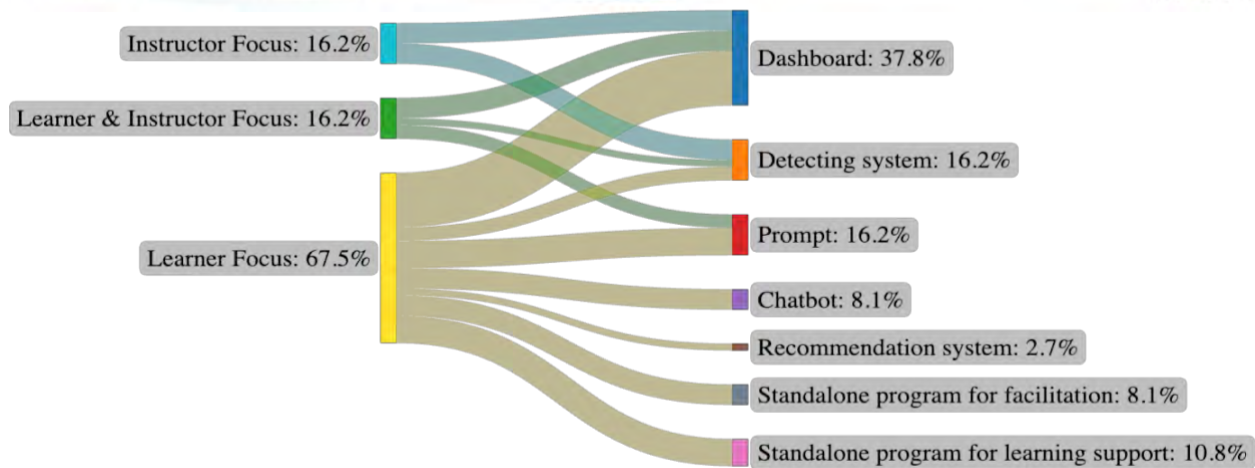
Figure 5. Association between functionality and user-focus.

5.5. The Prominence of SRL in Intervention-Design Frameworks

Among the 19 articles informing the intervention design framework, SRL was more prevalent ($n = 6$) than other frameworks. In addition, it is worth noting that all of the interventions informed by SRL were targeted solely to students, with the exception of one article that targeted both learners and instructors (Afzaal et al., 2021). This finding echoes previous empirical research that SRL skills are a crucial factor that can significantly impact how learners engage with and utilize the contents provided within the LMS (Shine & Heath, 2020). For instance, Abdul Rahman et al. (2017) discovered that students who possess higher levels of SRL skills tend to be more engaged with the LMS. Cultivating SRL skills among students can foster a greater sense of autonomy and motivation while interacting on the LMS (Khiat & Vogel, 2022), leading to improved academic achievement. By providing students with the dashboard information or prompts they need to effectively regulate their learning (Şahin & Yurdugül, 2019), instructors can empower them to take greater ownership of their learning process, which helps students become more proactive and independent learners, leading to better academic performance and success (Alotaibi et al., 2017), which explains why SRL was the dominant design framework in most LMS interventions. Furthermore, the abundance of usage log data generated by learners on the LMS provides a rich source of information for researchers to track effective learning strategies, and more importantly, time-stamped features of the log data — such as regular homework or quiz submissions in each learning module — allow researchers to establish a connection between learning patterns and SRL skills (Muljana et al., 2023). Consequently, researchers have harnessed this rich log data from LMSs to develop and implement educational interventions, including LADs and prompting systems, using the SRL framework to enhance learning activities. Similarly, as the application of SRL in designing interventions has demonstrated successful experiences in supporting students using learner-generated log data from LMSs, it serves as an example for future studies to expand the application of frameworks like self-directed learning and Goal Setting Theory.

5.6. The Calling of Innovative Log Data Processing

The collected studies revealed that behavioural log data was widely applied during the intervention design process (Atif et al., 2020; Tabuenca et al., 2015). For instance, Liu et al. (2015) incorporated log data in a static or cumulative manner. In another study, Şahin and Yurdugül (2019) utilized a range of usage log data, such as the total number of content visits, the amount of time spent on content, the number of new pages accessed within the content, the number of completed assessments, and the total time spent on assessment tasks. These data were incorporated into the design of In2S, which includes functionalities of dashboards, detecting, and prompting systems. Similarity, Atif et al. (2020) also utilized a series of LMS trace data including assignment submissions, forum interactions, and login metrics in designing their detecting system, MEAP+. Whereas Tabuenca et al. (2015) focused on learner time spent on different course activities in developing their detecting and prompting system, LearnTracker. This log data primarily consists of frequencies and durations, providing valuable insights into the system's operations. However, it holds immense potential beyond its conventional usage, as it can be leveraged in various alternative approaches that yield deeper understanding. For instance, the extraction of sequential patterns from the log data can uncover recurring sequences and learning trajectories, shedding light on learner behaviour over time (Poon et al., 2017). Additionally, exploring the hidden states of behaviours can reveal underlying states or conditions that might influence the observed behavioural patterns. Furthermore, applying clustering techniques to the log data can unveil similar learning behaviours and learner groups. Thus, although the utilization of log data in current LA intervention design has mainly utilized frequencies and durations, there is a need for further exploration to unlock its full

potential. By delving deeper into the possibilities inherent in log data, it is anticipated that more functionalities will be developed to enhance and empower teaching and learning practices via LA interventions on LMSs.

6. Limitations and Future Directions

A main limitation of this review is the coverage of the articles. The key terms used for searching the articles reviewed were intended to cover all the studies that applied LA in designing and implementing instructional interventions in educational contexts. However, it is possible that some articles conducted empirical research without referring to the search terms used in this review. In addition, we searched for studies in English in seven databases; it is possible that some studies were not included in these databases or were in other languages (Lima & Isotani, 2021). Therefore, future reviews should consider incorporating additional keywords from a wider range of databases for a more comprehensive review. Another limitation is subjectivity during the article screening and coding process (Mangaroska & Giannakos, 2019). Although researchers reviewed the articles selected by other researchers during the screening process, and coded the articles based on agreement, it is still possible to miss relevant articles or misinterpret the components when coding different themes. More rigorous screening and coding processes should be performed in future reviews. Furthermore, some studies (e.g., Tempelaar et al., 2021) have presented the utilities of LMS trace data alongside dispositional data to predict student performance and provide implications for intervention design. However, as these studies have not yet developed or evaluated the intervention, so they were not included in the current review. While these interventions are anticipated, future researchers could extend the review by encompassing these studies.

While this literature review primarily focused on LA-incorporated interventions in LMSs, it is important to note that other learning platforms, such as Massive Open Online Courses (MOOCs), have also enhanced functionalities similar to those of LMSs, such as assignment submission, assessment, and various types of discussion forums. Considering that learners on MOOCs also generate significant amounts of usage-log data, and due to the extensive and multifaceted research landscape surrounding MOOCs, future researchers could consider conducting reviews examining LA-incorporated interventions on MOOCs.

7. Conclusion

This systematic review examined 27 empirical studies that developed and implemented learning analytics–incorporated instructional interventions on learning management systems. The analysis of the articles provided valuable insights into the design characteristics and empirical impacts, as well as implications about the current interventions. The findings highlight the predominance of multifunction interventions, emphasizing the complementary effect of combining different interventions to improve academic outcomes and student engagement. Dashboards emerged as a prominent functionality in the interventions, offering real-time feedback and supporting self-regulated learning. The reliance on quantitative data in intervention design was observed, indicating the potential for researchers to fully utilize qualitative data generated by learners on LMSs. Learner-focused interventions were more prevalent than teacher-focused interventions, with self-regulated learning being a dominant framework in the design process. Psychological and behavioural outcomes were more commonly reported than academic outcomes, reflecting the challenges in collecting and analyzing academic data within interventions. The utilization of log data in intervention design primarily focused on frequencies and durations, suggesting the need for further exploration of its full potential. The studies presented diverse research contexts, mainly focusing on STEM subjects and participants at the undergraduate level or above. However, limited demographic information provided in the studies restricts the generalizability and precision of the conclusions. Collecting detailed demographic data in future research can provide valuable insights into the impact of interventions across different participant groups. Overall, these findings contribute to the understanding of learning analytics–incorporated interventions in the LMS and highlight implications for future research and development in this field.

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Appendix A: Summary and Differences of Related Works

Author	Summary and Focus	Differences
Alhazmi et al. (2021)	Analyzed the reasons for success and failure of LMS adoption by teachers and students, finding seven LMS features for success. Expert analysis was used to verify the feature selection by researchers.	Focused on LMS adoption and identifying key features for success. LA and the efficacy of learning interventions within LMS were not sufficiently addressed.
Araka et al. (2020)	Focused on trends and instructional tools used for measuring self-regulated learning within LMSs. They identified weaknesses in measuring SRL in online learning and the failure to utilize LA techniques.	Addressed the lack of LA used in assessing SRL in LMS. It focused primarily on SRL skills and measurements.
Prahani et al. (2022)	Focused on identifying LMS use trends and impacts on education from 1991–2021 using bibliometric analysis.	Focused on generalities of LMS uses but did not focus on LA learning interventions.
Altinpulluk & Kesim (2021)	Focused on identifying current and future use trends in LMS.	Focused on generalities of LMS use and did not address LA techniques or specific learning interventions.
Costa et al. (2020)	Focused on the relationship between LA and ontologies. It examined how the two have been applied.	The main focus was LA concept and ontologies, there was no discussion on LMS.
Mangaroska & Giannakos (2018)	Focused on empirical studies that utilized LA techniques to enhance the design of learning activities. Specifically, what LA measures inform learning design and how the LA are used.	There was no focus on LMSs, only LA measures.
Xin et al. (2021)	Compared various LMS, highlighted their general features, ease of use, security concerns, and the absence of a parental role.	This review did not address LA or provide a systematic evaluation of instructional interventions within the LMS.
Lima & Isotani (2021)	Assessed the effectiveness, challenges, and solutions related to GC's implementation. It primarily focused on the experience of teachers and students using Google Classroom (GC) during the pandemic.	Did not specifically concentrate on instructional interventions within the LMS. Furthermore, it did not provide a detailed analysis of general LMS interventions.
García-Murillo et al. (2020)	Assessed technological satisfaction among Moodle users in higher education institutions (HEIs), finding that high levels of user satisfaction, particularly among students, contribute to Moodle's widespread adoption in HEIs.	Focused on Moodle's technological satisfaction, may not be representative of all LMS platforms, and it did not address LA techniques.
Miah et al. (2020)	Discussed the broader context of big data technologies in higher education and their potential to improve LMS and other relevant processes and practices.	Did not explore specific LA-incorporated LMS interventions.
Larrabee Sønderlund et al. (2019)	Examined the efficacy of LA interventions in enhancing student retention and academic success, highlighted the challenges of high dropout rates in higher education, and the evolution of LA models.	Provided a comprehensive discussion of LA in higher education as a whole but did not specifically focus on LS interventions within LMSs.

Appendix B: Summary of the Collected Studies

Article	LMS type	Intervention functionality	Quantitative data involved in design and evaluation	Qualitative data involved in design and implementation	Theoretical framework applied in design	No. of design iteration and phase
Abazi-Bexheti et al. (2018)	Google Class-room	Dashboard	Usage log data	Not specified	Not specified	2
Afzaal et al. (2021)	Moodle	Prompt and dashboard	Usage log data and assessment data	Interviews	Self-regulated learning	9
Al-Shaikhli et al. (2022)	Moodle	Dashboard	Performance outcome	Not specified	Goal theory	3
Aljohani et al. (2019)	Black-board	Dashboard	Usage log data	Not specified	Course-adapted student learning analytics framework	Not specified
Asha & Chellappan (2011)	Not specified	Chatbot	User speech samples	Not specified	Not specified	6
Atif et al. (2020)	Moodle	Detecting system	Usage log data	Interviews	Not specified	2
Chen (2018)	Black-board	Standalone program for learning support	Performance outcome and survey	Not specified	Self-determination theory	Not specified
Chung et al. (2022)	Moodle	Standalone program for facilitation	Usage log data	Self-reflection	Theory of planned behaviour	1
Ferdiánová (2017)	Moodle	Standalone program for learning support	Performance outcome	Not specified	Not specified	2
Fung et al. (2019)	Not specified	Prompt and standalone program for learning support	Survey	Self-reflection	Self-regulated Learning	Not specified
García-Martín & García-Sánchez (2018)	Moodle	Standalone program for learning support	Survey	Writing performance outcome	Product vs process model of learning	4
Goomas & Czupryn (2021)	Black-board	Dashboard	Survey	Interviews	Not specified	3

Gutman (2017)	Moodle	Standalone program for facilitation	Usage log data and survey	Observations	Metacognitive theory	3–4
Karaoglan Yilmaz (2022a)	Moodle	Prompt and dashboard	Usage log data	Interviews	Not specified	3
Karaoglan Yilmaz (2022b)	Moodle	Dashboard	Usage log data	Interviews	Metacognition and metacognitive awareness	Not specified
Khiat & Vogel (2022)	Custom made ePSRL system	Dashboard	Survey	Self-reflection	Self-regulated Learning	1
Klein et al. (2019)	Not specified	Dashboard	Not specified	Scenario-based questions	Constructivism	1
Laeeq & Memon (2021)	Moodle	Chatbot	Usage log data	Not specified	Constructivism	Not specified
Liu et al. (2015)	Moodle	Detecting system	Performance outcomes and attendance	Interviews	IRAC (information, representation, affordances for action, change) framework	1
Lonn et al. (2015)	Not specified	Detecting system and dashboard	Survey	Not specified	Achievement goal theory	1
Odhiambo et al. (2017)	Moodle	Chatbot	Chatbot knowledge web database	Not specified	Not specified	Not specified
Ozdemir et al. (2020)	Desire-2Learn	Dashboard	Usage log data	Not specified	Not specified	Not specified
Saadati et al. (2023)	Not specified	Standalone program for facilitation	Usage log data and survey	Interviews	Self-regulated Learning	3
Safsouf et al. (2021)	Multiple	Dashboard, prompt, and detecting system	Usage log data	Not specified	Not specified	5
Şahin & Yurdugül (2019)	Moodle	Dashboard, prompt, and detecting system	Usage log data	Interviews	Self-regulated Learning	1
Tabuenca et al. (2015)	Learn-Tracker	Detecting system and prompts	Usage log data	Not specified	Self-regulated Learning	4
Wan et al. (2023)	Online Learning platform	Dashboards and recommendation system	Usage log data	Not specified	Not specified	Not specified