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Cultivating knowledge: the adoption experience of learning management systems in agricultural higher education

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Introduction: The emergence of COVID-19 and its associated challenges necessitated a rapid shift in Agricultural Higher Education (AHE) toward innovative non-attendance training methods, particularly Learning Management Systems (LMSs).

Methods: To investigate this paradigm shift, an integrated framework combining the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM) was employed to provide a comprehensive model for understanding LMS adoption. This study analyzed survey data collected from agricultural students in Iran (N = 385) using structural equation modeling (SEM).

Results: The findings indicate that the technological context of LMSs significantly influences both perceived usefulness and perceived ease of use, while the environmental context only affects perceived usefulness. In contrast, organizational factors were found to have no significant impact on these components. Furthermore, the analysis revealed a positive relationship between perceived ease of use and perceived usefulness, which subsequently fosters a favorable attitude toward LMSs and strengthens behavioral intention to adopt them.

Discussion: This study underscores the critical need for enhancing information technology infrastructure in agricultural education, advocating for a synergistic approach between government and universities to integrate e-learning with traditional educational methods. The proposed integrated model not only demonstrates strong explanatory power but also facilitates student engagement with LMSs, paving the way for innovation and knowledge exchange in the agricultural sector. These insights highlight the potential for LMSs to transform agricultural education, particularly in the context of global disruptions such as the COVID-19 pandemic.

KEYWORDS

e-learning, technology acceptance model, technology-organization-environment framework, agriculture, higher education

1 Introduction

The world is currently experiencing rapid technological advancements across various domains, including social and applied sciences (Yao et al., 2022; Al-Nuaimi et al., 2022). The widespread adoption of computers and significant technological innovations has led to transformative changes, particularly in education (Al-Mamary, 2022; Sobhani et al., 2016). These changes are evident in the delivery, accessibility, and engagement with educational content, marking a new era in teaching and learning methodologies (Hernández-García et al., 2024; Shirawia et al., 2024). As Khan and Qudrat-Ullah (2021) noted, integrating emerging technologies has profoundly reshaped traditional educational paradigms, enriching the learning experience. Technologies such as Learning Management Systems (LMSs), artificial intelligence (AI), virtual reality (VR), and online collaborative platforms have revolutionized pedagogical approaches by fostering interactive and personalized learning environments (Lai and Bower, 2019; Beirat et al., 2025). Additionally, online platforms and video conferencing tools have enabled remote and flexible learning, breaking geographical barriers and expanding access to education (Zamiri and Esmaeili, 2024).

Technological advancements and their integration into digital systems have become pivotal in enhancing teaching and learning processes, enabling learners to achieve greater success while improving operational efficiency (Tashtoush et al., 2025; Haleem et al., 2022). In this context, LMSs play a critical role in promoting sustainability by helping educational institutions achieve their environmental, social, and governance (ESG) goals (Troshkova et al., 2023). Key features of LMSs, such as versatility beyond formal education, corporate training capabilities, professional development opportunities, and applicability across diverse learning contexts, have established them as essential tools in modern education (Mohamed Riyath and Muhammed Rijah, 2022).

The COVID-19 pandemic significantly accelerated the adoption of LMSs, highlighting their importance in maintaining educational continuity during global disruptions (Yao et al., 2022; Lytras et al., 2022; Zhao and Mok, 2024). As a result, LMSs were widely implemented in higher education institutions worldwide (Mohamed Riyath and Muhammed Rijah, 2022). The pandemic fundamentally altered the dynamics of higher education, creating an urgent need for technology-driven learning solutions to address restrictions imposed by the crisis (Rosli and Saleh, 2022). This reliance on technology has persisted in the post-pandemic era, underscoring its vital role in modern education (Al-Mamary, 2022).

Today, many higher education institutions have integrated LMSs as a core component of their educational frameworks (Lytras et al., 2022). LMSs have emerged as indispensable tools, facilitating dynamic and collaborative approaches to teaching and learning (Mohamed Riyath and Muhammed Rijah, 2022). In Iran, LMSs have played a significant role in advancing higher education, particularly during and after the COVID-19 pandemic. These platforms enabled a seamless transition to remote learning, ensuring educational continuity and enhancing accessibility for students across the country (Kazemzadeh, 2022).

Despite their importance, the full potential of LMSs in education remains underexplored (Khan and Qudrat-Ullah, 2021). Radif (2016) identified several barriers to LMS adoption in higher education, including insufficient ICT competencies, a lack of confidence among users, inadequate training in instructional methodologies, the absence of suitable educational applications, and limited ICT infrastructure. Yao et al. (2022) further highlighted challenges such as technological proficiency gaps, insufficient technical support, and a strong preference for traditional teaching methods. Mohamed Riyath and Muhammed Rijah (2022) emphasized two major obstacles: unreliable internet connectivity and a lack of adequate training. Additionally, Al-Nuaimi and Al-Emran (2021) noted that integrating LMSs into higher education requires substantial investments, including hardware procurement, software licensing, faculty training, development of specialized course materials, and equipment maintenance. Consequently, identifying the key factors influencing LMS implementation in educational institutions is critical for effective investment and project management.

Given the multifaceted nature of technology adoption, various models have been proposed to understand and facilitate this process. Integrated models, in particular, have garnered significant interest. This study employs an integrated framework combining the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework to examine the adoption of LMS technology in Iranian AHE. By leveraging this integrated approach, the study aims to provide a comprehensive understanding of the factors driving LMS adoption and inform strategies for its effective implementation.

Despite the growing body of literature on LMS adoption, few studies have focused on the unique challenges and opportunities associated with AHE. AHE faces unique challenges, such as the need for hands-on training, fieldwork, and access to specialized resources, which make the adoption of LMS particularly complex. The COVID-19 pandemic further exacerbated these challenges, highlighting the urgent need for effective e-learning solutions in this domain (Alturki and Aldraiweesh, 2021; Zhao and Mok, 2024). Moreover, the integration of TAM and TOE frameworks has not been extensively explored in this context (Sulaiman et al., 2023). This study addresses these gaps by proposing an integrated model that combines TAM and TOE to investigate LMS adoption in AHE. Doing so, it contributes to the literature by providing a comprehensive understanding of the factors influencing LMS adoption in a specialized educational context and offering practical recommendations for policymakers and educators. This study makes several key contributions to the literature on LMS adoption in AHE. First, it integrates the TOE framework and the TAM to provide a comprehensive model for understanding LMS adoption. This integration addresses a gap in the literature by combining organizational, environmental, and technological factors with user perceptions. Second, the study focuses on the under-researched context of AHE in Iran, offering insights into how LMS can be effectively adopted in developing countries. Third, the findings provide practical recommendations for policymakers and educators to strengthen IT infrastructure and promote the integration of LMS in agricultural education. These contributions advance both theoretical understanding and practical application of LMS adoption in specialized educational contexts. This study employs SEM to achieve the following objectives:

1. To validate an integrated adoption model and assess its power to explain the influencing factors toward using LMS in AHE.
2. To provide practical recommendations that improve the use of LMS in AHE.

To address these objectives, this article is structured as follows: The introduction outlines the growing significance of LMSs in AHE and establishes the context for the study. The methodology section details the research design, data collection, and analytical approaches employed. The results section presents the key findings derived from the analysis. The discussion section interprets these findings and explores their implications for AHE. Finally, the conclusion summarizes the study's major contributions and offers insights for future research and practice.

2 Literature review

2.1 Core features of LMS

An LMS is a comprehensive digital platform designed to enable educational institutions to manage, deliver, and track educational content and activities in an organized and efficient manner (Al-Nuaimi and Al-Emran, 2021). Operating under the guidance and control of instructors and institutions, an LMS facilitates a structured teaching approach, allowing educators to maintain authority over the management and dissemination of information to learners (Dias et al., 2014). Furthermore, LMSs incorporate versatile tools and features that enhance communication, collaboration, and assessment between instructors and learners, effectively bridging the gap between traditional classroom settings and the expanding online learning environment (Khan and Qudrat-Ullah, 2021). As such, an LMS functions as an information system that not only manages and disseminates educational content but also provides support, guidance, and improved communication between teachers and students (Al-Mamary, 2022).

In general, LMSs are defined as digital platforms that facilitate the creation, distribution, and management of educational materials and data within an information technology framework (Al-Nuaimi and Al-Emran, 2021). LMS has evolved to encompass a wide range of features and types, each tailored to specific educational needs. Common features include content management, assessment tools, communication platforms (e.g., discussion forums and live chat), and analytics for tracking student progress (Humida et al., 2022). LMS platforms can be categorized into proprietary systems (e.g., Blackboard and Moodle) and open-source solutions, each offering unique advantages in terms of scalability, customization, and cost-effectiveness. In the context of AHE, LMS platforms must also support specialized content, such as agricultural simulations, remote fieldwork coordination, and collaborative research tools. These features make LMS a versatile tool for addressing the unique challenges of agricultural education, particularly in the post-COVID era (Alturki and Aldraiweesh, 2021; Sobhani et al., 2024).

Additionally, LMSs are recognized as innovative methods for delivering education, representing the integration of information technology into tertiary educational settings. They offer new opportunities and create an engaging learning experience for users (Al-Nuaimi and Al-Emran, 2021) (Table 1).

2.2 The importance of integrated modeling of technology adoption

Numerous theories have been proposed to examine the factors influencing the adoption of new technologies (Khan and Qudrat-Ullah, 2021; Mahlangu and Makwasha, 2023; Mohamed Riyath and Muhammed Rijah, 2022). These include the Diffusion of Innovation (DOI) (Rogers, 2003), the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1976), the Unified Theory of Acceptance and Use of Technology (UTAUT1 and UTAUT2) (Tarhini et al., 2017; Venkatesh, 2022), and the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer, 1990; Baker, 2012). Among these, TRA, TPB, and TAM are the most widely utilized frameworks for analyzing technology adoption dynamics (Yao et al., 2022; Al-Mamary, 2022).

Importantly, many studies have explored technology adoption using integrated models, which provide a more comprehensive understanding of the phenomenon under investigation (Alturki and Aldraiweesh, 2021). Integrated models capture a broader range of influencing factors, leading to more accurate predictions of adoption behavior (Davis, 1989). They also offer practical guidance for stakeholders in higher education (Al-Nuaimi et al., 2022).

In this context, TAM and the TOE framework are among the most widely adopted theories in technology adoption studies. These frameworks have not only demonstrated their individual effectiveness across various research contexts but also, when integrated, have the potential to significantly enhance the explanatory power of the proposed model (Sulaiman et al., 2023).

In summary, integrating TAM and TOE into a single model offers a more robust, comprehensive, and insightful framework. This integration enhances understanding, improves predictive accuracy, and provides practical applications while also contributing to academic discourse and inspiring further research. Specifically, TAM emphasizes the importance of Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as key determinants of technology adoption, while TOE considers the influence of organizational and environmental contextual factors. Together, they enable the development of holistic policies that address both user perceptions and broader organizational and environmental contexts. Consequently, this study aims to establish an integrated model of LMS adoption by combining TAM and TOE. The following sections provide a detailed explanation of these theories.

2.2.1 TOE framework

TOE framework was developed by Tornatzky and Fleischer (1990) using the Theory of Organizational Contingencies. TOE seems suitable for conducting organizational studies such as higher education institutes (Radif, 2016). In fact, it overarches the technical, external (environmental), and internal-organizational aspects of technology that lead to its successful adoption (Mahlangu and Makwasha, 2023).

In the beginning, the technological context refers to the availability and quality of LMS-related technologies, such as user-friendly interfaces, reliable internet connectivity, and advanced features such as AI-driven analytics (Buabeng-Andoh and Baah, 2020). A robust technological infrastructure enhances perceived usefulness by enabling students and educators to achieve their learning and teaching goals more effectively. Similarly, a well-designed LMS with intuitive features increases perceived ease of use, reducing the cognitive effort required to navigate the system (Rasheed and Tashtoush, 2023). Similarly, the environmental context includes external factors such as government policies, institutional support, and societal expectations. For instance, government initiatives to promote digital education can increase perceived usefulness by legitimizing LMS as a valuable tool for learning. Similarly, institutional support, such as training programs and technical assistance, can enhance perceived ease of use by equipping users with the skills and confidence needed to adopt LMS (Sobhani et al., 2024). Finally, the organizational context encompasses internal factors such as institutional culture, resource availability, and leadership support. A supportive organizational culture that values innovation can increase

TABLE 1 Main features of LMS.

LMS basics	Definition	LMS… …is one of the modern educational approaches that facilitate the educational process effectively using the advantages of both electronic and conventional education (Radif, 2016; Hernández-García et al., 2024). …integrates and organizes all teaching and learning initiatives (Mohamed Riyath and Muhammed Rijah, 2022). …is designed to streamline and enhance the process of teaching, learning, and course management. …is able to facilitate the creation, delivery, and organization of educational content while enabling seamless communication and collaboration (Al-Mamary, 2022; Hwa et al., 2015). …includes interactive features such as discussion forums, live chat, and video conferencing, fostering active engagement and a sense of community in both traditional classroom and online learning settings (Khan and Qudrat-Ullah, 2021).
	Function	LMS… …empowers educators to monitor student progress, identify areas of improvement, and tailor instruction to meet individual learning needs, using built-in tracking and reporting capabilities (Mohamed Riyath and Muhammed Rijah, 2022). …helps instructors to develop and share course materials, assignments, and assessments, ensuring a consistent and standardized learning experience for students (Çakiroğlu et al., 2024). …assists educational institutions in the creation, implementation, and evaluation of learning systems (Al-Mamary, 2022). …can streamline workflows, enhance collaboration, and foster a culture of sustainability within an organization (Sobhani et al., 2024).
Innovative contributions of LMS to this study		• LMS as an innovation The current study revolves around the adoption of LMS, a prime example of technological innovation. So, it investigates how LMS is used within the context of AHE. That is, the study highlights the driving force of innovation to ensure the continuity and quality of agricultural education facing disruptions posed by COVID-19. Additionally, it explores how external/internal factors affect the adoption of an innovative learning method in a traditionally hands-on field such as agriculture. • LMS as a culture promoter The study advocates fostering a culture that values innovation and knowledge sharing within AHE institutions. This includes promoting collaboration between universities, government bodies, and other stakeholders to facilitate the effective integration of technology in agricultural education.

perceived usefulness by fostering a positive attitude toward LMS adoption (Sulaiman et al., 2023). Additionally, adequate resources, such as funding for LMS implementation and maintenance, can enhance perceived ease of use by ensuring that the system operates smoothly and reliably (Humida et al., 2022). Therefore, The TOE framework examines how organizations operate within technological, organizational, and environmental contexts. These contexts collectively influence an organization's ability to adopt or reject new technologies (Radif, 2016). According to Baker (2012), the technological context encompasses both internal technologies currently in use and external technologies available but not yet adopted by the organization. The organizational context is rooted in the fundamental principles and unique identity of the institution, while the environmental context includes external factors such as governmental bodies, local communities, and various stakeholders. These external elements can significantly impact an institution's intention to adopt new technologies, as well as its ability to acquire and effectively utilize resources (Radif, 2016).

Although the TOE framework has been widely applied in various studies, many have limited their scope to the core components of TOE, neglecting the complex interplay between its antecedents (Nguyen et al., 2022; Hiran and Henten, 2020). Recent studies, however, have begun to explore the integrated use of TOE with other frameworks, such as the Technology Acceptance Model (TAM), to provide a more comprehensive understanding of technology adoption.

For instance, Sulaiman et al. (2023) investigated the slow adoption of Learning Management Systems (LMSs) among university lecturers in Iraq's Kurdistan Region following the COVID-19 pandemic. By integrating TAM and TOE, the study identified key determinants of LMS usage. The findings revealed a strong relationship between information quality and perceived usefulness (PU) and perceived ease of use (PEOU). Additionally, technological quality and environmental factors, such as policies, significantly influenced PU and PEOU. However, organizational support did not show a significant impact on these factors. Within the TAM framework, PU and PEOU were found to be strongly associated with the actual use of LMS. Similarly, Radif (2016) explored the adoption of LMS in Iraqi higher education by combining TAM and TOE. The study highlighted that technology integration in academic settings is influenced by user endorsement and broader factors, such as government support.

In another study, Mahlangu and Makwasha (2023) examined factors affecting the adoption of online assessments during the COVID-19 pandemic. They employed an integrated model combining TOE and TAM, expanding the TOE framework to include individual factors, digital skills, and user perceptions. This approach provided a more nuanced understanding of how these elements collectively influence the successful adoption of online assessment technologies.

Therefore, considering the necessity of integrating TAM and TOE in previous studies, relevant hypotheses toward the adoption of LMS usage in AHE are:

> *H1*: Technological context positively affects perceived usefulness.
>
> *H2*: Technological context positively affects perceived ease of use.

> *H3*: Environmental context positively affects perceived usefulness.
>
> *H4*: Environmental context positively affects perceived ease of use.
>
> *H5*: Organizational context positively affects perceived usefulness.
>
> *H6*: Organizational context positively affects perceived ease of use.

2.2.2 TAM

TAM is a widely used model introduced by Davis (1989). TAM has been mentioned as popular (Rosli and Saleh, 2022) in examining the adoption of innovations in various studies (Mahlangu and Makwasha, 2023). It is also a robust and powerful model in the study of technology adoption. So, TAM is regarded as a crucial theory (Al-Mamary, 2022; Bharadwaj and Deka, 2021) and its statistical validation extends to numerous higher education institutions (Hwa et al., 2015). Accordingly, TAM has the following components (Davis, 1989):

Perceived usefulness explains how performance can be improved using a specific technology (Davis, 1989). So, as Al-Mamary (2022) stated, PU is the extent to which an individual claims that using a technological system can increase his/her professional and personal performance.

Perceived ease of use is defined as the extent to which a person believes using a system will be effortless and free from hassle (Bharadwaj and Deka, 2021). Al-Mamary (2022) suggested that PEOU can be understood as an individual's initial assumption about the effort needed to operate a system or their conviction that a particular technology will be user-friendly. Attitude toward using a certain technology means the user's tendency or reluctance to adopt that technology. It reflects the user's overall evaluation of the technology based on their beliefs about its usefulness and ease of use (Davis, 1989). Behavioral intention, on the other hand, refers to the user's willingness or motivation to use the technology in the future (Humida et al., 2022; Tashtoush et al., 2023). It serves as a predictor of actual usage behavior and is influenced by the user's attitude and perceptions of the technology (Al-Rahmi et al., 2021; Bharadwaj and Deka, 2021; Sobhani et al., 2024).

Concerning online learning, Yao et al. (2022) integrated TAM with some components of behavioral models. Findings highlighted that learners' attitudes and behaviors are significantly influenced by their perceptions of usefulness and ease of use. Al-Nuaimi et al. (2022) adopted a comprehensive model that is the combination of the Information Systems success model, TAM, and TPB theories. Accordingly, various quality elements substantially affected PEU, with the technical quality of the system being paramount in shaping PU. Moreover, both PU and PEU were pivotal in shaping users' intention to utilize LMS. Mailizar et al. (2021) have also studied the influencing variables toward the adoption of LMS among college students. Therefore, TAM is used as the main research framework. As a result, this proposed model effectively explained relevant variables. Notably, the attitude toward using LMS was the most important determinant of intention to use. In another study, Al-Mamary (2022) applied TAM to study students' intention to use LMS. Consequently, the impact of PEOU on PU was supported. Moreover, PU and PEOU had an impact on attitude. In addition, PU and attitude influenced intention. In this way, Mohamed Riyath and Muhammed Rijah (2022) found that PU, PEU, and service quality impact attitude. The latter factor has an effect on the intention and actual use of LMS. Buabeng-Andoh and Baah (2020) have focused on the intention of pre-service teachers to use LMS. Considering the role of TAM, findings displayed that users' intentions have significantly affected by attitude and social influence. Furthermore, Abdullah and Ward (2016) conducted research on the external factors influencing the adoption of e-learning in support of the integrated TAM. They identified the most frequent external factors, including self-efficacy, subjective norms, computer anxiety, perceived enjoyment, and experience. So, these factors were applied to develop a comprehensive model of e-learning known as General Extended TAM for E-learning (GETAMEL).

The same, an integrated set of Self-Determination Theory, self-efficacy, and TAM, was used by Rosli and Saleh (2022), which considered the acceptance of technology-enhanced learning among students. Similarly, Al-Rahmi et al. (2021) conducted a study through the integration of innovation diffusion theory (IDT) and TAM. Findings were favorable to verify the proposed model for the adoption of e-learning systems. Building upon the literature, the current study utilizes TAM and TOE to investigate the factors driving the behavioral intention to implement LMS in the realm of AHE.

Hence, the relevant hypotheses are:

> *H7*: Perceived ease of use positively affects perceived usefulness.
>
> *H8*: Perceived ease of use positively affects attitude.
>
> *H9*: Perceived usefulness positively affects attitude.
>
> *H10*: Perceived usefulness positively affects behavioral intention.
>
> *H11*: Attitude positively affects behavioral intention.

2.3 Theoretical model

As mentioned, this study has benefited from the integration of the TAM and TOE frameworks to investigate the influencing factors related to the adoption of LMS in Iranian AHE (Figure 1). The integration of TAM and TOE is justified by their complementary strengths. TAM focuses on individual user perceptions, such as perceived usefulness (PU) and perceived ease of use (PEOU), which are critical for understanding how students and educators interact with LMS. On the other hand, TOE provides a macro-level perspective by considering the technological, organizational, and environmental contexts that influence LMS adoption. Combining these frameworks, our study offers a holistic understanding of LMS adoption, addressing both micro-level user behavior and macro-level institutional factors. This integrated approach is particularly relevant in the context of AHE, where institutional support, technological infrastructure, and environmental factors (e.g., government policies) play a significant role in shaping adoption outcomes.

As a major contribution, the integration provides richer theoretical lenses to the realization of adoption behavior. Accordingly, it is expected that findings will improve the existing understanding of the dynamics of LMS. It also can potentially facilitate the acceptance process. In addition, current gaps between developed and developing countries regarding the usage of LMS require the development of a comprehensive local model that will be a practical guidance for organizations, educators, and learners. However, the aforementioned acceptance models (TAM and TOE) have their strengths and weaknesses, and this integration will prepare a local model that seems suitable for the current condition of AHE in Iran.

3 Research methods

3.1 Participants

Like numerous nations, Iran transitioned to remote education for its official curriculum following the emergence of the COVID-19 pandemic. The focus of this study was to investigate the adoption of LMS within Iranian AHE throughout and after this pandemic. To do so, the study used survey data as the basis of its investigation. The target population consisted of all agricultural sciences and natural resources students ($N = 9{,}819$) who had used "Sama System," "Skyroom," or "Adobe Connect" as LMS tools during and after the pandemic.

The underlying reason for choosing students is the student-centered nature of LMS. So, it highlights the experiences of the main actors or stakeholders, i.e., students (Santoso et al., 2016; Kerimbayev et al., 2023). Moreover, relevant universities were Gorgan University of Agricultural Sciences and Natural Resources ($N = 4{,}000$), Sari Agricultural Sciences and Natural Resources University ($N = 3{,}500$), and Agricultural Sciences and Natural Resources University of Khuzestan ($N = 2{,}319$). The selection of these universities was based on their significant role in agricultural education in Iran and their diverse geographical locations, which provide a representative sample of the challenges and opportunities associated with LMS adoption in different regions. While the findings are context-specific, they offer valuable insights for other developing countries facing similar challenges in AHE. These universities have considerable independence in educational decision-making. Moreover, they can use different virtual education systems according to the conditions of agricultural fields. Therefore, this study can be of great help to educational planners.

Accordingly, "Sama Live," as the add-on of the SAMA, is one of the most widely used systems adopted by the selected universities. It is a comprehensive virtual program that plays a major role in providing online and offline education, exams, and educational management. So, Sama Live has been recognized as suitable for universities, schools, and educational institutions. It also was approved by the Iranian Ministry of Science, Research, and Technology.

Next, a cross-sectional and random sampling was used to investigate the determinants that influenced the uptake of LMS during this distinct time frame. Two criteria were established for the inclusion of the students in the sample: (1) agriculture and natural resources students at all levels of study (except first-year students), and (2) students who had used the virtual LMS during the academic semester. After the initial screening, 385 acceptable questionnaires were obtained, including Gorgan University of Agricultural Sciences and Natural Resources ($n = 157$), Sari Agricultural Sciences and Natural Resources University ($n = 137$), and Agricultural Sciences and Natural Resources University of Khuzestan ($n = 91$). Table 2 displays more details about the sample.

3.2 Data gathering

The research commenced on 21 May 2023, with the distribution of questionnaires and report finalization completed by 20 June 2024. A web-based survey was conducted from June 2023 to July 2023 in selected universities utilizing Google Forms. Accessibility of the survey was supported through the information channel and the announcements within the university online portal. The questionnaire comprised 30 measurement items. On average, 30 min were given to complete each questionnaire. To ensure data integrity, the form was configured to preclude multiple entries by the same student. Before answering, students were required to provide informed consent, showing their agreement to participate in the study. The study did not involve minors. Therefore, there was no need to obtain consent from parents or guardians. The study was approved by the Ethics Committee

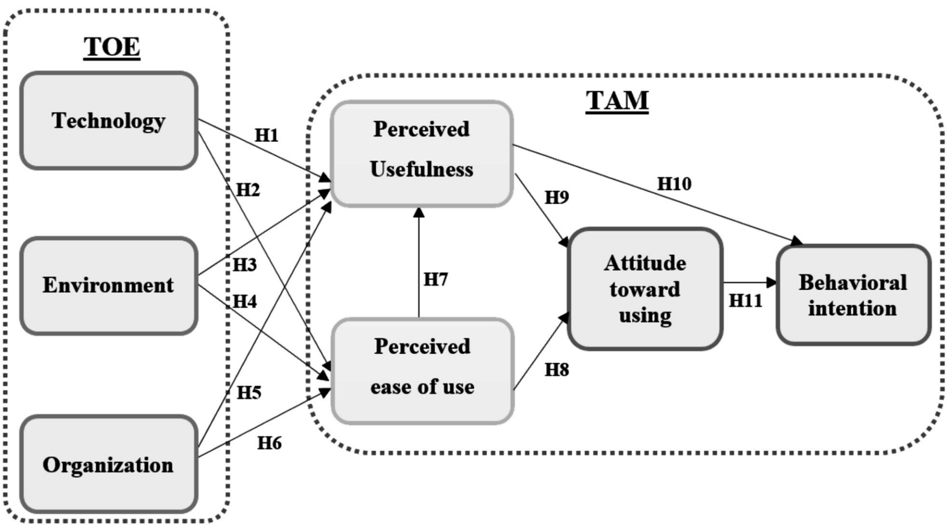

FIGURE 1
Proposed model.

of the Agricultural Sciences and Natural Resources University of Khuzestan (Approval No. ASNRUKH-1402-07). Informed consent was obtained from all participants, and data confidentiality was ensured by anonymizing responses and storing data securely. Participants were informed of their right to withdraw from the study at any time without any consequences.

3.3 Instrument

The questionnaire was structured into three parts, namely socio-demographic data, the dimensions encompassed by the Technology (4 items), Organization (3 items), and Environment (3 items) contexts (TOE framework), and the TAM, probing components such as PEOU (3 items), PU (3 items), attitude toward using (3 items), and behavioral intention (3 items). Responses were received on a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree (Table 3).

3.4 Analysis

The primary objective of this study was to present a validated model that probes the determinants of LMS adoption. In doing so, Partial Least Squares Structural Equation Modeling (PLS-SEM) is applied as an alternative analysis tool. While covariance-based Structural Equation Modeling (CB-SEM) is well-established and extensively utilized for exploring underlying constructs, the composite-based approach of PLS-SEM is gaining attraction within the social and behavioral sciences, as noted by Dash and Paul (2021). PLS-SEM employs weighted aggregates of measurable variables to depict their associated constructs. This deviates from the notion that all variations among indicators are due to a singular latent factor. The deviation allows PLS-SEM to operate without the rigid assumptions typically associated with CB-SEM (Hair et al., 2017). Such flexibility positions PLS-SEM as a preferred approach in efforts aimed at theory generation (Ghasemy et al., 2020; Sabol et al., 2023). Therefore, PLS-SEM was chosen over CB-SEM due to its flexibility in handling complex models with smaller sample sizes and its ability to predict relationships between constructs. Unlike CB-SEM, which requires strict assumptions about data distribution, PLS-SEM is more suitable for exploratory research and theory development, making it an ideal choice for this study, which aims to validate an integrated adoption model in a specialized context. To assess the potential for common method bias (CMB), Harman's single-factor test was conducted. All measurement items were loaded into an exploratory factor analysis (EFA) with no rotation. The results indicated that a single factor accounted for 32.4% of the variance, which is below the 50% threshold suggested by Podsakoff et al. (2003). This suggests that common method bias is not a significant concern in this study.

To that end, the study has engaged Smart PLS 4. Following Hair et al. (2023), this analysis adopted a two-stage analytical procedure. First, evaluating the efficacy of the measurement model, also known as the outer model, is conducted through the application of the PLS algorithm. This process is crucial for determining the model's validity and overall appropriateness. Subsequently, the structural model (inner model) was evaluated through bootstrapping procedures to ascertain the strength, trajectory, and statistical significance of the hypotheses.

TABLE 2 Respondents' profile (n = 385).

Characteristics	Frequency (%)
Gender	
Woman	178 (46.2)
Man	187 (48.6)
Unspecified	20 (5.2)
Education	
BSc	236 (61.2)
MSc	103 (26.8)
PhD	33 (8.6)
Unspecified	13 (3.4)
Age (years)	
≤ 19	50 (13.0)
20–24	187 (48.5)
25–29	43 (11.2)
30–34	23 (6.0)
≥ 35	80 (20.8)
Unspecified	2 (0.5)
LMS Usage experience (years)	
≤ 1	88 (22.8)
2	117 (30.4)
3	82 (21.3)
4	45 (11.7)
≥ 5	48 (12.5)
Unspecified	5 (1.3)
Internet access	
Home Wi-Fi	64 (16.6)
Mobile data	205 (53.2)
University internet	8 (2.1)
Use of all items	100 (26.0)
Unspecified	8 (2.1)
Device used	
Smartphone	183 (47.5)
Laptop	73 (19.0)
PC	24 (6.2)
Tablet	3 (0.8)
Use of all items	102 (26.5)
Type of system used	
SAMA	138 (35.8)
Adobe	38 (9.9)
Sky Room	27 (7.0)
Use of all items	171 (44.4)
Unspecified	11 (2.9)

According to the confirmatory factor analysis (CFA), all measures had an acceptable factor loading for building a reflective model. Moreover, the internal consistency reliability and convergent validity

TABLE 3 Measurement items used in the questionnaire.

Construct	Code	Item description	References
Technology	TECH1	The LMS platform is equipped with advanced technological features.	Tornatzky and Fleischer (1990), Humida et al. (2022), and Sulaiman et al. (2023)
	TECH2	The LMS platform is compatible with existing IT infrastructure.	
	TECH3	The LMS platform is user-friendly and easy to navigate.	
	TECH4	The LMS platform provides reliable technical support.	
Environment	ENV1	Government policies support the adoption of LMS in higher education.	Tornatzky and Fleischer (1990) and Sulaiman et al. (2023)
	ENV2	Institutional support is available for LMS implementation.	
	ENV3	Societal expectations encourage the use of LMS in education.	
Organization	ORG1	My university has a culture that supports technological innovation.	Tornatzky and Fleischer (1990) and Sulaiman et al. (2023)
	ORG2	My university provides adequate resources for LMS implementation.	
	ORG3	Leadership in my university encourages the use of LMS.	
Perceived usefulness	PU1	Using the LMS improves my academic performance.	Davis (1989), Sulaiman et al. (2023), Al-Nuaimi et al. (2022), and Humida et al. (2022)
	PU2	Using the LMS enhances my learning efficiency.	
	PU3	Using the LMS makes it easier to access course materials.	
Perceived ease of use	PEOU1	Learning to use the LMS is easy for me.	Davis (1989), Sulaiman et al. (2023), Al-Nuaimi et al. (2022), and Humida et al. (2022)
	PEOU2	Interacting with the LMS is clear and understandable.	
	PEOU3	The LMS is easy to use for my educational needs.	
Attitude toward using	ATU1	I have a positive attitude toward using the LMS.	Davis (1989), Al-Nuaimi et al. (2022), Humida et al. (2022), and Findik-Coşkunçay et al. (2018)
	ATU2	Using the LMS is a good idea.	
	ATU3	I enjoy using the LMS for my studies.	
Behavioral intention	BI1	I intend to use the LMS in the future.	Davis (1989), Sulaiman et al. (2023), and Al-Nuaimi et al. (2022)
	BI2	I plan to use the LMS frequently for my studies.	
	BI3	I will recommend the LMS to other students.	

were considered. Placing the calculated values, i.e., α and Composite Reliability (CR), at an acceptable level confirmed the internal consistency reliability. It indicates the validity of determined measures for measuring the relevant constructs.

Then, the study evaluated the convergent validity through the metric of Average Variance Extracted (AVE). The AVE values exceeded the threshold of 0.5, indicating that constructs elucidated over half of the variance for their respective indicators (Hair et al., 2017), as detailed further in section 4.2.1. For discriminant validity, the initial analysis employed the Fornell and Larcker (1981) criterion. It juxtaposes the AVE with the constructs' squared correlation coefficients. An alternative measure, the heterotrait-monotrait (HTMT) ratio, serves as the average of inter-construct item correlations against the geometric mean of intra-construct average correlations. Henseler et al. (2015) stated that the HTMT ratio might supplant the conventional Fornell-Larcker benchmark by conducting a comprehensive bootstrapping process with 5,000 iterations. Moreover, HTMT values were ascertained at a 95% confidence interval, all falling below the critical value of 1 (Hair et al., 2017).

Furthermore, the blindfolding technique was applied to evaluate the Q^2 values of dependent constructs, showing predictive relevance. Hence, a deletion interval (D) of 9 is specified. This indicates the omission of certain data points from each construct during the analysis. Consequently, the PLS algorithm interpolates the omitted information to appraise the missing values. It estimates latent constructs and indicators using observed data points (Zeng et al., 2021).

4 Results

4.1 Description of the sample

Table 2 describes the profile of research participants. Almost an equal number of male and female students answered the questionnaire (48.6 and 46.2, respectively), with an average age of 26.98 years. This sample had used LMS during the quarantine period of COVID-19. Accordingly, their mean experience of working with LMS was 1.97 years. Furthermore, most of the respondents accessed the virtual learning environment through smartphones and mobile data. SAMA, Adobe Connect, and Skyroom were the most prevalent LMS platforms in Iranian AHE.

4.2 Modeling process

At this stage, data were analyzed using structural equation modeling (SEM) with Smart PLS software. The modeling process has benefited from measurement and structural models.

4.2.1 Assessment of the measurement model

The measurement model was validated using various tests. Accordingly, the normality of data was assessed using skewness and kurtosis statistics. The calculated values showed that all items fell within the acceptable range of −2 to +2, and this dataset has a normal distribution. Additionally, items with loadings close to 0.7

were retained because they contribute to the overall reliability and validity of the constructs. According to Hair et al. (2022), loadings above 0.5 are acceptable in exploratory research, especially when the constructs are well-established in the literature. Retaining these items ensures that the measurement model captures the full range of variability in the constructs, enhancing the robustness of the analysis (Table 4).

Furthermore, the calculation of Cronbach's alpha (α), average variance extracted (AVE), and composite reliability (CR) was considered. So, the findings confirmed the estimations as acceptable, with values greater than 0.5 for AVE and values greater than 0.7 for CR. Moreover, all α values were higher than 0.7 (Hair et al., 2017; Hair et al., 2023). In other words, relevant constructs are estimated (see Kline, 2015), and convergent validity of the measurement model is supported (Fornell and Larcker, 1981; Hair et al., 2017).

Furthermore, the discriminant validity of the model was assessed in three methods: First, the Fornell-Larcker criterion showed that the AVE square root value for each construct was higher than its highest correlation with other constructs (Table 5) (Rasoolimanesh, 2022). Second, the cross-loadings matrix displayed that each indicator had a higher outer loading on its associated construct than any other latent variable (Appendix 1) (Hair et al., 2023). Third, the discriminant validity was substantiated by the heterotrait-monotrait (HTMT) ratio as proposed by Henseler et al. (2015). This ratio offers a correction for the limitations associated with the Fornell-Larcker criterion and the cross-loading approaches. So, all constructs had optimal HTMT values less than 0.85 (Appendix 2). Therefore, the suggested model demonstrated adequate discriminant validity.

4.2.2 Analysis of the structural model

During the structural modeling, the variance inflation factor (VIF) method was used. This assessment is conducted to identify any potential discrepancies arising from significant correlations between latent variables, as outlined by Hair et al. (2022). According to Appendix 3, all VIF values were lower than the threshold, indicating no multicollinearity problem.

TABLE 4 Assessment of measures.

Construct and items	Loadings	Alpha	CR	AVE
Technology		0.768	0.849	0.586
TECH1	0.671			
TECH2	0.787			
TECH3	0.768			
TECH4	0.827			
Environment		0.738	0.85	0.654
ENV1	0.823			
ENV2	0.844			
ENV3	0.756			
Organization		0.704	0.834	0.626
ORG1	0.812			
ORG2	0.818			
ORG3	0.741			
Perceived usefulness		0.921	0.95	0.863
PU1	0.914			
PU2	0.943			
PU3	0.929			
Perceived ease of use		0.714	0.746	0.501
PEOU1	0.827			
PEOU2	0.716			
PEOU3	0.552			
Attitude		0.848	0.908	0.767
ATU1	0.831			
ATU2	0.902			
ATU3	0.893			
Intention		0.874	0.923	0.799
BI1	0.875			
BI2	0.867			
BI3	0.938			

$p < 0.01$.

To evaluate the structural model, path coefficients (β), t-statistics, coefficients of determination (R^2), and predictive relevance (Q^2) were estimated. The significance of β values was conducted according to t (> 1.96) and p-values, with a 5% error probability. To ascertain the significance of the hypotheses, a bootstrapping algorithm utilizing 5,000 samples was employed within the PLS framework (Appendix 1). This algorithm is a resampling technique that estimates standard errors and confidence intervals of the parameters. Table 6 and Appendix 4 displays hypotheses testing. According to this, all hypotheses were supported except H4, H5, and H6.

Regarding the TOE framework, findings revealed that technology-related characteristics of LMS positively influence the users' perceived usefulness ($\beta = 0.315$, $t = 5.229$, $p < 0.05$), supporting the first hypothesis (H1). Moreover, this technological context showed its positive effect on perceived ease of use ($\beta = 0.532$, $t = 10.489$, $p < 0.05$). So, the second hypothesis (H2) is confirmed. Moreover, affirming H3 shows that environment-related context has a positive effect on the users' perceived usefulness ($\beta = 0.219$, $t = 3.571$, $p < 0.05$). Nevertheless, environmental context do not have a significant impact on the users' perceived ease of use ($\beta = -0.002$, $t = 0.028$, $p = 0.98$), meaning the rejection of H4. Similarly, organization context exerts no significant effects on perceived usefulness ($\beta = 0.044$, $t = 0.662$, $p = 0.51$) and perceived ease of use ($\beta = 0.006$, $t = 0.092$, $p = 0.93$). Therefore, these results lead to the rejection of H5 and H6. Regarding the TAM variables, findings indicate the support of H7 and H8. So, perceived ease of use positively affects perceived usefulness and attitude toward using LMS at $p < 0.05$ ($\beta = 0.148$, $t = 2.880$ and $\beta = 0.194$, $t = 4.481$, respectively). Additionally, the results confirmed that perceived usefulness has a positive influence on both attitude toward using (H9) and behavioral intention (H10) ($\beta = 0.582$, $t = 16.09$, $p < 0.05$ and $\beta = 0.375$, $t = 9.113$, $p < 0.05$, respectively). Finally, supporting H11 means that attitude toward using LMS had a positive effect on behavioral intention ($\beta = 0.561$, $t = 14.806$, $p < 0.05$).

4.2.3 Quality and fit assessment of the model

This study used the coefficient of determination (R^2) to determine the total variance of the dependent variable (behavioral intention) that was explained by the independent variables. According to Chin (1998), R^2 values are classified into three groups: strong (0.67), medium (0.33), and weak (0.19). These values show the extent to which the independent variables can explain the changes in the variance of the dependent variable. As shown in Table 7, most of the estimated R^2 values were considered as medium and higher. Similarly, technological, organizational, and environmental factors can explain the changes in the variance of perceived usefulness and perceived ease of use, namely 33.6 and 28.6%, respectively. Taken together, perceived usefulness and perceived ease of use can explain 46.5% of the variance in attitude toward using. Moreover, the suggested model explains 73.3% of the variance in behavioral intention (Table 7).

Moreover, Q^2 values of the latent variables were estimated using the Blindfolding procedure. To do so, the omission distance (D) was set to 9. It means that some data points were deleted for each construct, and then the suggested model and PLS parameters were applied to estimate the missing data (Zeng et al., 2021). To assess the predictive

TABLE 5 Assessment of discriminant validity.

Constructs	1	2	3	4	5	6	7
1. Technology	**0.765***						
2. Environment	0.481	**0.809**					
3. Organization	0.569	0.667	**0.791**				
4. Perceived ease of use	0.535	0.259	0.308	**0.707**			
5. Perceived usefulness	0.524	0.438	0.414	0.387	**0.929**		
6. Attitude	0.676	0.573	0.57	0.42	0.658	**0.876**	
7. Intention	0.636	0.529	0.532	0.439	0.744	0.808	**0.894**

* The diagonal bold values display AVE square roots. Correlations between each construct and others are presented below the diagonal.

TABLE 6 Hypotheses testing.

Hypothesis	Path	β	t-value	p-value	Result
H1	Technology → Perceived usefulness	0.315	5.229	0.00	Supported
H2	Technology → Perceived ease of use	0.532	10.489	0.00	Supported
H3	Environment → Perceived usefulness	0.219	3.571	0.00	Supported
H4	Environment → Perceived ease of use	−0.002	0.028	0.98	Rejected
H5	Organization → Perceived usefulness	0.044	0.662	0.51	Rejected
H6	Organization → Perceived ease of use	0.006	0.092	0.93	Rejected
H7	Perceived ease of use → Perceived usefulness	0.148	2.880	0.01	Supported
H8	Perceived ease of use → Attitude	0.194	4.481	0.00	Supported
H9	Perceived usefulness → Attitude	0.582	16.09	0.00	Supported
H10	Perceived usefulness → Intention	0.375	9.113	0.00	Supported
H11	Attitude → Intention	0.561	14.806	0.00	Supported

TABLE 7 Quality and fit assessment of the structural model.

Constructs	R^2	Adj. R^2	Q^2	SRMR	NFI	RMS_theta
Model quality				0.071	0.903	0.107
Perceived usefulness	0.336	0.329	0.274			
Perceived ease of use	0.286	0.281	0.132			
Attitude	0.465	0.462	0.342			
Intention	0.733	0.731	0.562			

quality of the model, a PLS-predict analysis was performed following the guidelines of Hair et al. (2022). The PLS-predict procedure involves generating out-of-sample predictions for the dependent variables and comparing them with the actual values. The results indicated that the model has strong predictive power, with Q^2 values for perceived usefulness (0.274), perceived ease of use (0.132), attitude (0.342), and behavioral intention (0.562) being positive and above the threshold of 0. This confirms the model's ability to predict the intention to adopt LMS in AHE (Sarstedt et al., 2014).

Furthermore, the quality of the model was assessed by the standardized root mean square residual (SRMR index), which indicates a better fit when the value is lower than 0.08. This index measures the average discrepancy between the observed and expected correlations in the model (see Henseler et al., 2014). Accordingly, measurement calculations showed that SRMR values regarding the saturated and estimated models were below 0.08 with a good fit, which is 0.047 and 0.071. In addition, the normed fit index (NFI) values for both models were above 0.90 (0.909 and 0.903, respectively), which met the preferred criterion of NFI $\geq$ 0.90 (Ringle et al., 2020).

As the last fit criterion, the RMS_theta index is the root mean square of the residual covariance matrix concerning the outer model. As the outer model residuals are meaningless for formative measurement models, this criterion is applicable toward reflective models (Henseler et al., 2014). So, the RMS_theta value shows a good fit at 0.107.

5 Discussion

This study has embarked on an enlightening exploration of the world of LMSs and their far-reaching impact on the AHE. To do so, it has presented a comprehensive LMS model that relies on the integration of TOE and TAM. This integrated model addresses the factors influencing toward the intention to use LMS in disrupted situations such as the COVID-19 outbreak. Since the inclusion of these systems into AHE was not considered seriously before this period, it is necessary to understand the factors affecting the successful adoption of LMS more precisely. More importantly, providing a context for creating LMS-oriented policies, programs, and curricula and providing necessary educational facilities and infrastructure are among the expected achievements of this study.

Accordingly, the adoption of LMS in AHE has proven to act as a game changer, empowering educators and students alike with an array of innovative tools designed to meet the unique demands of this specialized domain (Hwa et al., 2015; Mohamed Riyath and Muhammed Rijah, 2022). As agricultural-related fields encompass a diverse range, from agronomy and animal sciences to environmental management and forestry, LMS emerges as a crucial facilitator, catering to the diverse demands and learning styles (Rosli and Saleh, 2022). By shedding light on the influencing factors of LMS adoption, the aim is to equip educators, institutions, and other stakeholders with the knowledge and tools necessary to benefit from the full potential of this technology, empowering the next generation of agricultural leaders.

This is while the literature shows that few studies have investigated the LMS during disrupted conditions. Moreover, some fields, such as medical education, have received more attention, and AHE has had much fewer studies. That is, the integrated modeling to study the acceptance rate of these systems, particularly in AHE during the COVID-19 conditions, is not seen in previous studies. Nevertheless, the complex and practical nature of AHE requires the provision of a comprehensive LMS adoption model (Al-Nuaimi and Al-Emran, 2021).

Currently, the development of educational technologies, especially web-based ones, has accelerated the development of electronic learning methods in universities worldwide (Rosli and Saleh, 2022). Although the existence of some components, such as hardware facilities and specialized human resources, are necessary for the development of e-learning in higher education, the access and proper use of web-based software systems such as LMS are the main requirements for the expansion of e-learning (Çakiroğlu et al., 2024). This is an issue whose importance was greatly neglected in the past. The emergence of the COVID-19 pandemic caused an unprecedented change in higher education and accelerated the growth of these systems. The first and most important sign of this change was the increasing spread of electronic education instead of face-to-face education in universities.

Along with the global changes and the severe consequences of the epidemic, the changes in Iran also took place. Despite having a suitable foundation of knowledge, the implementation of LMS faced some problems and limitations, such as partial educational planning along with insufficient technical and human resources, limited capacity of educational tools, and some cultural conditions. So, important questions are raised in the post-COVID era:

- Is the usage of LMS significantly acceptable after the COVID-19 era?
- What factors affect the adoption of LMS among students of AHE?

Understanding individuals' intentions to adopt technology is crucial, as it can aid planners in the management process and contribute to the achievement of sustainable development goals, such as SDG 4 (Al-Nuaimi and Al-Emran, 2021; Mohamed Riyath and Muhammed Rijah, 2022). In addition, presenting the integrated model resulting from two theories, TOE and TAM, can show a better understanding of the intention to adopt LMS. This integration leads to providing clear solutions to reduce the challenges facing AHE. Moreover, the combination of these theories has a favorable potential to explain the level of intention to use LMS between stakeholders both during and after the COVID-19 era.

The results of the hypothesis tests provide valuable insights into the factors influencing LMS adoption in AHE. For instance, the positive effect of technological context on perceived usefulness (H1: $\beta = 0.315$, $p < 0.05$) and perceived ease of use (H2: $\beta = 0.532$, $p < 0.05$) aligns with previous studies (e.g., Sulaiman et al., 2023; Humida et al., 2022; Nguyen et al., 2022), which highlight the importance of robust technological infrastructure in facilitating LMS adoption. Similarly, the significant impact of environmental context on perceived usefulness (H3: $\beta = 0.219$, $p < 0.05$) underscores the role of external factors, such as government policies and societal expectations, in shaping user perceptions. However, the lack of significant effects for environmental context on perceived ease of use (H4: $\beta = -0.002$, $p = 0.98$) and organizational context on perceived usefulness (H5: $\beta = 0.044$, $p = 0.51$) and perceived ease of use (H6: $\beta = 0.006$, $p = 0.93$) suggests that these factors may play a less critical role in the Iranian context, which warrants further investigation.

The results of this study showed that the proposed model has a good explanation power (73%) in predicting the intention of users to adopt LMS. Nevertheless, findings related to TOE theory have indicated the unequal effects of its components. From a theoretical view, technological, organizational, and environmental contexts can have a major contribution to the rate of technology adoption but the effect of technological context has been more evident here. That is, the internal/ external technological factors have been able to exert significant effects on the perceived usefulness and perceived ease of use toward LMS. These show their prominent role in the final adoption of educational technology. In concordance with the perspectives of various scholars (Radif, 2016; Mahlangu and Makwasha, 2023; Nguyen et al., 2022; Hiran and Henten, 2020), the fortification of technological infrastructure within and beyond the realm of higher education is paramount. Such enhancement is crucial for expediting and refining of LMSs.

To explain more, the environmental context of the university can also has a remarkable role. If the stakeholders of an academic environment, including the government and the general public, provide reasons to strengthen and expand the use of LMS in community education, then the increase in perceived usefulness will lead to more usage of this technology in agricultural colleges. However, the effect of environmental context on the perceived ease of use has not been confirmed, which requires further adoption studies. Similarly, the effects of organizational context on perceived usefulness and perceived ease of use have not been supported here. However, more studies are needed to consider the components of organizational context. That is, the preparation of organizational factors is of importance in educational studies. The divergence in findings between this study and those of other researchers (Sulaiman et al., 2023; Nguyen et al., 2022) may be ascribed to the inherent adaptability of the TOE model. Such variability in results is understandable, given the model's flexible application across different contexts.

By examining the TAM theory, it seems that the role of perceived usefulness is more significant in two aspects. This variable acts on the intention to use LMS dually. First, improving perceived usefulness directly improves the intention to use. Of course, there is also an indirect path that the study implicitly includes. Perceived usefulness can increase the adoption intention by having a positive effect on attitude toward using LMS. Therefore, focusing on the indirect path, as a mediating role of perceived usefulness, leaves space for further studies. The confirmation of this effect is in line with the findings of Al-Nuaimi et al. (2022), Mailizar et al. (2021), Al-Mamary (2022), Mohamed Riyath and Muhammed Rijah (2022), and Yao et al. (2022). They found perceived usefulness and attitude to be important variables affecting the decision to use technology. Previously, the perceived ease of use had been able to exert similar effects in relation to the attitude. So, in addition to displaying a direct effect on attitude, perceived ease of use has influenced the attitude and then intention as a mediating variable. However, no direct effect of this variable on intention has been investigated, which needs further studies.

The rejection of H4, which posited a positive effect of environmental context on perceived ease of use, may be attributed to the unique challenges faced by AHE in Iran. For instance, the lack of reliable internet connectivity in rural areas, where many agricultural universities are located, may have diminished the perceived ease of use of LMS platforms. Similarly, the rejection of H5 and H6, which hypothesized positive effects of organizational context on perceived usefulness and perceived ease of use, may reflect the limited institutional support and resources available for LMS implementation in Iranian universities. These findings highlight the need for targeted interventions to address these contextual barriers and improve LMS adoption in AHE.

As study implications, the analysis revealed that having a more contextual understanding of LMS during disrupted conditions, such as the COVID-19 outbreak, is a prerequisite for the successful adoption and implementation of this technology. The contexts may work differently in various educational environments. So, relevant policymakers should clearly define the context of LMS.

Since findings support the good explanation power of the integrated model, relevant policymakers and managers in Iran (or other developing countries) are advised to employ strategies emphasizing the integrated use of technology adoption components at different educational levels. Moreover, strengthening various factors contributing to the adoption of LMS will improve the intention. Of course, necessary considerations should be taken into account when generalizing the results. Table 8 shows the main research contributions.

6 Conclusion

The emergence of concerns and deficiencies in disrupted conditions often reveals new educational demands and responses at different levels of education. Therefore, this study relies upon the concept of "knowledge sharing" through the adoption of LMS in Iranian AHE during the COVID-19 era. Recent studies from other regions, such as Southeast Asia and Sub-Saharan Africa, have also highlighted the importance of technological infrastructure and institutional support in LMS adoption (e.g., Nguyen et al., 2022; Mahlangu and Makwasha, 2023). These findings align with our results, suggesting that the challenges and opportunities associated with LMS adoption are not unique to the Middle East but are relevant to developing countries worldwide. It exemplifies how using educational technologies/innovations such as LMS drives

TABLE 8 Main contributions of the research.

Dimension	Research issue	Current findings	Future directions
Theoretical	• The understanding of LMS usage behavior in higher education and during the COVID-19 outbreak requires more comprehensive and integrated models. • The currently used single models do not explain all adoption behaviors in disrupted conditions.	• Providing an integrated adoption model using the TAM and TOE theories.	• The integrated usage of adoption theories in further studies is necessary, particularly during disruptions. • In order to fill the gap caused by single adoption theories, the modeling requires the assessment of appropriateness and relationships between alternative theories.
Practical	• The LMS literature has displayed different results regarding LMS adoption behavior. • The literature examines various influencing factors toward the adoption of LMS.	• The current study showed that technological and environmental contexts are significantly effective toward the components of TAM, which consequently influence the intention to use LMS.	• It is suggested to identify more variables that exert an effect on the intention to use electronic education. • More detailed experimental and longitudinal studies on the role of behavioral intention in usage behavior are needed. • Examining the validity and generalization of the suggested model in different situations and with different participants is useful.
Geographical	• There is still a gap regarding the local influencing factors of LMS adoption in developing countries.	• Current study was conducted in Iran aiming to identify the influencing factors of LMS.	• It is recommended to conduct similar comparative studies in other countries, particularly developing countries.
Policy	• There is still a gap toward the design of LMS adoption in disrupted conditions.	• Higher education policymakers/planners should clearly define the relevant contexts of LMS. • Educational policymakers/managers are advised to employ the integrated usage of technology adoption components.	• This study focuses on decentralization in the management and planning of LMS to provide context-based opportunities, drawing support policies based on the participation of all stakeholders.

progress in education and the sharing of knowledge between students. LMSs are an active process that outlines the role of modern education for effective presence, especially during the COVID-19 outbreak. This study contributes to the literature by integrating TAM and TOE frameworks to provide a comprehensive understanding of LMS adoption in AHE. The integration of these frameworks allows us to capture both individual-level perceptions (e.g., perceived usefulness and perceived ease of use) and contextual factors (e.g., technological, environmental, and organizational contexts) that influence LMS adoption. By doing so, we address a gap in the literature and provide a more holistic model for understanding LMS adoption in specialized educational contexts. Accordingly, findings will help educational policymakers and planners in making decisions for the optimal implementation of LMS in Iranian higher education. Moreover, it is suggested to assess the application of integrated adoption models in other educational backgrounds.

Based on our findings, we recommend that policymakers in Iran focus on strengthening the technological infrastructure for LMS adoption, particularly in rural areas where agricultural universities are often located. This could include investments in high-speed internet connectivity, user-friendly LMS platforms, and technical support services. Additionally, we recommend fostering a supportive organizational culture that encourages innovation and provides adequate resources for LMS implementation. Finally, we suggest that policymakers collaborate with stakeholders, such as government agencies and industry partners, to create a conducive environment for LMS adoption in AHE.

The lack of significant effects for organizational context on perceived usefulness and perceived ease of use may reflect the limited institutional support and resources available for LMS implementation in Iranian universities. This finding underscores the need for targeted interventions to address these barriers, such as providing training for faculty and staff, allocating sufficient funding for LMS implementation, and fostering a culture of innovation within the institution. The COVID-19 pandemic has significantly accelerated the adoption of LMS in AHE. While pre-pandemic adoption rates were low due to limited infrastructure and institutional support, the pandemic has highlighted the urgent need for effective e-learning solutions. Post-pandemic adoption rates have increased, driven by the necessity to ensure continuity of education in the face of disruptions. This shift underscores the importance of investing in technological infrastructure and institutional support to sustain the gains made during the pandemic.

This study has several limitations that should be acknowledged. First, the theoretical framework integrates TAM and TOE but does not account for all potential factors influencing LMS adoption, such as individual differences (e.g., self-efficacy, prior experience) or cultural factors. Second, the cross-sectional design limits our ability to establish causal relationships between the variables. Future studies could adopt a longitudinal approach to address this limitation. Third, the study focuses on AHE in Iran, which may limit the generalizability of the findings to other contexts. Future research could explore the applicability of the proposed model in different educational settings and cultural contexts.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the ethics committee of Agricultural Sciences and Natural Resources University of Khuzestan. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

SS: Conceptualization, Methodology, Resources, Software, Writing – original draft, Writing – review & editing. OJ: Conceptualization, Data curation, Investigation, Validation, Writing – original draft. ZF: Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1551546/full#supplementary-material

References

Abdullah, F., and Ward, R. (2016). Developing a general extended technology acceptance model for e-learning (GETAMEL) by analysing commonly used external factors. *Comp. In Human Behav.* 56, 238–256. doi: 10.1016/j.chb.2015.11.036

Ajzen, I. (1991). The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* 50, 179–211. doi: 10.1016/0749-5978(91)90020-T

Al-Mamary, Y. H. S. (2022). Why do students adopt and use learning management systems?: insights from Saudi Arabia. *Int. J. Inf. Manag. Data Insights* 2:100088. doi: 10.1016/j.jjimei.2022.100088

Al-Nuaimi, M. N., Al Sawafi, O. S., Malik, S. I., Al-Emran, M., and Selim, Y. F. (2022). Evaluating the actual use of learning management systems during the covid-19 pandemic: an integrated theoretical model. *Interact. Learn. Environ.* 31, 6905–6930. doi: 10.1080/10494820.2022.2055577

Al-Nuaimi, M. N., and Al-Emran, M. (2021). Learning management systems and technology acceptance models: A systematic review. *Educ. Inf. Technol.* 26, 5499–5533. doi: 10.1007/s10639-021-10513-3

Al-Rahmi, W. M., Yahaya, N., Alamri, M. M., Alyoussef, I. Y., Al-Rahmi, A. M., and Kamin, Y. B. (2021). Integrating innovation diffusion theory with technology acceptance model: supporting students' attitude towards using a massive open online courses (MOOCs) systems. *Interact. Learn. Environ.* 29, 1380–1392. doi: 10.1080/10494820.2019.1629599

Alturki, U., and Aldraiweesh, A. (2021). Application of learning management system (Lms) during the covid-19 pandemic: A sustainable acceptance model of the expansion technology approach. *Sustain. For.* 13:10991. doi: 10.3390/su131910991

Baker, J. (2012). The technology–organization–environment framework. *Inf. Syst. Ther.* 28, 231–245. doi: 10.1007/978-1-4419-6108-2_12

Beirat, M. A., Tashtoush, D. M., Khasawneh, M. A., Az-Zo'bi, E. A., and Tashtoush, M. A. (2025). The effect of artificial intelligence on enhancing education quality and reduce the levels of future anxiety among Jordanian teachers. *Appl. Math.* 19, 279–290. doi: 10.18576/amis/190205

Bharadwaj, S., and Deka, S. (2021). Behavioural intention towards investment in cryptocurrency: an integration of Rogers' diffusion of innovation theory and the technology acceptance model. *Forum Sci. Oecon.* 9, 137–159. doi: 10.23762/fso_vol9_no4_7

Buabeng-Andoh, C., and Baah, C. (2020). Pre-service teachers' intention to use learning management system: an integration of UTAUT and TAM. *Inter. Technol. Smart Educ.* 17, 455–474. doi: 10.1108/ITSE-02-2020-0028

Çakiroğlu, Ü., Kokoç, M., and Atabay, M. (2024). Online learners' self-regulated learning skills regarding LMS interactions: a profiling study. *J. Comput. High. Educ.* 36, 220–241. doi: 10.1007/s12528-024-09397-2

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Mod. Methods Bus. Res.* 295, 295–336.

Dash, G., and Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technol. Forecast. Soc. Chang.* 173:121092. doi: 10.1016/j.techfore.2021.121092

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* 13, 319–340. doi: 10.2307/249008

Dias, B. D., Diniz, J. A., and Hadjileontiadis, L. J. (2014). Towards an intelligent learning management system under blended learning: trends, profiles and modeling perspectives. *Intell. Syst. Ref. Lib.* 59:9. doi: 10.1007/978-3-319-02078-5

Findik-Coşkunçay, D., Alkiş, N., and Özkan-Yildirim, S. (2018). A structural model for students' adoption of learning management systems: an empirical investigation in the higher education context. *J. Educ. Technol. Society.* 21, 13–27. doi: 10.1037/t70573-000

Fishbein, M., and Ajzen, I. (1976). Misconceptions about the Fishbein model: reflections on a study by Songer-nocks. *J. Exp. Soc. Psychol.* 12, 579–584. doi: 10.1016/0022-1031(76)90036-6

Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* 18, 39–50. doi: 10.1177/002224378101800104

Ghasemy, M., Teeroovengadum, V., Becker, J. M., and Ringle, C. M. (2020). This fast car can move faster: A review of PLS-SEM application in higher education research. *High. Educ.* 80, 1121–1152. doi: 10.1007/s10734-020-00534-1

Hair, J. F., Hair, J., Sarstedt, M., Ringle, C. M., and Gudergan, S. P. (2023). Advanced issues in partial least squares structural equation modeling. London: Sage Publications.

Hair, J. F. M., Hult, G. T., Ringle, C. M., and Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM). *3rd* Edn. London: Sage Publishing.

Hair, J. F., Matthews, L. M., Matthews, R. L., and Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *Int. J. Multiva. Data Anal.* 1, 107–123. doi: 10.1504/IJMDA.2017.087624

Haleem, A., Javaid, M., Qadri, M. A., and Suman, R. (2022). Understanding the role of digital technologies in education: A review. *Sustain. Oper. Comput.* 3, 275–285. doi: 10.1016/j.susoc.2022.05.004

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., et al. (2014). Common beliefs and reality about PLS: comments on Rönkkö and Evermann (2013). *Organ. Res. Methods* 17, 182–209. doi: 10.1177/1094428114526928

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* 43, 115–135. doi: 10.1007/s11747-014-0403-8

Hernández-García, Á., Cuenca-Enrique, C., Del-Río-Carazo, L., and Iglesias-Pradas, S. (2024). Exploring the relationship between LMS interactions and academic performance: A learning cycle approach. *Comput. Hum. Behav.* 155:108183. doi: 10.1016/j.chb.2024.108183

Hiran, K. K., and Henten, A. (2020). An integrated TOE–DoI framework for cloud computing adoption in the higher education sector: case study of sub-Saharan Africa, Ethiopia. *Int. J. Syst. Assur. Eng. Manag.* 11, 441–449. doi: 10.1007/s13198-019-00872-z

Humida, T., Al Mamun, M. H., and Keikhosrokiani, P. (2022). Predicting behavioral intention to use e-learning system: A case-study in begum Rokeya university, Rangpur, Bangladesh. *Educ. Inf. Technol.* 27, 2241–2265. doi: 10.1007/s10639-021-10707-9

Hwa, S. P., Hwei, O. S., and Peck, W. K. (2015). Perceived usefulness, perceived ease of use and behavioural intention to use a learning management system among students in a Malaysian university. *Int. J. Concept. Manag. Soc. Sci.* 3, 29–35.

Kazemzadeh, T. (2022). E-learning acceptance among university students in Iran during the Covid-19 pandemic. *Asian J. Dist. Educ.* 17, 205–225.

Kerimbayev, N., Umirzakova, Z., Shadiev, R., and Jotsov, V. (2023). A student-centered approach using modern technologies in distance learning: a systematic review of the literature. *Smart Learn. Environ.* 10:61. doi: 10.1186/s40561-023-00280-8

Khan, R. A., and Qudrat-Ullah, H. (2021). Adoption of LMS in Higher Educational Institutions of the Middle East. New York: Springer.

Kline, R. B. (2015). Principles and practice of structural equation modeling. *4th* Edn. New York: The Guilford Press.

Lai, J. W., and Bower, M. (2019). How is the use of technology in education evaluated? A systematic review. *Comput. Educ.* 133, 27–42. doi: 10.1016/j.compedu.2019.01.010

Lytras, M. D., Serban, A. C., Ruiz, M. J. T., Ntanos, S., and Sarirete, A. (2022). Translating knowledge into innovation capability: an exploratory study investigating the perceptions on distance learning in higher education during the COVID-19 pandemic-the case of Mexico. *J. Innov. Knowl.* 7:100258. doi: 10.1016/j.jik.2022.100258

Mahlangu, G., and Makwasha, L. (2023). Factors affecting the adoption and use of online assessment for learning at polytechnics in Zimbabwe. *Cog. Educ.* 10:2177475. doi: 10.1080/2331186X.2023.2177475

Mailizar, M., Burg, D., and Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: an extended TAM model. *Educ. Inf. Technol.* 26, 7057–7077. doi: 10.1007/s10639-021-10557-5

Mohamed Riyath, M. I., and Muhammed Rijah, U. L. (2022). Adoption of a learning management system among educators of advanced technological institutes in Sri Lanka. *Asian Assoc. Open Univ. J.* 17, 161–177. doi: 10.1108/AAOUJ-03-2022-0032

Nguyen, T. H., Le, X. C., and Vu, T. H. L. (2022). An extended technology-organization-environment (TOE) framework for online retailing utilization in digital transformation: empirical evidence from Vietnam. *J. Open Innov.: Technol. Mark. Complex.* 8:200. doi: 10.3390/joitmc8040200

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., and Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J. Appl. Psychol.* 88, 879–903. doi: 10.1037/0021-9010.88.5.879

Radif, M. (2016). A learning management system adoption framework for higher education: the case of Iraq. England: School of Aerospace, Transport and Manufacturing (SATM), Cranfield University.

Rasheed, N. M., and Tashtoush, M. A. (2023). The impact of cognitive training program for children (CTPC) to development the mathematical conceptual and achievement. *J. High. Educ. Theory Pract.* 23:196. doi: 10.33423/jhetp.v23i10.6196

Rasoolimanesh, S. M. (2022). Discriminant validity assessment in PLS-SEM: A comprehensive composite-based approach. *Data Anal. Persp. J.* 3, 1–8.

Ringle, C. M., Sarstedt, M., Mitchell, R., and Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. *Int. J. Hum. Resour. Manag.* 31, 1617–1643. doi: 10.1080/09585192.2017.1416655

Rogers, E. M. (2003). Elements of diffusion. Diffusion of innovations. *Free. Press.* 5, 18–46.

Rosli, M. S., and Saleh, N. S. (2022). Technology enhanced learning acceptance among university students during COVID-19: integrating the full spectrum of self-determination theory and self-efficacy into the technology acceptance model. *Curr. Psychol.* 1-20, 1–20. doi: 10.1007/s12144-022-02996-1

Sabol, M., Hair, J., Cepeda, G., Roldán, J. L., and Chong, A. Y. L. (2023). PLS-SEM in information systems: seizing the opportunity and marching ahead full speed to adopt methodological updates. *Ind. Manag. Data Syst.* 123, 2997–3017. doi: 10.1108/IMDS-07-2023-0429

Santoso, H. B., Schrepp, M., Isal, R., Utomo, A. Y., and Priyogi, B. (2016). Measuring user experience of the student-centered e-learning environment. *J. Educ. Online* 13, 58–79. doi: 10.9743/JEO.2016.1.5

Sarstedt, M., Ringle, C. M., Henseler, J., and Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon. *Long Range Plan.* 47, 154–160. doi: 10.1016/j.lrp.2014.02.007

Shirawia, N., Qasimi, A., Tashtoush, M., Rasheed, N., Khasawneh, M., and Az-Zo'bi, E. A. (2024). Performance assessment of the calculus students by using scoring rubrics in composition and inverse function. *Appl. Math. Inform. Sci.* 18, 1037–1049. doi: 10.18576/amis/180511

Sobhani, S. M. J., Chizari, M., Sadighi, H., and Alambeig, A. (2016). Talent management in agricultural higher education system in Iran: based on grounded theory. *Int. J. Agric. Manag. Dev.* 6, 327–338. doi: 10.22004/ag.econ.262599

Sobhani, S. M. J., Jamshidi, O., and Fozouni Ardekani, Z. (2024). Behavioral analysis of students towards learning management system in agricultural education. *J. Agri. Educ. Adm. Res.* 15, 94–116. doi: 10.22092/jaear.2024.364436.1990

Sulaiman, T. T., Mahomed, A. S. B., Rahman, A. A., and Hassan, M. (2023). Understanding antecedents of learning management system usage among university lecturers using an integrated TAM-TOE model. *Sustain. For.* 15:1885. doi: 10.3390/su15031885

Tarhini, A., Masa'deh, R. E., Al-Busaidi, K. A., Mohammed, A. B., and Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modeling approach. *J. Int. Educ. Bus.* 10, 164–182. doi: 10.1108/JIEB-09-2016-0032

Tashtoush, M. A., Wardat, Y., AlAli, R., and Al-Saud, K. (2023). The impact of cyberbullying on student motivation to learn: insights from Abu Dhabi emirate schools. *Humanit. Soc. Sci. Lett.* 11, 461–474. doi: 10.18488/73.v11i4.3566

Tashtoush, M. A., Wardat, Y., Khasawneh, M. A., and Az-Zo'bi, E. A. (2025). The level of compliance to the criteria of the education evaluation Commission in Jordan in teaching and learning standards. *J. Stat. Appl. Probab.* 14, 17–26. doi: 10.18576/jsap/140102

Tornatzky, L. G., and Fleischer, M. (1990). The processes of technological innovation. Lexington: Lexington Books.

Troshkova, E. V., Bezrukikh, J. A., Safronov, M. V., and Luk'ianova, A. A. (2023). "Designing a new education ecosystem model for sustainable regional development using additive technologies" in Game strategies for business integration in the digital economy. ed. E. G. Popkova (Leeds, England: Emerald Publishing Limited).

Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Ann. Oper. Res.* 308, 641–652. doi: 10.1007/s10479-020-03918-9

Yao, Y., Wang, P., Jiang, Y., Li, Q., and Li, Y. (2022). Innovative online learning strategies for the successful construction of student self-awareness during the COVID-19 pandemic: merging TAM with TPB. *J. Innov. Knowl.* 7:100252. doi: 10.1016/j.jik.2022.100252

Zamiri, M., and Esmaeili, A. (2024). Methods and Technologies for Supporting Knowledge Sharing within learning communities: a systematic literature review. *Adm. Sci.* 14:17. doi: 10.3390/admsci14010017

Zeng, N., Liu, Y., Gong, P., Hertogh, M., and König, M. (2021). Do right PLS and do PLS right: A critical review of the application of PLS-SEM in construction management research. *Front. Eng. Manag.* 8, 356–369. doi: 10.1007/s42524-021-0153-5

Zhao, K., and Mok, K. H. (2024). The COVID-19 pandemic and post-graduation outcomes: evidence from Chinese elite universities. *Int. J. Educ. Res.* 124:102312. doi: 10.1016/j.ijer.2023.102312