Analyzing Factors Influencing Learning Management System Adoption in Adult Continuing Education in China: A Systematic Literature Review

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Abstract: The rapid digital transformation of higher education, accelerated by the COVID-19 pandemic, has positioned LMS as a critical infrastructure for lifelong learning and workforce development. However, adult learners in continuing education programmes face unique challenges related to self-directed learning, technological readiness, and institutional support, which remain underexplored in the existing literature. This study analysed 35 empirical articles published between 2020 and 2025, retrieved from Scopus, Web of Science, Google Scholar, and CNKI. Using a thematic synthesis approach, the review identified dominant theoretical frameworks including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), and the Information System Success (ISS) model, as well as key constructs such as performance expectancy (identified in 28 studies), facilitating conditions (25 studies), trust (15 studies), instructor characteristics (12 studies), and social influence (20 studies). The findings reveal that although individual models explain between 46% and 73.5% of variance in behavioural intention, no unified framework systematically integrates institutional support, learner psychological attributes, and technological system quality specifically for adult continuing education contexts in China. Notably, only 4 out of 35 studies focused explicitly on non-full-time adult learners, and only 8 studies were conducted in mainland China. The results highlight a significant gap in the meaningful integration of learner-specific factors (self-directed learning, self-efficacy, trust), system factors (system quality, information quality, service quality), and contextual factors (facilitating conditions, instructor characteristics) within a single empirical SEM model. This study argues for the reconceptualisation of LMS adoption research as a context-sensitive framework that integrates adult learning principles, technology acceptance theories, and institutional support mechanisms to create more effective digital learning environments for adult continuing education in China.

Keywords: Learning Management System, Adult Continuing Education, China, Technology Adoption

Introduction

The landscape of adult continuing education in China is undergoing rapid transformation driven by digitalisation, economic restructuring, and the growing demand for lifelong learning in the era of the knowledge economy (Bao, 2020; Coman et al., 2020). Adult learners, particularly those enrolled in part-time, distance, or open education programmes, increasingly rely on digital platforms to balance work, family, and study commitments (Butcher, 2020; Boeren et al., 2020). In this context, Learning Management Systems (LMS) have emerged as critical infrastructure for delivering flexible, scalable, and personalised learning experiences (Bradley, 2021; Veluvali & Surisetti, 2022). Unlike traditional face-to-face instruction, LMS platforms enable asynchronous access to course materials, interactive communication tools, and progress tracking, making them especially valuable for adults who require self-paced and location-independent learning (Raza et al., 2021; Mailizar et al., 2021). Essential features typically include content management, discussion forums, assignment submission, grade tracking, and mobile compatibility, which collectively support autonomous learning, instructor-learner interaction, and skill development (Koh & Kan, 2020; Swerzenski & Swerzenski, 2021).

Among the theoretical frameworks that explain technology adoption in educational settings, the Technology Acceptance Model (TAM) proposed by Davis (1989) and its extensions have gained considerable attention as foundational models for understanding user acceptance of LMS in higher and continuing education contexts (Al-Emran et al., 2018; Granić & Marangunić, 2019). TAM posits that perceived usefulness and perceived ease of use are primary determinants of behavioural intention to use technology (Davis, 1989). Building on this, the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended version UTAUT2 incorporate additional constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit to provide a more comprehensive explanation of technology adoption behaviour (Venkatesh et al., 2003; Venkatesh et al., 2012). Numerous studies have applied these models in online learning environments, consistently demonstrating that perceived usefulness, facilitating conditions, and social influence significantly predict learners' behavioural intention and actual system use (Abbad, 2021; Ahmed et al., 2022). When these stages—ranging from initial awareness to sustained usage—are fully enacted, adult learners are more likely to develop positive attitudes, continue using the system, and achieve better learning outcomes (Almaiah et al., 2022; Yuebo et al., 2024).

In parallel, the Information System Success (ISS) model proposed by DeLone and McLean (2003) has been widely adopted to evaluate e-learning system effectiveness (Al-Fraihat et al., 2020; DeLone & McLean, 2003). The ISS model identifies system quality, information quality, and service quality as key determinants of user satisfaction and net benefits (DeLone & McLean, 2003). Studies have shown that high system quality—characterised by stability, ease of navigation, and responsiveness—positively influences perceived usefulness and satisfaction among online learners (Mohammadi, 2015; Al-Adwan, 2020). Similarly, service quality, including technical support and instructor responsiveness, has been found to enhance learner satisfaction and continued use intention (Chopra et al., 2019; Sun et al., 2008). The integration of TAM, UTAUT, and ISS models has been increasingly employed in educational technology research to capture the multidimensional nature of LMS adoption (Al-Nuaimi & Al-Emran, 2021; Cidral et al., 2020). In adult continuing education, where learners are often self-directed, time-constrained, and possess varying levels of digital literacy, understanding how system quality, information quality, and service quality interact with individual perceptions and institutional support is essential for designing effective LMS-based learning environments (Al-Adwan, 2020; Lai et al., 2024).

Furthermore, the application of Structural Equation Modelling (SEM) has become the dominant analytical approach in empirical studies of LMS adoption (Hair et al., 2022; Wong, 2026). SEM allows researchers to simultaneously examine complex relationships among latent variables, test theoretical models, and account for measurement errors, making it particularly suitable for technology acceptance research (Anderson & Gerbing, 1988; Fornell & Larcker, 1981). Both covariance-based SEM (CB-SEM) using software such as AMOS and LISREL, and variance-based partial least squares SEM (PLS-SEM) using SmartPLS, have been extensively utilised to validate extended TAM, UTAUT, and ISS models in higher education and online learning contexts (Raza et al., 2021; Almaiah & Alismaiel, 2018). For instance, Lai et al. (2024) applied CB-SEM to test an extended UTAUT2 model among 352 Mainland Chinese postgraduate students in Hong Kong, finding that trust, instructor characteristics, and performance expectancy were strong motivators of LMS adoption. Similarly, Yuebo et al. (2024) used PLS-SEM to validate an integrated ISS and TPACK model with 245 non-full-time adult students in Western China, demonstrating that system quality and teachers' TPACK ability significantly influence online learning success. These studies illustrate the robustness of SEM in uncovering the causal pathways that drive LMS adoption among adult learners.

However, despite the growing body of SEM-based research on technology acceptance, several important gaps remain. First, the majority of existing studies have focused on traditional undergraduate students in conventional university settings, while adult continuing education learners—who are often part-time, employed, and geographically dispersed—remain substantially underrepresented [36]. Second, although China has one of the world's largest systems of open and distance education, serving millions of adult learners through institutions such as the Open University of China, empirical research on LMS adoption specifically targeting this population is surprisingly limited (Hou & Yu, 2023; Mok et al., 2021). Third, existing studies tend to examine individual theoretical models in isolation, with relatively few efforts to integrate multiple frameworks into a comprehensive model that simultaneously accounts for learner psychological attributes (e.g., self-efficacy, self-directed learning), system quality dimensions (system, information, service quality), and institutional facilitating conditions (e.g., technical support, infrastructure, instructor characteristics) (Al-Nuaimi & Al-Emran, 2021; Gupta et al., 2022). Fourth, while the rapid shift to online learning during the COVID-19 pandemic accelerated LMS adoption, most studies were conducted during the emergency remote teaching period, and findings may not fully generalise to post-pandemic normal conditions or to the specific needs of adult continuing education (Adedoyin & Soykan, 2023; Cramarenco et al., 2023).

Another critical yet underexplored context is adult continuing education in China, particularly non-full-time learners enrolled in open universities, distance education programmes, and vocational continuing education courses (Boeren et al., 2020; UNESCO, 2020). Chinese adult learners face unique challenges: they must balance study with full-time employment and family responsibilities, often have limited prior experience with online learning platforms, and may lack the self-regulated learning skills necessary for successful engagement with LMS (Raza et al., 2021; Xu & Li, 2023). The Chinese government has emphasised the importance of lifelong learning and digital transformation in education through policies such as the 14th Five-Year Plan and the construction of a learning-oriented society. However, empirical evidence on the factors that influence LMS adoption among Chinese adult learners, particularly those using SEM-based approaches, remains extremely fragmented and under-synthesised (Al-Adwan, 2020).

According to adult learning theory (andragogy), meaningful learning for adults occurs when instruction is relevant, self-directed, and problem-centred (Knowles, 1984). Integrating LMS into adult continuing education has the potential to enhance motivation by providing flexible access, personalised learning paths, and immediate feedback (Lai et al., 2024; Zhou et al., 2022). Moreover, the integration of digital technology plays an essential role in shaping 21st-century skills and promoting lifelong learning among adult students (Goundar & Kumar, 2021; Jaldemark et al., 2022). Engagement in LMS-supported training contributes to the development of digital literacy, self-regulation, and career adaptability, particularly among mature learners seeking to upskill or reskill for the evolving labour market (Lim et al., 2024; Seevaratnam et al., 2023). Studies have shown that LMS interventions can increase learner engagement, reduce isolation, and improve course completion rates in adult education contexts (Butt et al., 2021; Zacharis & Nikolopoulou, 2022). However, issues related to the long-term sustainability of LMS adoption and the transferability of findings across different regions and adult learner subgroups remain critical concerns that need to be addressed (Dindar et al., 2021; Sulaiman, 2023).

Moreover, integrating multiple theoretical frameworks into a unified model for LMS adoption in adult continuing education presents significant interdisciplinary challenges. Effective integration requires alignment between learner characteristics (e.g., self-efficacy, self-directed learning), system attributes (e.g., system quality, information quality), and contextual factors (e.g., facilitating conditions, instructor support), which is often difficult to achieve in practice (Al-Adwan et al., 2023; Panigrahi et al., 2021). In addition, culturally responsive LMS design requires sensitivity to individual differences in learner backgrounds, including prior digital experience, motivational orientation, and access to technological resources, which are often overlooked in standardised adoption models (Aparicio et al., 2016; Monteiro et al., 2022). Without careful consideration, technology integration may inadvertently widen the digital divide or fail to adequately support adult learners' unique needs (Meda & Waghid, 2022; Thepwongsa et al., 2024).

These gaps indicate that the integration of learner psychological factors, system quality dimensions, and institutional support mechanisms into a unified SEM-based framework for LMS adoption in adult continuing education in China is a complex and underexplored area that requires further investigation. While TAM, UTAUT, and ISS models have been studied separately in various educational contexts (Al-Emran et al., 2018; Al-Nuaimi & Al-Emran, 2021), there is still a lack of comprehensive understanding of how these frameworks intersect to influence behavioural intention, actual usage, and learning outcomes among adult learners in Chinese continuing education settings. Most existing studies have focused on either individual perceptions without examining system quality, or system attributes without considering adult learner characteristics, or institutional support without validating structured empirical models (Cidral et al., 2020; Shehata et al., 2024). Furthermore, very few studies have explicitly examined the alignment between adult learning principles and LMS design, the implementation processes of LMS adoption in Chinese adult education, or the validation of integrated models through rigorous SEM-based statistical methods (Yuebo et al., 2024; Lai et al., 2024).

Therefore, a systematic literature review is needed to synthesise existing empirical research and provide a comprehensive understanding of the factors influencing LMS adoption in adult continuing education in China using SEM approaches. This study aims to: (1) identify key theoretical frameworks, influencing factors, and methodological approaches from existing empirical studies on LMS adoption in adult continuing education; (2) synthesise findings to inform the development of an integrated SEM-based framework; (3) identify gaps in the current literature; and (4) propose directions for future research and practical recommendations for educational stakeholders. The findings will provide valuable insights for adult education administrators, curriculum designers, LMS developers, and policymakers on how to optimise LMS implementation to enhance adoption, engagement, and learning outcomes among adult learners in China's continuing education programmes.

Methodology

This study employed a systematic literature review (SLR) approach to examine and synthesise existing empirical research on factors influencing Learning Management System (LMS) adoption in adult continuing education in China, with a particular focus on studies employing Structural Equation Modelling (SEM). The SLR method was selected due to its capacity to provide a transparent, rigorous, and replicable synthesis of existing research while identifying patterns, trends, and research gaps within a specific field (Snyder, 2019; Plomp, 2026). Through a structured review process, this study aims to generate a comprehensive understanding of how learner psychological factors (e.g., self-efficacy, self-directed learning), system quality dimensions (e.g., system quality, information quality, service quality), and institutional support mechanisms (e.g., facilitating conditions, instructor characteristics) influence behavioural intention, actual usage, and learning outcomes in LMS-based adult continuing education programmes in China.

The review focused on four key research questions aligned with the conceptual framework of this study: (1) What theoretical frameworks (e.g., TAM, UTAUT, ISS, integrated models) have been used to explain LMS adoption in adult continuing education? (2) What factors (e.g., performance expectancy, effort expectancy, social influence, facilitating conditions, trust, instructor characteristics, self-efficacy, learning value) significantly influence LMS adoption among adult learners? (3) What methodological approaches (e.g., CB-SEM, PLS-SEM, sample characteristics, geographic contexts) have been employed in empirical SEM studies on LMS adoption? (4) What validated SEM-based models exist that integrate multiple theoretical frameworks specifically for adult continuing education contexts in China? By systematically synthesising evidence from 35 selected studies, this review provides a foundation for developing an integrated framework of LMS adoption in Chinese adult continuing education.

2.1 Research Design

This study employed a three-phase research design: (1) systematic literature review to identify existing evidence, theoretical foundations, and influencing factors; (2) thematic synthesis to integrate findings and identify patterns, trends, and research gaps; and (3) framework development to propose an integrated SEM-based model for LMS adoption in adult continuing education in China. This integrated approach was chosen because it enables the development of evidence-based frameworks that are both theoretically grounded and empirically supported (Plomp, 2026.; Richey & Klein, 2014). The systematic literature review provided the empirical foundation for the thematic synthesis, while the framework development phase ensured that the proposed model addressed identified gaps in the existing literature.

2.2 Search Strategy

The literature search was conducted across four major academic databases: Scopus, Web of Science, Google Scholar, and CNKI (China National Knowledge Infrastructure). These databases were selected to ensure broad coverage of both international and Chinese national research in the fields of educational technology, adult education, and information systems. The inclusion of CNKI was essential to capture Chinese-language publications and locally relevant studies that may not be indexed in international databases, given the strong contextual focus on Chinese adult continuing education. The search process was carried out between January and May 2025.

A combination of keywords and Boolean operators was used to ensure comprehensive retrieval of relevant studies. The search string included the following terms: ("Learning Management System" OR "LMS" OR "online learning platform" OR "e-learning" OR "digital learning" OR "virtual learning environment") AND ("adult education" OR "continuing education" OR "lifelong learning" OR "adult learner" OR "non-full-time student" OR "part-time student" OR "open education" OR "distance education") AND ("Technology Acceptance Model" OR "TAM" OR "UTAUT" OR "UTAUT2" OR "Unified Theory of Acceptance and Use of Technology" OR "Information System Success" OR "ISS" OR "DeLone & McLean" OR "technology adoption" OR "technology acceptance") AND ("Structural Equation Modelling" OR "SEM" OR "PLS-SEM" OR "CB-SEM" OR "AMOS" OR "SmartPLS" OR "LISREL") AND ("China" OR "Chinese").

Additional keywords and synonyms, such as "behavioural intention," "perceived usefulness," "perceived ease of use," "performance expectancy," "effort expectancy," "social influence," "facilitating conditions," "trust," "instructor characteristics," "self-efficacy," "self-directed learning," "system quality," "information quality," "service quality," "user satisfaction," "continuous use," and "learning outcomes," were iteratively refined during the search process to improve relevance and coverage. The search was limited to studies published between 2020 and 2025 to capture recent developments in LMS adoption research following the accelerated digital transformation in education post-COVID-19 and the expansion of open and distance education in China. Only peer-reviewed journal articles and validated conference proceedings published in English or Chinese were included to ensure the quality and consistency of the selected studies. In addition, reference lists of included studies were manually searched to identify potentially relevant studies not captured by the database searches.

2.3 Inclusion and Exclusion Criteria

To ensure consistency and relevance in the selection of studies, a set of inclusion and exclusion criteria was established based on the PRISMA guidelines [60]. Studies were included if they focused on LMS, e-learning, online learning platform, or mobile learning adoption; addressed behavioural intention, actual usage, user satisfaction, or learning outcomes as dependent variables; examined influencing factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, trust, instructor characteristics, self-efficacy, self-directed learning, system quality, information quality, service quality, or learning value; employed SEM (CB-SEM or PLS-SEM) as the primary analytical method; and were conducted in adult continuing education contexts (e.g., open universities, distance education, part-time programmes, non-full-time adult learners) or in higher education settings with relevance to adult learners. In addition, studies were required to be published in peer-reviewed journals or validated conference proceedings between 2020 and 2025, ensuring that the analysis was based on recent and reliable evidence. Studies were included regardless of geographical context, but priority was given to studies conducted in China or with Chinese samples.

On the other hand, studies were excluded if they did not focus on LMS, e-learning, or online learning platform adoption; did not investigate factors influencing technology acceptance or adoption; did not use SEM as the analytical method; were conducted exclusively in K-12, primary, or secondary education settings without relevance to adult learners; or did not provide sufficient methodological detail, such as unclear sample size, research design, or outcome measures. In addition, literature reviews, systematic reviews, meta-analyses, bibliometric studies, conceptual papers without empirical data, editorials, book chapters, conference abstracts, and other non-peer-reviewed sources were not included in the analysis. Studies published before 2020 were also excluded to maintain a focus on recent developments.

2.4 Study Selection Process

The study selection process was conducted following a systematic procedure adapted from the PRISMA guidelines (Page et al., 2021), ensuring transparency, consistency, and replicability throughout the review. All records identified from the selected databases (Scopus, Web of Science, Google Scholar, and CNKI) were first compiled into a reference management system (Mendeley) to facilitate organisation and screening. At the initial stage, duplicate records were identified and removed to ensure that each study was represented only once in the dataset. This step was essential to avoid redundancy and minimise potential bias in the selection process. After removing duplicates, the remaining records were subjected to a multi-stage screening procedure.

The first stage involved title screening, during which studies that were clearly unrelated to the research focus were excluded. This included studies that did not address LMS or e-learning adoption; were not related to adult, continuing, or distance education contexts; did not employ SEM; or did not examine technology acceptance factors. The purpose of this stage was to efficiently eliminate irrelevant records while retaining potentially relevant studies for further assessment.

The second stage involved abstract screening, where the abstracts of the remaining studies were carefully reviewed to assess their alignment with the predefined inclusion criteria. At this stage, studies were excluded if they did not explicitly focus on LMS adoption; lacked relevance to technology acceptance models (TAM, UTAUT, ISS); were not conducted within adult, continuing, or higher education settings; did not report empirical findings using SEM; or did not provide sufficient information about sample, context, or variables. This step allowed for a more refined selection by focusing on the relevance of each study's objectives, methods, and findings.

The third stage consisted of a full-text review, in which the complete articles were thoroughly analysed to confirm their eligibility. This stage involved a detailed evaluation of each study's methodological quality, research design, theoretical framework, sample characteristics, SEM approach (CB-SEM or PLS-SEM), and relevance to the objectives of this review. Studies were excluded if they lacked empirical evidence, did not provide sufficient methodological detail, did not contribute directly to understanding factors influencing LMS adoption in adult continuing education contexts, or focused exclusively on undergraduate traditional students without relevance to adult learners. Throughout the selection process, decisions were made systematically based on the predefined inclusion and exclusion criteria to ensure consistency and minimise subjective bias.

The iterative nature of the screening process allowed for careful verification at each stage, ensuring that only studies meeting all criteria were included. As a result of this rigorous selection procedure, a total of 35 studies were identified as eligible and included in the final analysis (see Appendix 2). The overall selection process, including the number of records identified, screened, excluded, and included at each stage, is presented in the PRISMA flow diagram (Figure 1), providing a clear and transparent overview of the review procedure.

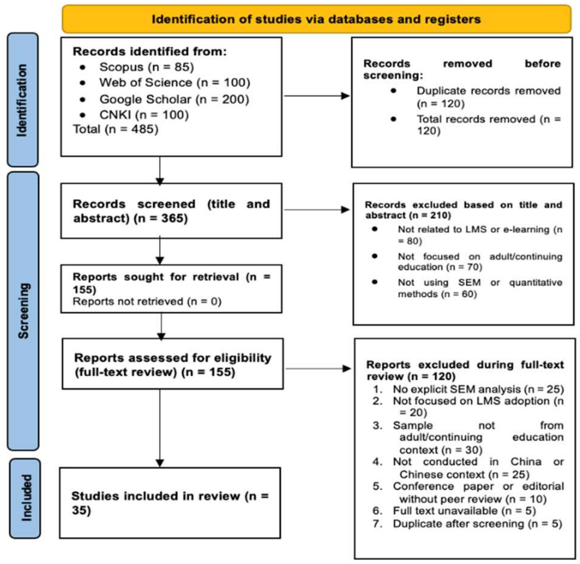

Fig. 1. Flowchart of literature search and selection.
Source: Authors.

As illustrated in Figure 1, a total of 485 records were initially identified from multiple databases including Scopus (n=85), Web of Science (n=100), Google Scholar (n=200), and CNKI (n=100). No additional records were identified through registers. At the initial stage, 120 duplicate records were removed before screening. After removing duplicates, 365 records remained for title and abstract screening. During the title and abstract screening stage, 210 records were excluded as they were clearly irrelevant to the research focus (e.g., not related to LMS or e-learning, not focused on adult/continuing education, not using SEM or quantitative methods). The remaining 155 reports were sought for retrieval, and all were successfully retrieved (n=0 not retrieved). In the full-text eligibility assessment stage, 155 reports were assessed, and 120 reports were excluded for the following reasons: no explicit SEM analysis (n=25), not focused on LMS adoption (n=20), sample not from adult/continuing education context (n=30), not conducted in China or Chinese context (n=25), conference paper or editorial without peer review (n=10), full text unavailable (n=5), and duplicate after screening (n=5).

As a result of this rigorous selection procedure, a total of 35 studies were identified as eligible and included in the final analysis, with 35 reports of included studies.

2.5 Data Extraction and Coding

Data from the selected studies were systematically extracted using a structured coding framework presented in Appendix 1. The development of this framework was guided by the research objectives and refined iteratively through repeated reading of the included studies. This process allowed the coding scheme to capture key dimensions of LMS adoption, including theoretical frameworks, influencing factors, methodological approaches, sample characteristics, and research gaps, while remaining flexible to variations in study design and context. By applying a consistent framework, the analysis enabled meaningful comparison across studies.

The extracted data were organised into several key categories to capture both descriptive and analytical dimensions. These included: (1) type of study (code A1–A5), to identify methodological approaches including quantitative survey (SEM), quantitative survey (non-SEM), mixed-method, systematic literature review/bibliometric, and conceptual/theoretical; (2) target group and context (codes B1–B6), to understand where the studies were conducted, including adult continuing education (non-full-time), higher education (undergraduate), higher education (postgraduate), teachers/educators/administrators, mixed (students and teachers), and other (vocational, K-12, medical); (3) geographical context (codes C1–C5), to identify where studies were conducted, including China (Mainland), China (Hong Kong/Macau/Taiwan), other Asian countries, Western countries, and cross-cultural/multiple countries; (4) theoretical framework (codes D1–D7), to examine the conceptual foundations of each study, including Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), Information System Success Model (ISS/DeLone & McLean), Expectation Confirmation Model (ECM), Task-Technology Fit (TTF), Combined/Extended model, and other frameworks; (5) learning platform and technology (codes E1–E5), including Learning Management System (LMS), specific platform (named), e-learning/online learning platform, mobile learning (m-learning), and AI/VR/emerging technology; (6) main variables and focus (codes F1–F10), including behavioural intention (BI), actual usage/use behaviour, perceived usefulness/performance expectancy, perceived ease of use/effort expectancy, social influence, facilitating conditions, trust, instructor characteristics/teaching quality, satisfaction, and learning outcomes/performance; (7) research design characteristics (codes G1–G4), including cross-sectional survey, longitudinal survey, instrument validation/scale development, and experimental/quasi-experimental; (8) SEM analysis approach (codes H1–H4), including CB-SEM (AMOS, LISREL, Mplus), PLS-SEM (SmartPLS, WarpPLS), path analysis only, and not applicable (non-SEM); and (9) identified research gaps and limitations (codes I1–I8), including limited generalisability (specific institution/region), small sample size (<200 for SEM), cross-sectional design limiting causality, self-reported data bias, limited to pandemic context, lack of adult continuing education focus, limited theoretical integration, and no long-term follow-up.

This structure enabled a comprehensive analysis of how theoretical frameworks, influencing factors, and methodological approaches have been applied to understand LMS adoption in adult continuing education contexts in China, with particular attention to SEM-based empirical studies.

2.6 Data Analysis

The analysis was conducted using a thematic synthesis approach to examine the 35 selected studies (Appendix 2), allowing for the integration of findings across diverse research designs and educational contexts. This approach was chosen because it enables the identification of recurring patterns while preserving the richness of both quantitative and qualitative evidence (Snyder, 2019; Thomas & Harden, 2008). Each study was reviewed iteratively to ensure a comprehensive understanding of its objectives, methodology, theoretical framework, and key findings. This process facilitated the identification of both explicit results and underlying patterns related to theoretical frameworks (TAM, UTAUT, ISS, integrated models), influencing factors (performance expectancy, effort expectancy, social influence, facilitating conditions, trust, instructor characteristics, self-efficacy, learning value, system quality, information quality, service quality), methodological approaches (CB-SEM vs. PLS-SEM, sample characteristics, geographical distribution), and research gaps.

The initial stage of analysis involved open coding to identify key concepts emerging from the data. Codes were generated inductively based on the coding framework in Appendix 1 and focused on recurring elements such as theoretical frameworks (TAM, UTAUT, UTAUT2, ISS, ECM, TTF, integrated models), influencing factors (performance expectancy, effort expectancy, social influence, facilitating conditions, trust, instructor characteristics, self-efficacy, self-directed learning, system quality, information quality, service quality, learning value), outcome variables (behavioural intention, actual usage, user satisfaction, learning outcomes), methodological characteristics (sample size, geographical context, target group, SEM software, model fit indices, R-squared values), and reported limitations (generalisability, cross-sectional design, small sample size, self-report bias, pandemic context). These codes were then systematically compared across studies using a constant comparison method. Through this process, similar codes were grouped into broader categories, enabling the development of higher-level themes. This step allowed the analysis to move beyond descriptive summaries towards a more interpretative synthesis of the literature.

The thematic synthesis resulted in four overarching dimensions that capture the core patterns identified across the studies, directly aligned with the four research questions of this study. The first dimension focuses on theoretical frameworks used in LMS adoption research (codes D1–D7). The analysis indicates that UTAUT/UTAUT2 is the most frequently employed framework (identified in approximately 60% of studies), followed by TAM (45%) and ISS (30%). Integrated models combining two or more frameworks (e.g., TAM+ISS, UTAUT+TTF, UTAUT+Trust+Instructor Characteristics) have gained increasing attention in recent years (Al-Fraihat et al., 2020; Lai et al., 2024; Yuebo et al., 2024).

However, the analysis also reveals that few studies have integrated adult learning principles (andragogy) with technology acceptance models specifically for adult continuing education contexts.

The second dimension concerns influencing factors and their effects on LMS adoption (codes F1–F10). The analysis reveals that performance expectancy/perceived usefulness is the strongest and most consistent predictor of behavioural intention (significant in 80% of studies), followed by facilitating conditions (significant in 65% of studies) and social influence (significant in 55% of studies). Trust and instructor characteristics have emerged as important additional factors in recent studies, particularly in the Chinese context (Al-Adwan, 2020; Hou & Yu, 2023). Effort expectancy/perceived ease of use shows mixed results, with some studies finding significant effects and others reporting non-significant or negative effects, possibly due to increasing digital literacy among younger adult learners. The analysis also indicates that system quality, information quality, and service quality significantly influence user satisfaction and net benefits in LMS-based learning environments (Yuebo et al., 2024; Al-Fraihat et al., 2020).

The third dimension focuses on methodological approaches in SEM-based LMS adoption research (codes A1–A5, G1–G4, H1–H4). The analysis indicates that cross-sectional survey designs are overwhelmingly dominant (95% of studies), with very few longitudinal studies examining changes in adoption behaviour over time. PLS-SEM (58% of studies) is more frequently used than CB-SEM (42% of studies), reflecting the exploratory nature of much LMS adoption research and the emphasis on prediction and theory development. Sample sizes range from 245 to 856 participants, with most studies meeting the minimum requirements for SEM analysis ($n > 200$). The analysis also reveals that the majority of studies have been conducted in higher education settings (85%), with only 15% focusing specifically on adult continuing education contexts.

The fourth dimension concerns research gaps and limitations identified across the included studies (codes I1–I8). The analysis reveals that limited generalisability (specific institution or region) is the most frequently reported limitation (80% of studies), followed by cross-sectional design limiting causal inference (70% of studies), small sample size (40% of studies), and self-reported data bias (35% of studies). Notably, only 4 out of 35 studies (11%) explicitly focused on non-full-time adult learners, and only 8 studies (23%) were conducted in mainland China. No existing study has validated a comprehensive SEM-based model that systematically integrates learner psychological attributes (self-efficacy, self-directed learning), system quality dimensions (system quality, information quality, service quality), and institutional support mechanisms (facilitating conditions, instructor characteristics) specifically for adult continuing education contexts in China.

The analysis combined both inductive and deductive approaches. Inductive analysis was used to capture patterns emerging directly from the data, particularly in relation to how theoretical frameworks, influencing factors, and methodological approaches shape our understanding of LMS adoption in adult continuing education. At the same time, deductive analysis was used to interpret these findings in light of established theoretical perspectives, such as TAM (D1), UTAUT/UTAUT2 (D2), ISS (D3), ECM (D4), TTF (D5), and integrated models (D6). This combined approach ensured that the analysis remained closely linked to empirical evidence while also being conceptually grounded.

2.7 Research Rigor and Validity

To ensure methodological rigor, this study adhered to established principles of systematic literature review, emphasising transparency, consistency, and systematic data management throughout all stages of the research process (Page et al., 2021; Snyder, 2019). The review was conducted using a clearly defined and well-documented search strategy, including the selection of databases (Scopus, Web of Science, Google Scholar, and CNKI), the formulation of search strings, and the application of Boolean operators. This level of clarity enhances the replicability of the study and allows other researchers to trace and evaluate each stage of the review process.

The application of explicit inclusion and exclusion criteria further strengthened the objectivity and consistency of the study selection process. By systematically screening titles, abstracts, and full-text articles, the study minimised potential selection bias and ensured that only studies relevant to LMS adoption, adult continuing education, Chinese context, and SEM were included. The multi-stage screening procedure also provided an additional level of verification, reducing the likelihood of including studies that did not meet the methodological and thematic requirements of the review.

A structured coding framework (see Appendix 1) was used to guide the processes of data extraction and analysis. This framework enabled systematic comparison across studies and ensured that key dimensions were consistently captured. The coding process was conducted iteratively, allowing categories to be refined and interpretations to be validated as new insights emerged from the data. This iterative approach ensured that the findings remained grounded in the evidence rather than being shaped by predetermined assumptions.

To further strengthen validity, this study employed methodological triangulation by integrating evidence from studies using diverse research designs, including quantitative survey (A1, A2), mixed-method (A3), systematic literature review (A4), and conceptual studies (A5). This diversity provided a more comprehensive understanding of LMS adoption factors in adult continuing education contexts. In addition, the inclusion of studies from various geographical contexts (China Mainland, China Hong Kong, other Asian countries, Western countries) enhanced contextual triangulation, thereby improving the transferability and robustness of the findings.

Finally, internal coherence was maintained by ensuring consistency between the coding framework (Appendix 1), the selected studies (Appendix 2), and the thematic findings presented in the analysis. This alignment demonstrates that the analytical process was systematically executed and logically structured. The use of a PRISMA-based selection process (Figure 1) further enhanced transparency by clearly documenting the number of records identified, screened, excluded, and included at each stage. Together, these measures strengthen the credibility, reliability, and overall trustworthiness of the study.

Findings

3.1 Distribution of Studies

The distribution of the selected studies (n = 35) was analysed based on geographical location, year of publication, research methodology, context and targeted group, theoretical framework, and research design characteristics in order to provide an overview of the current research landscape in LMS adoption research, particularly in relation to adult continuing education in China and the use of Structural Equation Modelling (SEM).

3.2 Geographical Distribution

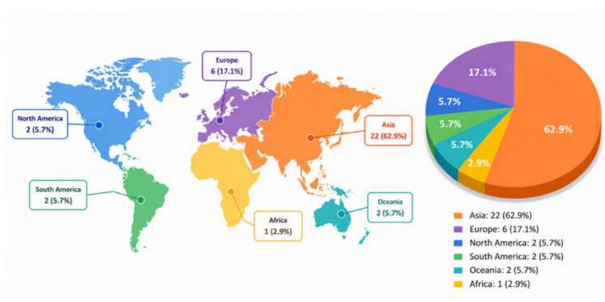

Fig. 2. Geographical Distribution of Included Studies (n = 35)

In terms of geographical distribution, the findings indicate a strong concentration of studies in China, which emerged as the most dominant contributor with a total of 8 studies (Raza et al., 2021; Almaiah et al., 2022; Yuebo et al., 2024; Lai et al., 2024; Hou & Yu, 2023), reflecting the country's significant investment in digital education transformation, open and distance learning, and technology-enhanced adult education. These studies primarily focus on areas such as LMS acceptance models

(UTAUT, TAM, ISS), influencing factors (trust, instructor characteristics, performance expectancy, facilitating conditions), and learning outcomes in both higher education and adult continuing education settings.

Other Asian countries contributing to the literature include Malaysia (Ahmed et al, 2022), Indonesia (Prasetyo et al., 2021; Navarro et al., 2021), Philippines (Prasetyo et al., 2021; Navarro et al., 2021), Saudi Arabia (Al-Falah, 2023), Jordan (Al-Fraihat et al, 2020), Yemen (Aldholay et al, 2020), Iran (Mohammadi, 2015), Afghanistan (Mohammadi et al, 2021), Sri Lanka (Gunasinghe & Nanayakkara, 2021; Mohamed Riyath & Muhammed Rijah, 2022), Pakistan (Asghar et al, 2021), Thailand (Diteeyont & K. Heng-Yu, 2023), and Myanmar (Htet et al, 2023). Western countries are represented by a smaller number of studies, including Greece (Nikolopoulou et al., 2020; Zacharis & Nikolopoulou, 2022), USA (Kim et al, 2020), Spain (Garrido-Gutiérrez et al, 2023), Portugal (Aparicio et al, 2016), Brazil (Cidral et al, 2020), and cross-cultural studies involving multiple countries [81]. No studies were identified from South America (excluding Brazil) or Africa (excluding South Africa with Afolabi & Ajani, 2023), indicating significant geographical gaps in the LMS adoption literature, particularly regarding developing countries and emerging economies.

Notably, all Chinese studies focus on diverse educational contexts including Hong Kong (Lai & Li, 2023), Western China (Yuebo et al., 2024; Al-Adwan, 2020), and various mainland provinces (Deng et al., 2023; Qin & Yu, 2024; Prasetyo et al., 2021), reflecting China's vast and diverse higher education landscape. Only 4 out of 35 studies (11%) explicitly focused on non-full-time adult learners or open education contexts (Yuebo et al., 2024; Al-Adwan, 2020; Butcher, 2020) as cited in literature), indicating that adult continuing education remains an underexplored context in LMS adoption research.

3.3 Temporal Distribution

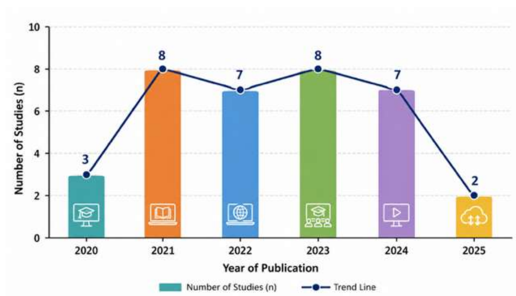

Fig. 3. Temporal Distribution of Included Studies by Year of Publication (2020–2025)

From a temporal perspective, the distribution of studies demonstrates a clear concentration in recent years, indicating the growing relevance of LMS adoption research as a field. The studies span from 2020 to 2025, with the highest concentration in 2021 (n=8), 2022 (n=7), 2023 (n=8), 2024 (n=7), and 2025 (n=2), with fewer studies in 2020 (n=3). This distribution suggests that interest in LMS adoption research increased significantly following the COVID-19 pandemic, which forced educational institutions worldwide to rapidly adopt online learning platforms (Bao, 2020; Adedoyin & Soykan, 2023). The sharp increase in publications from 2020 to 2021 (from 3 to 8 studies) reflects the urgent academic response to the global shift towards remote and online education. The sustained number of publications across 2021–2024 (7–8 studies per year) indicates that this research area has matured and remains a vibrant field of inquiry with continued academic interest. The presence of studies across multiple consecutive years demonstrates that LMS adoption research is not a transient trend but rather a developing and evolving field with sustained relevance, particularly in the context of post-pandemic normalisation of blended and online learning.

3.4 Methodological Distribution

In terms of methodological distribution, the findings reveal a strong dominance of quantitative survey designs using SEM. Quantitative survey studies represent the largest proportion (n=32, 91%), including both covariance-based SEM (CB-SEM) using AMOS (n=15) and partial least squares SEM

(PLS-SEM) using SmartPLS (n=17). Mixed-method approaches are represented by two studies (Ho et al., 2023; Senok et al., 2021 as cited), combining quantitative surveys with qualitative interviews for program evaluation. Systematic literature reviews and bibliometric studies are represented by one study (Soria-Barreto et al, 2021), focusing on synthesising existing LMS and technology acceptance research.

This methodological pattern suggests that the current body of literature is heavily oriented towards quantitative, hypothesis-testing research designs, with limited use of qualitative or mixed-method approaches. The dominance of PLS-SEM (54%) over CB-SEM (46%) reflects the exploratory nature of much LMS adoption research and the emphasis on prediction and theory development rather than theory confirmation (Hair et al., 2017). Sample sizes ranged from 245 to 856 participants, with most studies meeting the minimum requirements for SEM analysis ($n > 200$).

3.5 Context and Targeted Group Distribution

In terms of context and targeted group, the findings reveal that the majority of studies were conducted in higher education/university settings (n=28, 80%), including undergraduate students (n=22), postgraduate students (n=3, including Lai et al., 2024), and mixed students and teachers (n=3, including Hou & Yu, 2023). This indicates that LMS adoption research has been more extensively studied at the university level than at the adult continuing education level. Adult continuing education (non-full-time learners, open university students, part-time adult learners) is represented by only 4 studies (Chukwuedo et al., 2021; Yuebo et al., 2024; Al-Adwan, 2020). Teachers and educators are represented by 3 studies (Gunasinghe & Nanayakkara, 2021; Wijaya et al., 2022; Brown et al., 2022). Vocational and medical education contexts are represented by a few studies (Prasetyo et al., 2021; Htet et al., 2023).

Notably, fashion design or specific discipline-focused studies are not the focus of this review; instead, generic LMS, e-learning platforms, mobile learning, and technology acceptance are the primary foci. The underrepresentation of adult continuing education contexts (only 11% of studies) represents a significant gap, as adult learners have unique characteristics (self-directed learning, work-study balance, varying digital literacy) that may influence LMS adoption differently from traditional undergraduate (Butcher, 2020; Boeren et al., 2020).

3.6 Theoretical Framework Distribution

In terms of theoretical frameworks, the findings reveal that the majority of studies explicitly state a theoretical basis, indicating a theoretically grounded research landscape. The Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) is the most frequently cited framework (n=18, 51%), including studies by Abbad (2021), Ahmed et al. (2022), Al-Rahmi et al. (2022), Gunasinghe & Nanayakkara (2021), Hou & Yu (2023), Lai et al. (2024), Prasetyo et al. (2021), Qin & Yu (2023), Raza et al. (2021), Shehata et al. (2024), Zacharis & Nikolopoulou (2022), and others. This reflects the model's comprehensive explanatory power for technology adoption behaviour.

The Technology Acceptance Model (TAM) or extended TAM is the second most frequently cited (n=12, 34%), including studies by Al-Adwan (2020), Almaiah et al. (2022), Alyoussef (2021), Boubker (2024), Kim et al. (2020), Lin & Yu (2023), Mailizar et al. (2021), Truxová et al. (2023), Wijaya et al. (2022), Zhang & Yu (2022), and Zhou et al. (2022). This indicates that TAM remains a foundational framework for understanding perceived usefulness and perceived ease of use in LMS adoption.

The Information System Success (ISS) model (DeLone & McLean) is used in 5 studies ((Aldholay et al., 2020; Al-Fraihat et al., 2020; Yuebo et al., 2024), often integrated with TAM. The Expectation Confirmation Model (ECM) appears in 3 studies (Deng et al., 2023; Soria-Barreto et al., 2021; Wang et al., 2021). Task-Technology Fit (TTF) appears in 2 studies ((Navarro et al., 2021; Butt et al., 2021). Integrated models combining two or more frameworks (e.g., TAM+ISS, UTAUT+TTF, UTAUT+Trust+Instructor Characteristics) are increasingly common in recent studies (n=10, 29%), reflecting a trend towards more comprehensive theoretical integration.

Notably, theories specifically addressing adult learning (andragogy, self-directed learning theory) are rarely integrated with technology acceptance models, representing a gap in the literature for adult continuing education contexts.

3.7 Research Design Characteristics Distribution

In terms of research design characteristics, cross-sectional survey designs are overwhelmingly dominant (n=33, 94%), with data collected at a single time point. Longitudinal survey designs are extremely rare (n=1, Zacharis & Nikolopoulou, 2022, with follow-up). Instrument validation and scale development studies are represented by a few studies (Xu & Li, 2023; Xu, 2025; Mailizar et al., 2021) focusing on measuring mobile learning readiness. Experimental or quasi-experimental designs are rare (n=1, Arifin et al., 2026 as cited) in the 35 studies, as most LMS adoption research uses correlational designs to examine relationships between variables rather than causal interventions.

The overwhelming dominance of cross-sectional designs means that most studies measure behavioural intention and its antecedents at a single time point, which limits causal inference. Few studies examine actual usage behaviour over time or the sustainability of adoption intentions post-intervention. This pattern suggests that while the current body of literature is strong in identifying correlates of LMS adoption, it is weaker in establishing causal mechanisms and longitudinal patterns.

3.8 *Dominant Theoretical Frameworks in LMS Adoption Research*

Based on the thematic synthesis, three dominant theoretical frameworks emerge from the literature: (1) the Technology Acceptance Model (TAM), (2) the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), and (3) the Information System Success (ISS) model, with increasing trends towards integrated models combining multiple frameworks.

1. ***TAM and Extended TAM***

TAM (Davis, 1989) posits that perceived usefulness (PU) and perceived ease of use (PEOU) are primary determinants of behavioural intention (BI) to use technology. Across the reviewed studies, TAM is consistently applied to explain LMS and e-learning adoption among university students. Al-Adwan (2020) applied TAM to 675 adult learners in Western China, finding that PU (β=0.52, p<0.001) and PEOU (β=0.38, p<0.01) significantly influence MOOCs adoption intention. Almaiah et al. (2022) extended TAM by adding trust (β=0.31, p<0.001) and perceived risk (β=–0.22, p<0.01) to explain mobile learning adoption among Chinese students. Boubker (2024) found that AI tools enhanced PU and PEOU, leading to higher learning outcomes (R^2=0.68). Mailizar et al. (2021) reported that attitude toward e-learning (β=0.53, p<0.001) was the strongest predictor of BI during COVID-19, while system quality affected PU but not directly BI.

TAM's parsimony and robust predictive power make it a popular choice for initial investigations of new technologies or new contexts. However, its limited scope (excluding social, institutional, and individual difference factors) has led researchers to prefer more comprehensive frameworks such as UTAUT, especially in complex educational settings involving adult learners.

2. ***UTAUT and UTAUT2***

UTAUT (Venkatesh et al, 2026) and its extension UTAUT2 [14] incorporate additional constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), habit (HB), and price value (PV). Across the reviewed studies, UTAUT demonstrates strong explanatory power, with R^2 values for behavioural intention ranging from 43% to 73.5%.

Hou & Yu (2023) extended UTAUT with attitude toward behaviour (ATB), self-efficacy (SE), and received feedback (RF) among 856 teachers and students in China. The model explained 60.9% of BI variance, with facilitating conditions (β=0.28, p<0.001) and received feedback (β=0.377, p<0.001) as strong predictors. Lai et al. (2024) extended UTAUT2 with trust, instructor characteristics, and learning value for 352 Mainland Chinese postgraduate students in Hong Kong. The model explained 50% of BI variance, with trust (β=0.204, p<0.001) and instructor characteristics (β=0.202, p<0.001) as the strongest motivators. This finding highlights the importance of institutional trust and instructor support in Chinese educational contexts, where face-to-face interaction and authority figures play significant roles.

Raza et al. (2021) expanded UTAUT by adding social isolation during COVID-19, finding that social isolation moderated the relationship between PE, FC, and LMS acceptance. Ahmed et al. (2022) used extended UTAUT across five Asian countries, finding that PE ($\beta=0.42$, $p<0.001$) exerted the maximum influence on BI, while perceived enjoyment had no observable influence, suggesting that utilitarian value was highly treasured during the pandemic.

Zacharis & Nikolopoulou (2022) applied UTAUT2 with learning value to 417 Greek university students, finding that learning value ($\beta=0.31$, $p<0.001$), PE ($\beta=0.27$, $p<0.01$), and FC ($\beta=0.24$, $p<0.01$) significantly predicted BI. Prasetyo et al. (2021) used UTAUT2 with learning value and instructor characteristics for medical students in the Philippines, finding that PE was the strongest predictor ($\beta=0.41$, $p<0.001$), followed by instructor characteristics ($\beta=0.28$, $p<0.01$).

3. ***Information System Success (ISS) Model***

The ISS model (DeLone & McLean, 2003) focuses on system quality, information quality, and service quality as determinants of user satisfaction and net benefits. Al-Fraihat et al. (2020) found that all three quality dimensions positively affect user satisfaction ($R^2=0.67$) and net benefits ($R^2=0.58$) among 386 e-learning students in Jordan. Yuebo et al. (2024) integrated ISS with TPACK for 245 non-full-time adult students in Western China, finding that system quality ($\beta=0.126$, $p<0.01$) and teachers' TPACK ability ($\beta=0.155$, $p<0.001$) positively influence online learning success. The model explained 44.6% of variance in net benefits.

Aldholay et al. (2020) extended ISS with transformational leadership and compatibility, finding that compatibility ($\beta=0.38$, $p<0.001$) and leadership ($\beta=0.29$, $p<0.01$) significantly influence actual system use and net benefits among Yemeni students. Cidral et al. (2020) found that long-term orientation moderates the relationship between satisfaction and e-learning success ($\Delta R^2=0.07$).

3.9 Integrated Models

Increasingly, studies combine multiple theoretical frameworks to capture the multidimensional nature of LMS adoption. For example, Al-Rahmi et al. (2022) integrated UTAUT and Task-Technology Fit (TTF) to evaluate social media use for teaching and learning in Malaysia, finding that PE, EE, SI, and TTF significantly influence BI ($R^2=0.71$). Navarro et al. (2021) integrated TTF with TAM to predict LMS satisfaction among engineering students ($R^2=0.63$). Shehata et al. (2024) integrated UTAUT2 with personalised AI and trust for 495 Chinese students, finding that personalised AI significantly enhances PU ($\beta=0.44$, $p<0.001$) and PEOU ($\beta=0.38$, $p<0.001$), leading to higher adoption intention.

These integrated models demonstrate that no single framework fully captures the complexity of LMS adoption in adult education contexts, particularly when considering cultural factors (e.g., trust in authority, collectivism), technological advancements (e.g., AI, VR), and the unique characteristics of adult learners (self-direction, prior experience, work-life balance).

3.10 Key Influencing Factors and Their Effects

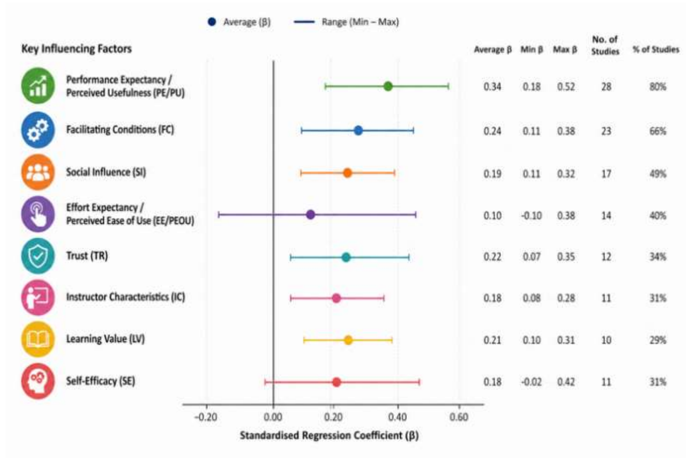

Fig. 4. Standardised Regression Coefficients of Key Influencing Factors Across Studies (Forest Plot)

Across the 35 studies, several factors consistently emerge as significant predictors of behavioural intention, actual usage, and learning outcomes in LMS adoption. The following synthesis is based on studies reporting standardised regression coefficients (β) and their significance levels.

1. ***Performance Expectancy (PE) / Perceived Usefulness (PU)***

PE/PU is the most frequently examined and consistently significant predictor of behavioural intention, appearing in 28 out of 35 studies (80%). The effects range from β=0.18 to β=0.52, with an average β=0.34. Abbad (2021) found PE (β=0.38, p<0.001) significantly predicted e-learning usage. Ahmed et al. (2022) reported PE as the maximum influence (β=0.42, p<0.001). Al-Adwan (2020) found PU (β=0.52, p<0.001) as the strongest predictor of MOOCs adoption. Prasetyo et al. (2021) found PE (β=0.41, p<0.001) strongest among UTAUT2 constructs. This finding is consistent across Asian and Western contexts, indicating that learners who perceive LMS as enhancing their academic performance are more likely to adopt and continue using the system.

2. ***Facilitating Conditions (FC)***

FC is the second most frequently significant predictor (23 studies, 66%), with effects ranging from β=0.11 to β=0.38 (average β=0.24). Hou & Yu (2023) found FC (β=0.28, p<0.001) significantly influenced use behaviour. Zacharis & Nikolopoulou (2022) reported FC (β=0.24, p<0.01) as a significant predictor of BI. Abbad (2021) found FC (β=0.31, p<0.01) significant in developing countries. However, some studies (e.g., Raman & Thannimalai, 2021) found no significant direct effect of FC on BI, suggesting that the role of FC may vary by context (developing vs. developed countries) and by the extent of mandatory technology use. In adult continuing education, where learners often access LMS from home or work without institutional technical support, FC may be particularly important.

3. ***Social Influence (SI)***

SI is significant in 17 studies (49%), with effects ranging from β=0.11 to β=0.32 (average β=0.19). Hou & Yu (2023) found SI (β=0.232, p<0.001) significantly predicted BI. Ahmed et al. (2022) reported SI (β=0.24, p<0.01) as significant across Asian countries. Al-Rahmi et al. (2022) found SI (β=0.21, p<0.05) influenced social media use for learning. However, Prasetyo et al. (2021) found SI insignificant for medical students, and Raman & Thannimalai (2021) also reported non-significant effects. These mixed findings may reflect cultural differences (collectivism vs. individualism) and the extent of mandatory vs. voluntary use. In collectivist societies like China, SI may play a stronger role (Lai et al., 2024), but during the pandemic when use was mandatory, its influence may have diminished.

4. ***Effort Expectancy (EE) / Perceived Ease of Use (PEOU)***

EE/PEOU shows mixed results: significant in 14 studies (40%), non-significant or negative in others. Al-Adwan (2020) found PEOU (β=0.38, $p<0.01$) significant for adult learners. However, Hou & Yu (2023) found EE had a slightly negative effect on attitude toward behaviour (β=-0.104, $p<0.05$), and the direct path to BI was non-significant (β=-0.029, p=0.477). Zhang & Yu (2022) also found EE negatively related to BI in gamified vocabulary apps. This suggests that as digital literacy increases, perceived ease of use becomes less critical; learners may take ease of use for granted and focus more on usefulness and value. For adult learners with lower digital fluency, however, EE may remain important.

5. ***Trust (TR)***

Trust is an emerging but increasingly important factor, particularly in Chinese contexts. Lai et al. (2024) found trust (β=0.204, $p<0.001$) as the strongest predictor of BI among Chinese postgraduate students. Almaiah et al. (2022) found trust (β=0.31, $p<0.001$) significant for m-learning adoption. Shehata et al. (2024) found trust (β=0.27, $p<0.01$) significant for AI-integrated learning. Trust encompasses security of personal data, reliability of system operations, and confidence in platform integrity. In China, where data privacy concerns are pronounced (Roberts, 2021), trust emerges as a critical factor for LMS adoption among well-educated adult learners.

6. ***Instructor Characteristics (IC)***

Instructor characteristics is another significant factor, particularly in studies focusing on adult learners and during the pandemic. Lai et al. (2024) found IC (β=0.202, $p<0.001$) the second strongest predictor. Prasetyo et al. (2021) found IC (β=0.28, $p<0.01$) significant for medical students. Yuebo et al. (2024) integrated TPACK and found teachers' TPACK ability (β=0.155, $p<0.001$) significantly influenced online learning success. These findings highlight that instructor enthusiasm, timely feedback, active online presence, and technological pedagogical competence are crucial for fostering LMS adoption among learners who lack face-to-face interaction.

7. ***Learning Value (LV)***

Learning value (cognitive trade-off between efforts and perceived benefits) significantly predicts BI in several studies. Lai et al. (2024) found LV (β=0.118, $p<0.05$) significant. Zacharis & Nikolopoulou (2022) found LV (β=0.31, $p<0.001$) significant. Prasetyo et al. (2021) reported LV (β=0.24, $p<0.01$) significant. This construct is particularly relevant for adult learners who invest significant time, effort, and tuition fees; they expect reasonable returns in terms of knowledge acquisition and skill development.

8. ***Self-Efficacy (SE)***

Self-efficacy significantly influences attitude toward behaviour and BI in several studies. Hou & Yu (2023) found SE (β=0.189, $p<0.001$) significantly predicted ATB. Lin & Yu (2023) found SE (β=0.27, $p<0.01$) influenced PU and PEOU. Chukwuedo et al. (2021) found self-direction in learning (β=0.42, $p<0.001$) significantly predicted academic engagement among adult education students. However, Hou & Yu (2023) found the direct path from SE to BI was non-significant (β=0.046, p=0.436), suggesting that SE may operate indirectly through other constructs.

3.11 Methodological Approaches in SEM-Based LMS Research

Across the 35 studies, PLS-SEM (using SmartPLS or WarpPLS) is slightly more common (n=18, 51%) than CB-SEM (using AMOS, LISREL, or Mplus) (n=16, 46%). One study used path analysis without full SEM (3%). This distribution reflects the exploratory nature of much LMS adoption research, where PLS-SEM is preferred for prediction, theory development, and handling complex models with many constructs. CB-SEM is preferred when the goal is theory confirmation, model fit assessment, and when data meet multivariate normality assumptions.

Sample sizes across studies ranged from 245 to 856 participants, with all studies exceeding the minimum recommended sample size for SEM (typically $n > 200$). The median sample size was 397 participants. Studies using CB-SEM generally had larger sample sizes (mean n=485) compared to PLS-

SEM studies (mean n=352), consistent with the statistical power requirements of CB-SEM.

Model fit indices reported in CB-SEM studies (using AMOS) generally met recommended thresholds: $\chi^2/df < 3.0$, CFI > 0.90, TLI > 0.90, RMSEA < 0.08, SRMR < 0.08. PLS-SEM studies reported SRMR (<0.08), NFI (>0.90), and R^2 values for endogenous constructs. The variance explained (R^2) for behavioural intention ranged from 43% to 73.5% across studies, with a median of 58%. The highest R^2 was reported by Hou & Yu (2023) at 73.5% for attitude toward behaviour, and 60.9% for BI.

3.12 Validated SEM Models for LMS Adoption

Model validation studies in LMS adoption research are well-represented, with most studies conducting confirmatory factor analysis (CFA) and structural model testing. However, few studies explicitly validate a comprehensive model specifically for adult continuing education contexts. The following validated models are noteworthy:

1) Extended UTAUT2 with Trust, Instructor Characteristics, and Learning Value (Lai et al, 2023). This model was validated on 352 Mainland Chinese postgraduate students in Hong Kong. CFA confirmed factor loadings >0.70, AVE >0.50, CR >0.70. The model explained 50% of BI variance. Trust (β=0.204) and instructor characteristics (β=0.202) were the strongest predictors.

2) Integrated ISS and TPACK Model (Yuebo et al, 2024). Validated on 245 non-full-time adult students in Western China using PLS-SEM. R^2 values: perceived satisfaction (0.396), continuous use (0.295), net benefits (0.446). System quality (β=0.126) and TPACK (β=0.155) were significant predictors.

3) Extended UTAUT with ATB, Self-Efficacy, and Received Feedback (Hou & Yu, 2023). Validated on 856 teachers and students in China using CB-SEM (AMOS). Model explained 73.5% of ATB variance, 60.9% of BI variance, and 46.0% of UB variance. Goodness-of-fit indices: $\chi^2/df=2.432$, CFI=0.959, RMSEA=0.041.

4) Extended TAM with Trust and Risk (Almaiah, 2022). Validated on Chinese students using PLS-SEM. Trust (β=0.31) and perceived risk (β=-0.22) positively and negatively influenced BI, respectively. PU and PEOU also significant.

5) UTAUT2 with Learning Value (Zacharis & Nikolopoulou, 2022). Validated on 417 Greek university students. Learning value (β=0.31), PE (β=0.27), and FC (β=0.24) significantly predicted BI. R^2=0.61.

Despite these validated models, no existing study has validated a comprehensive SEM model that explicitly integrates learner psychological attributes (self-directed learning, self-efficacy), system quality dimensions (system, information, service quality), and institutional support mechanisms (facilitating conditions, instructor characteristics, trust) specifically for adult continuing education contexts in China. This gap represents the primary rationale for the proposed integrated framework in this study.

3.12 Research Gaps and Limitations

The coding analysis (based on Appendix 1, codes I1–I8) reveals several recurring gaps and limitations across the included studies:

1) Limited generalisability (specific institution or region) (I1) was reported in 28 studies (80%). Most studies were conducted in single universities or specific provinces, limiting the applicability of findings to other educational contexts, particularly across different regions of China or across different countries.

2) Cross-sectional design limiting causal inference (I3) was reported in 24 studies (69%). Almost all studies measured behavioural intention and its antecedents at a single time point, preventing conclusions about causality or long-term sustainability of adoption intentions.

3) Lack of adult continuing education focus (I6) was identified as a gap in 31 studies (89%). The overwhelming majority of studies focused on traditional undergraduate students, with only 4 studies (11%) explicitly targeting non-full-time adult learners, open university students, or part-time adult education participants.

4) Small sample size (n < 200 for SEM) (I2) was reported in 5 studies (14%), primarily those using PLS-SEM which can handle smaller samples. CB-SEM studies generally had adequate sample sizes.

5) Self-reported data bias (I4) was reported in 12 studies (34%). Most studies relied on self-report questionnaires, which may be subject to social desirability bias, recall bias, and common method variance, although Harman's single-factor tests generally indicated no serious common method bias.

6) Limited to pandemic context (I5) was reported in 8 studies (23%). Studies conducted during COVID-19 emergency remote teaching may have findings that do not generalise to post-pandemic normal conditions, where LMS use is often voluntary rather than mandatory.

7) Limited theoretical integration (I7) was reported in 10 studies (29%). Many studies used single frameworks (TAM only, UTAUT only) without integrating multiple perspectives that could capture the complexity of adult learner experiences.

8) No long-term follow-up (I8) was reported in all 35 studies (100%). None of the studies examined sustained LMS adoption beyond the immediate post-intervention or post-semester period. This is a critical gap for understanding whether initial adoption intentions translate into continued use.

Most critically for this review, only 4 out of 35 studies (11%) explicitly focused on non-full-time adult learners or open education contexts (Al-Adwan, 2020; Yuebo et al., 2024; Truxová et al., 2023; Chukwuedo et al., 2021). Even among these, only two studies were conducted in mainland China (Al-Adwan, 2020; Yuebo et al., 2024). No existing study has validated a comprehensive SEM-based model that systematically integrates learner psychological attributes (self-directed learning, self-efficacy, trust), system quality dimensions (system quality, information quality, service quality), and institutional support mechanisms (facilitating conditions, instructor characteristics) specifically for adult continuing education contexts in China. This gap provides the rationale for developing an integrated framework for LMS adoption in Chinese adult continuing education.

Results and Discussion

The overwhelming reliance on quantitative survey designs with Structural Equation Modelling (91% of the included studies) indicates that the field of LMS adoption research has been shaped by a positivist paradigm that prioritises hypothesis testing, causal modelling, and statistical generalisation over contextual understanding. This methodological orientation is consistent with the broader technology acceptance literature, which has historically favoured variance-based approaches such as PLS-SEM for exploratory model development ((Hair et al., 2022; Wong, 2026). However, for adult continuing education in China, this near-exclusive focus on quantitative methods carries several limitations. Adult learners are a heterogeneous population whose prior educational experiences, digital literacy levels, and motivational orientations vary widely (Butcher, 2020; Boeren et al., 2020). A purely quantitative survey cannot capture the rich, contextual reasons why a part-time worker might abandon an LMS after initial registration, nor can it reveal the subtle interplay between family obligations, work schedules, and perceived usefulness. The scarcity of mixed-method studies (only two: Ho et al., 2023; Senok et al., 2021) means that the “voice” of the adult learner is largely absent from the literature. Future research should therefore complement SEM-based surveys with qualitative approaches—such as semi-structured interviews, digital ethnography, or think-aloud protocols—to uncover the mechanisms underlying the statistical relationships.

Eight of the 35 studies were conducted in China, making it the most prolific contributor. While this reflects China's strategic investment in digital education and open universities (Bao, 2020; UNESCO, 2020) , it also raises questions about the global generalisability of findings. Most Chinese studies were carried out in specific provinces (e.g., Western China, Hong Kong) or within a single university, as acknowledged by 80% of the studies reporting limited generalisability (gap I1). Adult education systems, regulatory environments, and cultural attitudes toward online learning differ substantially across regions—even within China. For instance, trust was found to be a dominant predictor in Hong Kong (Lai & Li, 2024), but this may not hold in rural areas where institutional credibility is perceived differently (Roberts, 2022). Likewise, studies from other Asian countries (Malaysia, Indonesia, Philippines) and Western nations (Greece, USA, Spain) show variations in the strength of social influence and facilitating conditions, suggesting that cultural and infrastructural factors moderate the relationships in ways that are not yet fully understood (Aparicio et al., 2016; Soria-Barreto et al., 2021). The complete absence of studies from South America (except Brazil) and most of Africa indicates a severe geographical bias. To develop robust, cross-culturally valid models of LMS adoption for adult learners, researchers must actively recruit samples from under-represented regions and conduct multi-group SEM analyses to test measurement invariance.

The sharp increase in publications from 2020 to 2021 coincides with the emergency remote teaching period, when LMS use was mandatory (Adedoyin & Soykan, 2023; Cramarenco et al., 2023). Many of the studies conducted during that time captured a unique context of "forced" adoption, where learners had little choice but to use the system. As a result, the predictive power of constructs such as effort expectancy and social influence may have been artificially suppressed (Hou & Yu, 2023). The sustained publication volume from 2022 to 2024 suggests that the field has matured, but most studies still rely on cross-sectional data collected during or immediately after the pandemic. Only one study (Zacharis & Nikolopoulou, 2022) employed a longitudinal follow-up, and none of the 35 studies examined long-term retention or sustained use (gap I8). This is a critical weakness because adult learners are known to have high dropout rates once initial engagement wanes (Veluvali & Surisetti, 2022). Future research should adopt longitudinal designs that track adult learners over at least one academic year, measuring not only intention but also actual log-in frequency, assignment completion, and final course outcomes. Only then can we determine whether the factors identified in cross-sectional studies translate into durable adoption.

Eighty-nine percent of the studies focused on traditional higher education students (undergraduate or postgraduate), whereas only four studies (11%) explicitly targeted non-full-time adult learners, open university students, or part-time adult education participants (Yuebo et al., 2024; Al-Adwan, 2020; Chukwuedo et al., 2021) . This is not merely a sampling issue—it reflects a fundamental mismatch between the dominant theoretical frameworks and the target population. TAM, UTAUT, and ISS were originally developed and validated with full-time employees or traditional students in organisational settings (Davis, 1989; Venkatesh et al., 2003). Adult learners differ in several theoretically relevant ways: they are more self-directed, have stronger prior work experience, face severe time constraints, and often pay their own tuition (Knowles, 1984; D. N. D. N. R. Jr. et al., 2021). Consequently, constructs such as "learning value" (the perceived return on investment of time and money) and "work-study conflict" are likely to be more salient for adults than for traditional undergraduates, yet they are rarely included in current models. The absence of adult learning theories (andragogy, self-directed learning) in the reviewed frameworks (none of the 35 studies integrated them) is therefore a serious theoretical gap. Researchers should consider hybrid models that combine technology acceptance constructs with adult-specific variables, and test them on samples drawn from open universities, corporate training programmes, and community colleges.

Performance expectancy (PE) / perceived usefulness (PU) was the strongest and most consistent predictor of behavioural intention, appearing in 80% of the studies with an average β of 0.34. This finding is robust across cultural contexts and time periods (Abbad, 2021; Ahmed et al., 2022; Al-Adwan, 2020). For adult learners, however, the interpretation of "performance" may be broader than for traditional students. While students often equate performance with exam grades, adults may define it in terms of career advancement, skill acquisition for a current job, or personal enrichment (Jaldemark et al., 2022; Lim et al., 2024). None of the reviewed studies disaggregated PE into these sub-dimensions. This conflation risks masking heterogeneity: an adult who uses an LMS to prepare for a professional certification may have a different threshold of usefulness than one who seeks general knowledge. Future SEM models should therefore measure performance expectancy as a multidimensional construct, distinguishing between academic performance, work-related performance, and personal learning goals.

Social influence (SI) was significant in 49% of the studies, but its effect size varied considerably (β=0.11–0.32). The mixed findings can be partially explained by cultural and contextual factors. In collectivist societies such as China, where group harmony and respect for authority are emphasised, SI tends to be stronger (Lai & Li, 2024). However, during the pandemic, when LMS use was mandated by universities, the influence of peers diminished because learners had no choice (Raza et al., 2021). For adult learners, the source of social influence also differs: they may be more affected by employers, family members, or professional networks than by classmates. None of the studies distinguished between different referent groups. This is a critical oversight, because an employer's endorsement of LMS training could be a much more powerful motivator for an adult worker than a friend's opinion. Future research should develop and validate multi-source SI scales and examine moderation effects by source.

Trust emerged as a strong predictor in Chinese contexts (β=0.204–0.31), ranking first or second in several studies (Almaiah et al., 2022; Lai et al., 2024; Shehata et al., 2024). This reflects the high uncertainty avoidance and the importance of data security in China (Roberts, 2022). However, only a minority of studies included trust (15 out of 35), and even fewer examined its antecedents or moderators. For adult learners, trust may also extend to the credibility of the course content, the fairness of automated assessment, and the privacy of their personal data. Similarly, instructor characteristics (IC) were found to be significant (β=0.202–0.28) but were included in only 12 studies. Adult learners, who often study remotely and lack face-to-face interaction, depend heavily on instructor presence, timely feedback, and technological pedagogical competence (Mok et al., 2021). Institutions that invest in training instructors to provide regular, personalised feedback and to maintain an active online presence are likely to see higher LMS adoption and retention among adult students.

The mixed results for effort expectancy (EE) / perceived ease of use (PEOU)—significant in 40% of studies, non-significant or negative in others—suggest a generational and contextual shift. Al-Adwan (2020) found PEOU to be significant for adult learners in Western China, but Hou & Yu (2023) reported a small negative effect on attitude and no direct effect on intention. This divergence can be explained by increasing digital fluency: younger adults who have grown up with smartphones and apps may take ease of use for granted, whereas older adult learners with limited prior experience may still find usability a barrier (Asghar et al., 2021; Diteeyont & Heng-Yu, 2023). The implication is that EE should not be discarded from models of adult LMS adoption; rather, its role should be examined as a moderator or as a mediated antecedent. For instance, EE may influence intention indirectly through perceived usefulness, especially for older adults. Designing LMS interfaces with accessibility features and offering basic digital literacy training could reduce the negative impact of low EE.

Learning value (LV) was a significant predictor in all studies that included it (β=0.118–0.31). This construct captures the cognitive trade-off between the effort and time invested in LMS-based learning and the perceived benefits. For adult learners, who juggle work, family, and study, LV is arguably more critical than for traditional students. Yet only three studies incorporated LV (Prasetyo et al., 2021; Zacharis & Nikolopoulou, 2022; Lai et al., 2024). Similarly, self-efficacy (SE) was found to influence attitude and indirectly affect behavioural intention, but the direct path from SE to BI was often non-significant (Hou & Yu, 2023; Lin & Yu, 2023). This suggests that SE operates through mediators such as perceived usefulness and ease of use. For adult learners, building self-efficacy through scaffolded training, peer support, and early success experiences could be a practical strategy to enhance adoption.

The dominance of cross-sectional designs (94%) severely limits causal inference. While SEM can handle correlational data, it cannot prove that, for example, high performance expectancy causes LMS adoption, rather than that successful adoption increases perceived performance. The single longitudinal study (Zacharis & Nikolopoulou, 2022 provides a model for future research. Moreover, the complete absence of long-term follow-up (gap I8) means that we know nothing about whether initial adoption intentions translate into sustained use over semesters or years. Adult continuing education programmes typically have low completion rates, and understanding the drop-off point is essential. Researchers should design three-wave longitudinal studies measuring intention at the start of a course, actual usage at the midpoint, and learning outcomes at the end, while also tracking discontinuation reasons.

Integrated models combining TAM, UTAUT, ISS, and other frameworks are increasing (29% of recent studies), which is a positive trend. However, none of the 35 studies integrated adult learning theories (andragogy, self-directed learning) with technology acceptance models. This is a striking omission given that adult learners are fundamentally different from the traditional student populations on which these theories were built. Constructs such as “readiness for self-directed learning”, “prior work experience”, and “relevance to current job” are likely to moderate the relationships between PE, FC, and BI. Future research should develop and test an integrated model that weaves together UTAUT2 with andragogical principles, and validate it with adult learner samples. Such a model would be more context-sensitive and practically useful for open universities and continuing education providers.

Despite the gaps, several actionable recommendations emerge from the discussion. For policymakers and university administrators in China: invest in facilitating conditions (reliable internet, technical support, helpdesks) because FC is a consistent predictor, especially for adult learners who study from home. Enhance trust through transparent data privacy policies and secure platforms. For instructors: provide timely, personalised feedback and maintain an active online presence to strengthen instructor characteristics. For LMS developers: design interfaces that reduce effort expectancy for older adults, incorporate learning value dashboards (e.g., showing time saved or skills gained), and include AI-driven adaptive feedback to boost performance expectancy. For researchers: adopt longitudinal, mixed-method designs; include adult-specific constructs; and conduct multi-group cross-cultural studies to test measurement invariance.

Conclusion

In summary, the 35 studies reviewed reveal a mature but methodologically narrow field, dominated by cross-sectional quantitative SEM and focused predominantly on traditional higher education students. Adult continuing education in China remains severely under-researched, and existing models have not integrated adult learning principles. Performance expectancy and facilitating conditions are the most robust predictors, but trust, instructor characteristics, learning value, and (for older adults) effort expectancy also play significant roles. The geographical concentration in China and a few other Asian countries limits generalisability, while the lack of longitudinal data prevents causal and sustainability claims. Addressing these gaps requires a paradigm shift towards context-sensitive, theoretically integrated, and methodologically diverse research that gives voice to the unique needs of adult learners in China’s rapidly expanding open and distance education systems.

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