The Mediating Role of Learning Analytics Engagement in Enhancing Learning Efficacy: A Mixed-Methods Study in Chinese Private Higher Education

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ABSTRACT

Digital transformation in higher education has unlocked new opportunities for data-driven pedagogical innovation. Nevertheless, how digital teaching practices translate into improved student learning outcomes remains insufficiently understood, especially within China's private higher-education sector. This study examines the mediating function of Learning Analytics Engagement (LAE) in the association between the Digital Teaching Model (DTM) and Learning Efficacy (LE) among undergraduate students enrolled at Chinese private universities. Drawing on a sequential explanatory mixed-methods design, this research combines quantitative survey data from 398 undergraduates at Shandong Xiehe University with qualitative evidence from 18 semi-structured student interviews. Quantitative results reveal that DTM positively predicts LAE ($\beta=0.487$, $p<0.001$); LAE, in turn, exerts a significant positive influence on LE ($\beta=0.423$, $p<0.001$). LAE partially mediates the DTM-LE association, with an indirect effect of $\beta=0.206$($p<0.001$, 95% bias-corrected confidence interval [0.138, 0.281]). Within this sample, the mediated proportion reached 39.3%, though this effect magnitude may differ across institutional and student subgroups. The structural model accounts for 48.6% of the variance in Learning Efficacy. Qualitative findings unpack the behavioral, cognitive, and emotional dimensions of LAE, highlighting the indispensable roles of instructor scaffolding, self-regulated learning, and context-specific constraints in private higher education. Theoretically, this study extends the Technology Acceptance Model by integrating sociocultural and self-regulation perspectives to unpack technology-pedagogy-learner interactions. Practically, it generates context-aware recommendations for institutional leaders, educators, and policymakers seeking to advance digital learning within resource-constrained higher-education contexts.

Keywords: Digital Teaching Model; Learning Analytics Engagement; Learning Efficacy; Private Higher Education; Mixed-Methods Research; Self-Regulated Learning; Sociocultural Theory; Technology Acceptance Model

1. Introduction

The 21st-century higher-education landscape has undergone profound digital transformation, propelled by widespread digital technologies and growing societal demands to equip learners with competencies for data-rich work environments. Globally, universities have adopted digital learning platforms not merely as content repositories, but as integrated ecosystems capable of capturing, analyzing, and harnessing learner-generated data to refine pedagogy and boost student performance (Siemens & Long, 2011; Ferguson et al., 2022). Such shifts align with global "Education 4.0" agendas that prioritize adaptability, collaborative problem-solving, creativity, and data literacy among university graduates (World Economic Forum, 2022).

In China, national policy initiatives including the Education Informatization 2.0 Action Plan and Smart Education of China have vigorously advanced higher-education digitalization (Ministry of Education, 2022). By 2024, over 51 900 educational institutions, 18.8 million teachers, and 293 million learners had accessed the national Smart Education Platform (Ministry of Education, 2024). Domestic massive open online course platforms (XuetangX, iCourse, Zhihuishu) host more than 76 800 courses, serving 454 million registered users (Alwihda Info, 2023). Despite substantial infrastructure investment, translating technological affordances into tangible learning gains remains uneven across institutional types. This challenge is particularly salient for private higher-education institutions in China, which face persistent constraints in funding, faculty digital training, and system-level integration of digital tools (Chen & Wang, 2022; Kamarudin et al., 2022; Zhang & Liu, 2023; Saleem et al., 2025).

The value of digital teaching lies beyond operational efficiency. It holds promise to realize core constructivist principles: learner-centered instruction, formative feedback, and scaffolded learning within learners' zones of proximal development (Vygotsky, 1978). Yet these benefits can only materialize when digital tools are embedded within theoretically informed pedagogical frameworks. Emerging scholarship posits that Learning Analytics Engagement (LAE)—learners' behavioral, cognitive, and emotional involvement with data-informed feedback systems—acts as a critical mechanism bridging digital infrastructure and desirable learning outcomes (Ifenthaler & Yau, 2020; Viberg et al., 2020). Empirical evidence validating this mediating pathway, however, remains sparse, especially for the under-researched private higher-education context in China. Moreover, prior international studies have yielded mixed findings regarding learning-analytics effects: analytics-driven feedback may trigger learner anxiety and defensive disengagement under certain conditions and does not automatically generate learning gains. This calls for further empirical examinations of such mediating mechanisms within context-specific higher-education settings.

Private universities constitute one of the fastest-growing segments of China's higher-education system. As of 2024, more than 780 private higher-education institutions enroll over seven million undergraduate students, representing approximately 26% of national undergraduate enrollments (Ministry of Education, 2024). Despite their expanding scale, private colleges encounter structural disadvantages: limited financial resources, uneven faculty development opportunities, and restricted access to premium digital educational resources (Chen & Wang, 2022; Saleem et al., 2023). Students at private institutions often report lower academic motivation and less developed self-regulated learning capacities (Wu et al., 2023), while many instructors lack systematic training in digital pedagogy and learning-analytics-enhanced teaching (Huang & Zhou, 2022). Although private universities tend to be agile in adopting educational innovations, insufficient analytics literacy and structured engagement frameworks prevent them from fully capitalizing on digital learning to foster learning efficacy.

Against this backdrop, the present study investigates the interrelationships among the Digital Teaching Model (DTM), Learning Analytics Engagement (LAE), and Learning Efficacy (LE) within Chinese private higher education. Synthesizing Vygotsky's Sociocultural Theory (1978), the Technology Acceptance Model (Davis, 1989), and Self-Regulated Learning Theory (Zimmerman, 2000), this paper proposes and empirically validates an integrated conceptual model where LAE mediates how digital teaching practices associate with student learning outcomes. Four research questions guide this inquiry:

RQ1. To what extent is the Digital Teaching Model associated with Learning Efficacy?

RQ2. To what extent does Learning Analytics Engagement contribute to Learning Efficacy?

RQ3. To what extent is the Digital Teaching Model associated with Learning Analytics Engagement?

RQ4. Does Learning Analytics Engagement mediate the relationship between the Digital Teaching Model and Learning Efficacy?

We adopt a sequential explanatory mixed-methods design, combining survey data from N=398 undergraduates and semi-structured interviews with 18 students. By generating both population-level statistical evidence and contextualized experiential insights, this study makes two key contributions. First, it theoretically extends the Technology Acceptance Model by integrating sociocultural and self-regulation perspectives to unpack how digital teaching translates into learning outcomes. Second, it delivers practically actionable insights for institutional leaders, teachers, and policymakers striving to optimize digital learning environments within resource-constrained higher-education settings.

2. Literature Review and Theoretical Framework

2.1 Conceptual Foundations of Key Constructs

2.1.1 Learning Efficacy

Rooted in Bandura's (1997) self-efficacy theory, learning efficacy describes learners' confidence and perceived capability to complete academic tasks successfully. Within educational contexts, it goes beyond general self-efficacy to focus specifically on learners' beliefs regarding learning processes and achievement of learning goals (Usher & Pajares, 2008; Saleem et al., 2022). Contemporary scholarship conceptualizes learning efficacy as a multi-faceted construct encompassing cognitive efficacy (knowledge comprehension and application), self-regulatory efficacy (learning planning and monitoring), motivational efficacy (persistence and effort investment), and technological efficacy (competent use of digital learning tools) (Zimmerman, 2021; Hodges et al., 2020). In digital learning ecosystems, technological efficacy gains heightened importance. Students must navigate complex learning platforms and interpret analytic feedback to optimize study strategies (Clark & Mayer, 2016; Shoaib & Saleem, 2023). In this study, learning efficacy is operationalized as the extent to which learners achieve intended learning outcomes through precision-oriented instruction and digital learning analytics, covering cognitive accuracy, metacognitive adaptability, and affective learning engagement.

2.1.2 Digital Teaching Model

The Digital Teaching Model (DTM) refers to an instructional framework embedding digital technologies, online platforms, and learning analytics into everyday pedagogical practice (Anderson, 2008; Garrison & Vaughan, 2013). A robust DTM comprises four interconnected layers: (a) the instructional-design layer aligning curricula and pedagogy with intended learning outcomes; (b) the digital-infrastructure layer supporting synchronous and asynchronous learning activities; (c) the analytic-feedback layer enabling continuous data collection to trace learner behaviors and academic performance; and (d) the reflective-practice layer, where instructors leverage analytics to revise instruction and enable adaptive learning (Koehler & Mishra, 2009; Bond et al., 2020). For the current investigation, DTM is measured from student perceptions covering platform usability, learning-resource quality, student-instructor interaction, access flexibility, instructional-design quality, and timeliness of feedback.

2.1.3 Learning Analytics Engagement

Learning Analytics Engagement (LAE) captures learners' participation, reflective thinking, and behavioral responses triggered by data-driven feedback and interactions with learning-analytics tools (Siemens, 2013; Ifenthaler & Yau, 2020). It consists of three interwoven dimensions: behavioral engagement (active interactions with analytics systems such as reviewing feedback or revisiting course materials), cognitive engagement (deep processing of analytic insights to inform learning decisions), and emotional engagement (learners' attitudes and motivational responses toward analytic feedback) (Fredricks et al., 2004; Jivet et al., 2020; Saleem et al., 2026). Within digital learning contexts, LAE represents an active mediating process through which learning analytics foster self-regulated, data-informed learner behaviors (Viberg et al., 2020; Matcha et al., 2020).

It is critical to distinguish LAE from general digital-learning engagement. General digital-learning engagement describes broad-spectrum student participation in course videos, discussion forums, and assignment completion within learning-management systems. By contrast, LAE in this study specifically refers to learners' interpretation, reflection, and subsequent behavioral adjustments triggered by learning-analytics outputs (e.g., dashboards, performance feedback, and progress reports), rather than routine platform interactions unrelated to analytic data. Given that no universally validated off-the-shelf scale exists for this emerging construct, the present measurement adapts existing frameworks while deliberately narrowing the scope to data-driven feedback processing.

2.2 Theoretical Framework

This study builds upon a synthesized theoretical framework integrating Vygotsky's Sociocultural Theory, the Technology Acceptance Model (TAM), and Self-Regulated Learning Theory (SRL). This multi-theory lens enables holistic analysis of how digital teaching models shape learning efficacy via LAE as a mediating pathway.

2.2.1 Sociocultural Theory

Vygotsky's (1978) Sociocultural Theory posits that learning is inherently socially mediated. Knowledge is co-constructed through interpersonal interactions and engagement with cultural tools. The core notion of the Zone of Proximal Development (ZPD) describes the performance gap between learners' independent capacities and what they can accomplish with appropriate guidance. In digital-learning settings, learning-management systems, online discussion forums, and analytics dashboards function as modern cultural mediating artifacts extending

Vygotsky's original conceptualization (Wertsch, 1991). These tools facilitate communication, collaboration, and pedagogical scaffolding to support learners across their ZPD (Reiser & Tabak, 2014; Lantolf & Poehner, 2014).

From this viewpoint, learning analytics operates as a meta-scaffolding instrument. It furnishes both educators and students with actionable insights into learning behaviors to dynamically adjust pedagogical support. Such adaptive support can further enhance learners' self-awareness and learning-related efficacy (Järvelä et al., 2020). This research conceptualizes digital platforms and learning analytics as cultural tools enabling scaffolding, collaborative participation, and guided meaning-making, laying the sociocultural foundation for digital-learning effectiveness.

2.2.2 Technology Acceptance Model

Davis's (1989) Technology Acceptance Model (TAM) is a foundational framework for explaining user adoption of technological systems. TAM establishes that perceived usefulness and perceived ease-of-use jointly shape user attitudes toward technology, further determining behavioral intentions and actual system usage. Within digital teaching contexts, TAM helps interpret students' willingness to interact with digital platforms and analytics functions (Scherer et al., 2019; Teo, 2021). When students perceive digital tools as useful and user-friendly, they exhibit higher propensity to actively engage with analytics features, fostering greater LAE (Ifenthaler & Yau, 2020). Subsequent extensions of TAM incorporate social influence, facilitating conditions, and self-efficacy to better account for technology adoption within educational environments (Venkatesh & Bala, 2008; Sinha & Bag, 2023). In this paper, TAM illuminates perceptual and motivational dimensions of technology use, complementing the social-mediation focus of Sociocultural Theory.

2.2.3 Self-Regulated Learning Theory

Zimmerman's (2000) Self-Regulated Learning Theory frames learners as agentic actors who engage in goal formulation, self-monitoring, self-evaluation, and strategic regulation of cognition, motivation, and behavior. SRL unfolds cyclically across forethought (goal-setting and planning), performance (self-monitoring and strategy deployment), and self-reflection (evaluation and adaptive adjustment) phases (Panadero, 2017). These cycles align closely with learning-analytics functionalities within digital environments. Students track progress, receive feedback, and modify learning strategies accordingly (Ifenthaler & Schumacher, 2016; Matcha et al., 2020). Analytics dashboards, performance indicators, and predictive feedback supply real-time data to strengthen metacognitive awareness of learning progress and knowledge gaps, supporting more effective self-monitoring and decision-making (Jivet et al., 2021). For this study, SRL theory explains the mediating mechanism of LAE. Engagement with analytics tools is not passive exposure, but an active interpretive process through which learners utilize feedback to regulate study behaviors and improve learning outcomes (Viberg et al., 2020).

2.2.4 Integrated Theoretical Framework

The synthesis of Sociocultural Theory, TAM, and SRL generates a multi-layer explanatory model capturing reciprocal interactions between technology, pedagogy, and learner agency. At the technology-adoption layer, TAM accounts for how perceived platform qualities drive students' acceptance of digital systems. At the learning-mediation layer, Sociocultural Theory explains how digital platforms and analytics serve as mediating artifacts for interaction, collaboration, and instructional scaffolding. At the learning-regulation layer, SRL describes how learners interpret analytic feedback to self-regulate learning activities. These three layers are connected through LAE, which embodies behavioral-cognitive interactions between learners and analytics tools, bridging external technological affordances and internal learning processes. This integrated framework fits the empirical context of Chinese private universities, where digital transformation is advancing rapidly yet student autonomous-learning competencies vary considerably (Wang & Chen, 2021; Zhang & Chen, 2022).

These three theoretical perspectives operate in a sequential and constraining relationship rather than functioning as isolated interpretive lenses. TAM accounts for learners' initial willingness to access analytics tools but cannot explain how mere tool exposure translates into concrete learning improvements, hence the necessity of SRL to unpack internal cognitive-behavioral regulation processes. Nevertheless, SRL largely focuses on individual agency and overlooks external social-environmental constraints such as instructor support and institutional resources, which are addressed by sociocultural theory. Taken together, TAM provides the precondition of technology acceptance; sociocultural factors serve as external contextual constraints; SRL describes intra-individual learning regulation; and LAE stands at their intersection to materialize the link between digital teaching environments and learning outcomes.

2.3 Empirical Relationships and Hypotheses Development

2.3.1 Digital Teaching Model and Learning Efficacy

Cumulative empirical evidence demonstrates generally positive associations between digital teaching approaches and learning efficacy. Blended instruction, flipped classrooms, and platform-supported teaching are linked to improved academic performance, cognitive engagement, and learning satisfaction (Means et al., 2020; Bond et al., 2021). Such models grant flexible access to learning materials, foster interactive learning communities, and enable personalized instruction, all of which contribute to enhanced learning outcomes (Martin et al., 2020; Hodges et al., 2020). Nevertheless, effect magnitudes vary substantially contingent on implementation quality, instructor preparedness, and student digital literacy (Hodges et al., 2020; Rapanta et al., 2020). For Chinese private universities, uneven institutional resources and variable instructional-design quality further moderate this link. We therefore propose:

H1: The Digital Teaching Model (DTM) exerts a significant positive predictive association with students' Learning Efficacy (LE).

2.3.2 Digital Teaching Model and Learning

Analytics Engagement

Digital teaching models generate large-scale learner datasets from learning-management systems, online assessments, and interactive learning activities. These datasets constitute the empirical foundation for LAE, empowering instructors and students to monitor, interpret, and act upon learning-related behaviors (Siemens & Baker, 2012; Viberg et al., 2018). Prior research confirms that well-designed digital platforms can substantially boost student engagement with analytics dashboards, feedback modules, and performance-tracking functions (Ifenthaler & Yau, 2020; Jivet et al., 2020). Still, the magnitude of LAE depends on student competencies, motivational states, and the pedagogical embedding of analytics within teaching practice (Matcha et al., 2020). Given that many instructors at Chinese private institutions lack systematic analytics-integrated teaching training, the DTM-LAE relationship merits empirical testing in this setting. Hence:

H2: The Digital Teaching Model (DTM) exerts a significant positive predictive association with Learning Analytics Engagement (LAE).

2.3.3 Learning Analytics Engagement and Learning Efficacy

Growing empirical literature supports a positive association between LAE and learning efficacy. When engaging with learning analytics, students identify knowledge gaps, observe learning trajectories, and revise study strategies, yielding improved academic performance and self-efficacy (Ifenthaler & Yau, 2020; Matcha et al., 2019). Self-regulated learning constitutes the core underlying mechanism. Analytics tools underpin SRL by delivering timely feedback, goal-setting opportunities, and progress-monitoring features (Zimmerman, 2002; Viberg et al., 2020). Students meaningfully engaging with analytics develop stronger metacognitive awareness and adopt more effective learning strategies, translating into superior learning outcomes (Jivet et al., 2020; Schumacher & Ifenthaler, 2018). It should be noted, however, that superficial engagement yields limited benefits. The quality rather than mere frequency of analytics interaction determines learning gains (Jivet et al., 2020). Accordingly:

H3: Learning Analytics Engagement (LAE) exerts a significant positive predictive association with students' Learning Efficacy (LE).

2.3.4 The Mediating Role of Learning Analytics Engagement

Recent scholarly work has begun to probe whether LAE mediates the DTM-LE relationship. Theoretically, DTM supplies the technological and pedagogical infrastructure generating learner data. LAE represents the extent to which learners actively interpret and capitalize upon such data to optimize learning processes (Ifenthaler, 2017; Viberg et al., 2020). Digital teaching environments alone cannot improve learning efficacy unless learners meaningfully engage with embedded analytics outputs (Ifenthaler & Yau, 2020; Jivet et al., 2020). LAE thereby acts as a pivotal bridge translating digital-teaching affordances into tangible learning improvements. Despite its theoretical plausibility, empirical evidence for this mediating pathway remains fragmented, particularly for Chinese private higher education. This motivates our final hypothesis:

H4: Learning Analytics Engagement (LAE) mediates the relationship between the Digital Teaching Model (DTM) and students' Learning Efficacy (LE).

Figure 1 visualises the conceptual framework depicting hypothesised associations among DTM, LAE, and LE.

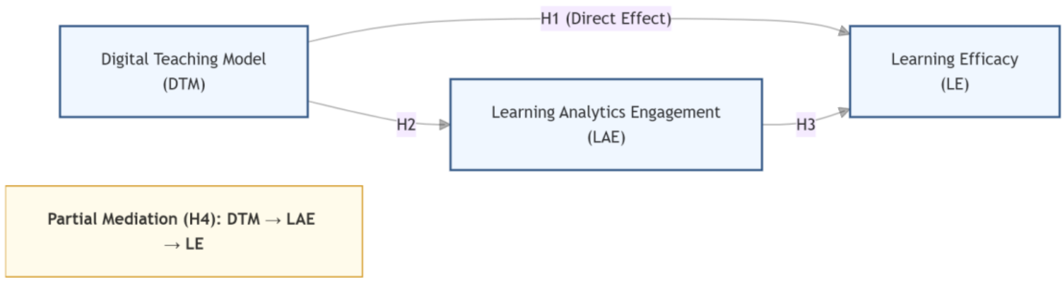

Figure 1. Conceptual framework of the partial-mediation model.

H1 = direct predictive association between the Digital Teaching Model (DTM) and Learning Efficacy (LE); H2 = path from DTM to Learning Analytics Engagement (LAE); H3 = path from LAE to LE; H4 = partial-mediation pathway DTM → LAE → LE.

3. Methodology

3.1 Research Design

This study employs a sequential explanatory mixed-methods design (Creswell & Creswell, 2018). We first implement quantitative survey research to test hypothesised paths within the conceptual model using Partial Least-Squares Structural Equation Modelling (PLS-SEM). We then conduct qualitative semi-structured interviews to elaborate, contextualise, and interpret quantitative statistical results. This design delivers both generalisable population-level evidence and nuanced experiential accounts, avoiding the limitation of purely variable-oriented quantitative analysis (Tashakkori & Teddlie, 2021). Mixed-methods integration is implemented at two stages: during research design, and when synthesising quantitative and qualitative outputs in Section 4.3.

3.2 Research Setting and Participants

Empirical investigation took place at Shandong Xiehe University, a representative private undergraduate university in China with approximately 18 000 enrolled students. This institution has widely deployed the Chaoxing Learning Platform, an integrated learning-management system supporting course delivery, behavior tracking, assignment administration, real-time feedback, and built-in learning-analytics functions. The university encompasses 11 academic schools covering engineering, natural sciences, business administration, humanities, education, law, and health sciences.

For the quantitative phase, stratified random sampling was applied to guarantee representation across disciplines and academic year cohorts. In total, 500 questionnaires were distributed; 398 valid responses were retained for final analysis, corresponding to a valid response rate of 79.6%. The sample includes 182 male participants (45.7%) and 216 female participants (54.3%), covering all four undergraduate years (Year 1: 23.6%, Year 2: 28.1%, Year 3: 27.1%, Year 4: 21.1%). Respondents span four broad disciplinary clusters: Humanities and Social Sciences (31.7%), Sciences and Engineering (29.6%), Business and Management (24.1%), and Health and Medical Sciences (14.6%). Most participants interact frequently with the Chaoxing platform: 74.9% report daily or multiple-times-per-week usage, and 63.9% have used this system for more than 12 months.

For the qualitative strand, 18 participants were purposefully selected from survey respondents following a maximum-variation sampling strategy. Respondents were stratified into high-, medium-, and low-LAE groups based on the 25th and 75th percentiles of self-reported LAE total scores. Participants were recruited to ensure variation across gender, year group, academic discipline, and LAE engagement levels (high, medium, low). The interview sample includes 10 female and eight male undergraduates covering all year cohorts and disciplinary categories.

3.3 Instrumentation

The questionnaire was developed through systematic adaptation of validated scales published within digital-learning and learning-analytics scholarship. It comprises four sections: demographic background, Digital Teaching Model (6 items), Learning Analytics Engagement (6 items), and Learning Efficacy (8 items). All survey items adopt a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). A rigorous back-translation procedure was completed to translate instruments from English into Chinese to preserve semantic equivalence and contextual fit. Original English scales were adapted by revising item wording to align with the institutional characteristics of Chinese private universities and the functional features of the Chaoxing Learning Platform. Two bilingual scholars specialising in educational technology independently conducted forward-translation and back-translation; any semantic discrepancies were discussed and reconciled to guarantee contextual appropriateness.

The DTM scale measures student perceptions of platform usability, learning-resource quality, instructor-student interaction, access flexibility, instructional-design quality, and feedback timeliness (adapted from Davis, 1989; Anderson, 2008). The LAE scale captures awareness of analytics outputs, behavioural interaction with platform feedback, reflective use of learning data, and responsiveness to analytic recommendations (adapted from Ifenthaler & Yau, 2020; Jivet et al., 2020). The LE scale assesses perceived cognitive gains, skill development, learning confidence, and improvement in self-regulated learning (adapted from Bandura, 1997; Zimmerman, 2000).

Content validity was established via expert review by three independent scholars specialising in educational technology, psychometric measurement, and online learning. A pilot study with 30–50 undergraduate students confirmed item clarity and preliminary scale reliability; Cronbach's α for every construct exceeded 0.70. A semi-structured interview protocol was developed drawing on the study's theoretical framework as well as preliminary quantitative results from the survey. Specifically, interview questions were designed to unpack the psychological processes, emotional barriers, and instructor-support mechanisms underlying the DTM-LAE-LE mediating pathway that quantitative modelling alone could not fully capture. The qualitative phase was not intended to re-verify statistical hypotheses but to offer contextual explanations for observed statistical associations. Open-ended questions were organised around four thematic domains: (1) student experiences with the digital teaching model; (2) engagement with learning-analytics functions; (3) perceptions of learning efficacy; (4) contextual constraints and practical suggestions. Interviews were conducted in Mandarin Chinese, lasting between 35 and 55 minutes each. Audio-recording was performed only after securing explicit informed consent from every participant.

All participants took part voluntarily. Implied consent was obtained via survey submission, and explicit verbal consent for audio-recording was collected before each interview. All personal identifiers were removed in data analysis to ensure participant anonymity, and all data were used exclusively for academic research.

3.4 Data Analysis

We performed data pre-processing, descriptive statistics, and normality screening in SPSS 26.0. Harman's single-factor test was performed to assess potential common-method bias originating from self-reported data. The unrotated exploratory factor analysis indicated that the largest single factor explained 34.21% of total variance, below the critical threshold of 50%. No single dominant factor emerged, suggesting common-method bias was not a major concern for this dataset. Measurement-model evaluation, structural-model testing, and mediation analysis were carried out using SmartPLS 4.0. PLS-SEM was selected because it performs well for complex mediation-focused exploratory research and demonstrates robustness against non-normal data distributions (Hair et al., 2022; Henseler et al., 2016).

The measurement model was evaluated based on indicator outer loadings, internal-consistency reliability (Cronbach's α, composite reliability), convergent validity (Average Variance Extracted – AVE), and discriminant validity (HTMT ratio, Fornell-Larcker criterion). The structural model was assessed using R^2, f^2 effect sizes, predictive relevance Q^2, path coefficients β, and model-fit indices (SRMR, NFI). Bootstrapping with 5 000 resamples was implemented to test the statistical significance of indirect mediation effects.

Qualitative interview data were analysed via thematic analysis following the six-phase analytical protocol proposed by Braun and Clarke (2006, 2021). NVivo 14 software supported systematic coding, theme generation, and data organisation. Trustworthiness of qualitative findings was secured through prolonged researcher engagement, data triangulation, participant member-checking, a complete audit trail, and researcher reflexivity.

4. Results

4.1 Quantitative Findings

4.1.1 Measurement Model Assessment

The measurement model exhibits satisfactory psychometric properties. Most indicator outer loadings surpass the threshold value of 0.708, ranging from 0.691 to 0.801. Two items show slightly lower loadings (DTM6 = 0.691; LE4 = 0.695) yet were retained given their conceptual relevance to respective latent constructs. These minor reductions in outer loadings did not compromise overall construct validity. Cronbach's α values span 0.812–0.873, composite reliability ranges 0.845–0.892, all above the 0.70 benchmark for internal consistency. AVE values for all constructs exceed 0.50: DTM = 0.562; LAE = 0.584; LE = 0.538, confirming convergent validity. Discriminant validity is supported by both HTMT (all values < 0.85, range = 0.612–0.683) and the Fornell-Larcker criterion. The square root of each construct's AVE exceeds correlation coefficients with other latent variables.

4.1.2 Structural Model Assessment

The structural model achieved acceptable fit for exploratory PLS-SEM research (SRMR = 0.061, NFI = 0.832). Following Hair et al. (2022), SRMR serves as the primary fit indicator for PLS-SEM, whereas NFI is treated as an auxiliary reference metric rather than a rigid cut-off criterion. The model explains 48.6% of variance in Learning Efficacy (R^2=0.486) and 26.2% of variance in Learning Analytics Engagement (R^2=0.262). Positive Q^2 values for LAE (Q^2=0.184) and LE (Q^2=0.267) confirm predictive relevance. f^2 effect sizes indicate medium-magnitude effects for DTM → LAE (f^2=0.169) and LAE → LE (f^2=0.197), alongside small-to-medium effect size for DTM → LE (f^2=0.118). Following Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively.

4.1.3 Hypothesis Testing

All four hypothesised relationships receive empirical support, as summarised in Table 1.

Table 1. Hypothesis testing results

Hypothesis	Path	β	t	p	Result
H1	DTM → LE	0.318	5.124	<0.001	Supported
H2	DTM → LAE	0.487	8.234	<0.001	Supported
H3	LAE → LE	0.423	6.891	<0.001	Supported
H4	DTM → LAE → LE	0.206 (indirect)	4.567	<0.001	Supported

Note. β= standardized path coefficient; CI = confidence interval. All reported p<0.001.

DTM demonstrates a significant positive direct predictive association with LE (H1: β=0.318, t=5.124, p<0.001). DTM positively predicts LAE (H2: β=0.487, t=8.234, p<0.001). LAE significantly and positively predicts LE (H3: β=0.423, t=6.891, p<0.001). Consistent with H4, LAE partially mediates the DTM-LE association: indirect effect β=0.206, t=4.567, p<0.001, 95% bias-corrected confidence interval (CI) [0.138, 0.281]. The 95% bias-corrected CI for the indirect effect did not contain zero, and the direct effect of DTM on LE remained significant, supporting partial mediation. The mediated proportion reached 39.3% within this sample. It should be noted that this magnitude is sample-specific and may vary across different institutional and student subgroups.

4.2 Qualitative Findings

Thematic analysis across 18 semi-structured interviews generated six overarching themes complementing and enriching quantitative outputs.

Theme 1: Perceived affordances of the Digital Teaching Model

Participants highlighted three core affordances of the Chaoxing platform: flexible anytime-anywhere access, abundant learning resources, and interactive functions. Learners valued flexibility for self-paced study: "The best thing about Chaoxing is that I can review the course materials whenever I want. If I don't understand something in class, I can go back to the videos and rewatch them. This flexibility really helps me learn at my own pace" (Participant 7, female, Year 2, Humanities). At the same time, respondents noted that such flexibility demands substantial self-discipline, which not all undergraduates possess.

Theme 2: Engagement with Learning Analytics

Students exhibited heterogeneous awareness and utilisation of platform analytics features. Some participants regularly consulted learning-progress dashboards, while others barely noticed these functions or only accessed them sporadically. Students actively engaging with analytics leveraged data for progress monitoring, goal-setting, and study-strategy adjustment: "When I see that my quiz scores are lower in a particular module, I know I need to go back and review that section. The analytics help me identify my weak points so I can focus my study time more effectively" (Participant 8, male, Year 3, Sciences).

Analytics also evoked diverse emotional responses including motivation, anxiety, and reassurance. Positive progress feedback boosted confidence and motivation. By contrast, unfavourable performance outputs could trigger discouragement. Instructor framing of analytic data shaped emotional experiences: "Our teacher always emphasises that the data is for our own improvement, not for judgement. That makes me feel more comfortable checking my progress" (Participant 17, female, Year 4, Humanities).

Theme 3: Determinants of Learning Efficacy

Participants identified self-regulation and time management, instructor feedback and support, plus peer collaboration as central drivers of learning efficacy. Self-discipline emerged as decisive for digital-learning success: "The key to learning effectively online is discipline. You have to set a schedule and stick to it. If you just passively watch videos without actively engaging, you won't learn much" (Participant 18, male, Year 4, Business). High-quality instructor feedback fostered learning confidence: "The feedback from my instructor has been instrumental in my learning. She doesn't just tell me what I did wrong; she helps me understand the concepts better. That builds my confidence" (Participant 8, male, Year 3, Sciences).

Theme 4: Barriers to digital-learning engagement

Key barriers include technical malfunctions, cognitive overload and digital fatigue, low motivation, and procrastination. Unstable internet and platform glitches disrupted learning activities. Information overload from abundant digital content created confusion regarding learning priorities: "There's so much information on the platform—videos, readings, discussions, announcements. Sometimes it's overwhelming, and I don't know where to focus my attention" (Participant 3, female, Year 1, Sciences). Without in-person classroom accountability structures, many students struggled with procrastination: "Without the structure of physical classes, it's easy to procrastinate. There's no one physically there to remind you to study or to keep you accountable" (Participant 15, male, Year 4, Engineering).

Theme 5: Context-specific features of private higher education

Participants acknowledged resource constraints characterising their private university, alongside institutional efforts advancing digital infrastructure. Substantial variability existed in instructors' digital-teaching proficiency: "Some teachers are really good at using the platform. They create interactive activities, use the analytics to track our progress, and provide timely feedback. Other teachers just upload the slides and don't do much else" (Participant 13, female, Year 3, Humanities). Individual-level digital literacy also shaped platform usage quality: "I'm quite comfortable with technology, so I find the platform easy to use. But I can see how some students might struggle, especially if they're not familiar with digital tools" (Participant 2, female, Year 1, Humanities).

Theme 6: Recommendations to improve digital-learning practice

Student recommendations covered enhanced analytics functionalities, expanded faculty training, and more interactive learning content. Participants desired personalised analytic recommendations targeting individual knowledge gaps: "I wish the platform could provide more personalised recommendations based on my learning data. Like, if I'm struggling with a particular topic, it could suggest additional resources or practice questions" (Participant 6, female, Year 2, Business). Interviewees underscored the need for systematic faculty training for analytics-enhanced pedagogy: "If teachers were more skilled in using the platform, our learning experience would be much better. They could create more engaging activities and provide better feedback" (Participant 13, female, Year 3, Humanities).

4.3 Integration of Quantitative and Qualitative Findings

This mixed-methods synthesis identifies

convergence, complementarity, and nuanced divergence across quantitative and qualitative datasets.

Convergence: Interview accounts corroborate the statistically significant paths (H1-H4). Students described how digital-platform features promoted analytics engagement; how LAE supported self-regulated learning; and how digital environments directly facilitated learning gains. Narratives of monitoring progress, diagnosing weaknesses, adjusting study strategies offer concrete real-world illustrations for the DTM → LAE → LE mediating pathway.

Complementarity: Qualitative data extend quantitative results by unpacking concrete platform features driving LAE, illuminating under-measured emotional-motivational dimensions of LAE, and highlighting contextual moderators (instructor scaffolding, resource constraints, student digital literacy). These contextual factors cannot be fully captured by survey-based latent variables.

Divergence: Aggregate survey mean scores mask substantial inter-individual variation in awareness and depth of analytics engagement. Interview data further reveal that engagement quality outweighs engagement frequency. Superficial, cursory interaction with analytics generates minimal learning benefits. This distinction between deep versus surface-level LAE delivers critical nuance for interpreting the LAE-LE association.

5. Discussion

5.1 Theoretical Contributions

This study yields four major theoretical contributions to digital-learning scholarship, especially for China's private higher-education context.

First, this research extends the Technology Acceptance Model by shifting focus from pure technology adoption to mediated learning outcomes. Prior TAM-informed educational research largely centres on whether learners accept and use digital tools. This study positions LAE as a critical intermediate construct. Platform acceptance is merely the starting point; meaningful, reflective engagement with learning analytics translates technological affordances into enhanced learning efficacy. By integrating Self-Regulated Learning perspectives into an extended TAM, our model demonstrates that technology acceptance fosters analytics engagement, which in turn enables cyclical self-regulatory learning behaviors (Davis, 1989; Scherer et al., 2019; Zimmerman, 2000).

Second, it validates the complementary interplay between Sociocultural Theory and Self-Regulated Learning Theory within digital-analytics-enhanced learning. From a sociocultural lens, digital platforms and analytics dashboards serve as cultural-psychological tools delivering instructional scaffolding. From an SRL perspective, LAE operationalises self-regulation via monitoring, goal-setting, and strategic adaptation. The synthesised framework acknowledges bidirectional relationships. Social-cultural contexts shape individual cognitive processing, and learner self-regulated actions further reshape participation within digital learning communities.

Third, this paper develops and empirically validates a context-sensitive model for private higher education in China. Private universities face distinctive structural constraints including limited funding, uneven faculty digital readiness, and heterogeneous student digital literacy, all of which moderate digital-teaching effectiveness. The partial mediation result (39.3%) demonstrates that LAE constitutes a vital pathway yet does not fully explain DTM's association with LE. Within resource-limited private institutions, analytics-enabled feedback becomes particularly valuable for cultivating learner self-efficacy and self-regulation, highlighting the indispensable roles of faculty development and student digital-literacy building.

Fourth, this study empirically conceptualises LAE as a multi-dimensional construct incorporating behavioral, cognitive, and emotional components. Qualitative evidence distinguishes deep reflective analytics engagement from superficial surface-level usage. This moves beyond viewing LAE simply as frequency of system interaction. For future scholarship, measuring engagement quality rather than only behavioural quantity is essential when investigating learning-analytics interventions.

5.2 Practical Implications

Institutional-level implications

Findings justify strategic investment in user-centred digital infrastructure with advanced analytics modules. Nevertheless, infrastructure alone is insufficient. The highest institutional priority should be sustained, systematic faculty professional development targeting digital pedagogy and learning-analytics literacy. Interview data consistently show instructors act as linchpins of digital-learning ecosystems. Without well-trained educators, high-quality platforms cannot realise their educational potential. Universities should also design curricular or co-curricular programmes to foster student digital literacy and self-regulated-learning capacities to support agentic learner behaviour. Consistent with qualitative findings distinguishing deep reflective LAE from superficial surface-level engagement, institutions should avoid evaluating analytics engagement merely by counting students' click frequency on dashboards. Interventions ought to prioritise fostering reflective, meaning-oriented engagement rather than increasing passive platform interaction.

Instructor-level implications

Teachers ought to move beyond merely uploading resources onto digital platforms. Instructors should integrate learning analytics as core formative-assessment tools to enable just-in-time teaching and targeted support for at-risk students. Learning activities should intentionally scaffold self-regulation. Feedback informed by analytics should be timely, constructive, and growth-minded, avoiding triggering unnecessary learner anxiety.

Student-level implications

Learners need to proactively cultivate time-management, goal-setting, and self-regulatory competencies. They are encouraged to engage with analytics outputs reflectively rather than passively consume data, treating analytic feedback as actionable guidance for improvement rather than fixed judgements of personal ability.

5.3 Policy Implications

Empirical findings align with China's national smart-education strategies while addressing unmet needs within the private higher-education sector. Policymakers are advised to shift investment priorities from pure digital-infrastructure construction towards supporting high-quality learner engagement. Nationally standardised, funded faculty-training programmes for digital pedagogy and analytics literacy are recommended. Formal ethical guidelines are required for student-centred learning-analytics deployment to safeguard learner privacy and promote data literacy. Most importantly, targeted funding and support should mitigate digital inequities across institutional types, ensuring that benefits from national digital-education reforms extend to private-university students.

5.4 Limitations and Directions for Future Research

Several study limitations should be acknowledged. First, the cross-sectional research design limits definitive causal inference. All key variables rely on student self-reports collected at one single time-point. Even though Harman's single-factor test indicated common-method bias was not severe, cross-sectional data cannot rule out reverse associations. Higher learning efficacy may also encourage students to engage more actively with learning analytics. Therefore, the significant paths reported reflect empirical associations rather than strict causal relationships. Future research can adopt longitudinal or quasi-experimental designs to unpack temporal dynamics among DTM, LAE, and LE.

Second, data collection was restricted to a single private university, constraining cross-institutional generalisability. Multi-site comparative studies covering public and private universities across diverse Chinese regions are needed. Third, this investigation relies predominantly on self-reported data. Subsequent work should combine objective platform log-file data and academic performance metrics to triangulate self-report measures. Fourth, the sample consists exclusively of undergraduate students. Findings cannot be directly transferred to postgraduate or vocational-education populations. Finally, results are situated within the Chaoxing learning-management system. Generalisation to other digital platforms requires further validation.

Future research avenues include: examining individual- and contextual-level moderators (e.g., learner motivation, digital literacy, instructor support); designing and evaluating theory-driven interventions to boost DTM quality, LAE, and LE; deeper investigation of affective and emotional dimensions of LAE; exploring instructor and instructional-designer perspectives on analytics integration; and cross-cultural comparative research testing whether this model holds in other national higher-education contexts.

6. Conclusion

This mixed-methods study provides robust empirical evidence confirming Learning

Analytics Engagement as a key mediating mechanism explaining how Digital Teaching Models associate with Learning Efficacy within Chinese private higher education. A well-designed digital teaching environment characterised by accessibility, rich learning resources, and interactive features predicts higher student LAE. In turn, meaningful analytics engagement enhances learning efficacy through self-monitoring, goal-setting, and adaptive study-strategy adjustment. The partial mediating effect (39.3%) demonstrates that DTM also exerts direct positive associations with learning outcomes via improved resource access and enhanced social interaction among learners and educators.

By combining quantitative PLS-SEM analysis and qualitative thematic interviews, this work captures not only statistical associations but also underlying mechanisms, emotional dimensions, and contextual contingencies shaping digital learning. The integrated theoretical framework synthesising Sociocultural Theory, TAM, and SRL highlights learning as a dialectical process combining social mediation and individual learner agency.

Beyond theoretical advancement, this study generates actionable recommendations for university administrators, educators, and education policymakers. It underscores the urgency of faculty digital-pedagogy training, student-focused support for digital literacy and self-regulated learning, and policy interventions addressing digital inequity within China's private higher-education sector. Amid ongoing digital transformation across higher education, this research supplies an empirical foundation for building more effective, equitable, and empowering digital-learning environments to improve student learning outcomes.

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