

A Systematic Review of College Students' Digital Technology Application Based on the UTAUT Framework

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ABSTRACT

Digital teaching platforms, virtual simulators and generative AI are deeply embedded in university teaching, while students show a clear contradiction: they readily adopt digital tools but rarely maintain autonomous long-term usage. Venkatesh et al.'s (2003) UTAUT has become the leading analytical framework for digital learning research due to its integrative strengths. This systematic review collates 2003–2026 literature from Web of Science, Scopus and CSSCI journals and unfolds analysis from seven dimensions. The four core UTAUT constructs positively predict usage intention with effect disparities across grades, majors and digital literacy groups. Supplementing UTAUT with cognitive load, self-efficacy, burnout and digital justice greatly elevates its explanatory capacity; continuous usage intention serves as the central mediator; and digital proficiency is the most reliable moderator. Existing research is hampered by instrumental rational bias, overused cross-sectional designs, inadequate disadvantaged student samples and immature AI-oriented theories. This paper puts forward multi-future research proposals and delivers standardized theoretical support for higher education digitalization studies.

Keywords: cognitive load; digital learning; digital justice; UTAUT; university students;

1. INTRODUCTION

Driven by the national strategy of educational digitalization, online teaching platforms, immersive simulation systems and generative artificial intelligence have transitioned from emergency teaching alternatives during the pandemic to regular instructional carriers, forming a complete digital learning chain covering pre-class preparation, in-class activities and after-school review (Wu, 2023). However, abundant empirical evidence and instructional practice reveal a structural contradiction: despite the rising coverage rate of digital learning tools in universities, few students maintain consistent, voluntary long-term digital learning routines. Most learners only log into platforms to fulfil mandatory course assignments, and autonomous sustained digital participation remains scarce, restricting the full realization of digital educational values (Bond & Buntine, 2024). Clarifying the internal mechanisms underlying students' transition from passive adoption to proactive long-term usage has become a pivotal research agenda in higher educational technology studies.

In 2003, Venkatesh and colleagues integrated eight classical behavioral theories including the Technology Acceptance Model (TAM) and Theory of Planned Behavior to develop the UTAUT framework, with four core baseline constructs for technology use analysis. In 2012, they put forward UTAUT2 targeting individual consumption scenarios, adding hedonic motivation, price value and habit to better accommodate voluntary learning contexts. Thanks to superior explanatory power, UTAUT has replaced the single TAM model as the foundational framework for domestic and international research on learners' digital behaviors. Nonetheless, recent meta-analyses and critical studies published in top educational technology journals point out inherent flaws of the original UTAUT. Derived from mandatory workplace settings, the framework is confined to instrumental rationality and neglects learners' intrinsic cognitive consumption, emotional exhaustion and unequal

resource distribution. When applied independently to student samples, the model accounts for less than 40% of the variance in long-term digital learning behaviors (Rasa, 2025; Naidoo & Singh-Pillay, 2025).

Domestic scholars mostly conduct simple localized validations based on foreign extended models, while overseas literature discusses model expansions scattered across different disciplinary contexts. No integrated review has yet synthesized instrumental rationality, cognitive psychology, digital equity and post-digital dissensus perspectives to systematically map the research landscape. Against this backdrop, this paper carries out a systematic review to categorize empirical findings accumulated over the past two decades, distinguish the applicable boundaries of baseline constructs, compare the theoretical contributions of diverse extended variables, and unpack consensus and divergence in mediating and moderating mechanisms. It further identifies theoretical blind spots and methodological drawbacks of extant research, and proposes forward-looking research agendas with critical and empirical feasibility, so as to refine the research context and offer theoretical support for localized, cutting-edge empirical inquiries.

2. LITERATURE RETRIEVAL AND RESEARCH METHODOLOGY

2.1 Retrieval Scope and Search Terms

For foreign literature, databases including Web of Science and Scopus were accessed, limiting sources to SSCI journals in education and educational technology fields. Chinese literature was retrieved from CNKI and Wanfang, confined to CSSCI and Peking University core journals. The unified retrieval time frame spans 2003 to 2026.

Foreign search keywords are UTAUT, UTAUT2, undergraduate students, digital learning, online platform, AI chatbot, cognitive load, learning self-efficacy. Chinese search keywords is UTAUT, college students, digital learning, online teaching platform, cognitive load, learning self-efficacy, continuous usage behaviour.

2.2 Inclusion and Exclusion Criteria

2.2.1 Inclusion Criteria

Full-time undergraduate and postgraduate students as core research participants. Explicit adoption of UTAUT and UTAUT2 as the core theoretical framework. Empirical studies combining questionnaire surveys and structural equation modelling (SEM). Research topics focusing on adoption or long-term usage of online learning, AI-assisted tools and hybrid digital resources.

2.2.2 Exclusion Criteria

Master's and doctoral dissertations, purely theoretical papers without empirical testing. Studies targeting K-12 teachers, corporate employees or other non-college populations. Replicated validation research without theoretical innovation or localized expansion. Low-quality short journal articles with insufficient empirical depth.

2.3 Basic Distribution of Included Literature

After multi-stage screening of titles, abstracts and full texts, a total of 92 foreign empirical articles and 67 Chinese core papers were incorporated, amounting to 159 valid works. Temporally, publication volume surged after 2020, as the COVID-19 pandemic pushed hybrid learning to the forefront of academic inquiry. In terms of research contexts, general online learning platforms constitute the largest proportion, followed by generative AI learning tools and mobile fragmented learning software. Methodologically, 91% of the literature relies on cross-sectional questionnaires paired with PLS-SEM or AMOS for static model verification. Longitudinal tracking and mixed quantitative-qualitative designs account for less than 8% of all included studies, indicating a prominent homogenization of research approaches.

3. EMPIRICAL CONSENSUS AND GROUP HETEROGENEITY OF ORIGINAL UTAUT BASELINE CONSTRUCTS

The original UTAUT proposed by Venkatesh et al. (2003) establishes four exogenous variables: performance expectancy, effort expectancy, social influence and facilitating conditions, with behavioral intention as the mediator to predict actual usage behavior. Synthesizing quantitative results from all included studies, the four baseline constructs demonstrate generally stable positive effects on college students, yet their effect magnitudes differ across grades, disciplines and digital literacy groups. Meanwhile, the inherent limitations of

the original framework is fully exposed when deployed in educational contexts.

3.1 Unified Empirical Conclusions of Four Baseline Constructs

3.1.1 Performance Expectancy

As the core exogenous predictor within the canonical UTAUT framework proposed by Venkatesh et al. (2003), performance expectancy consistently exerts salient positive predictive power over learners' continuous usage intention across digital learning scenarios (Tamilmani et al., 2021). When students subjectively perceive digital learning tools as capable of streamlining academic workflows, boosting learning efficiency and elevating overall academic outcomes, their willingness to sustain long-term autonomous use rises markedly (Patterson et al., 2024). This causal linkage becomes even more pronounced in empirical research targeting generative AI educational tools. Multiple cross-regional SEM studies have verified that this nomological path usually yields higher standardized regression coefficients than other UTAUT core dimensions (Saihi et al., 2025). The underlying rationale, as summarized by Kasneci et al. (2023), lies in students' universal recognition of generative AI's multi-faceted instrumental value: such tools deliver instant responses to obscure academic questions, sort and categorize scattered literature resources efficiently, outline thesis frameworks and clarify complex disciplinary logic, thereby drastically cutting down learners' time cost for preliminary academic exploration.

3.1.2 Effort Expectancy

Intuitive interface design and multi-terminal compatibility reduce operational costs for learners by unifying interaction logic across devices and lowering learning curves (Bond & Buntine, 2024; Lin, 2026; Wilson et al., 2022). Cumbersome functional hierarchies and frequent page switching, by contrast, elevate extrinsic cognitive load and suppress autonomous usage willingness, as fragmented navigation wastes limited working memory resources on non-learning operational tasks (Sweller,

1988; Zhang et al., 2023; Xue et al., 2024). Poor cross-device consistency further amplifies this burden: inconsistent menu structures force repeated relearning of basic operations, driving down sustained self-directed learning engagement (Abuhassna et al., 2020; Sakdavong et al., 2026).

3.1.3 Social Influence

Curriculum requirements from instructors and peer learning atmospheres generate external driving forces for digital learning adoption (Venkatesh et al., 2003; Zhang, 2023). STEM students are more susceptible to peer effects and group normative pressure when selecting learning tools (Riegle-Crumb et al., 2019), while arts and humanities learners tend to make usage decisions based on individual subjective judgment rather than peer group consensus (Chen & Liu, 2025).

3.1.4 Facilitating Conditions

Stable campus internet, free digital resources and after-class technical support serve as fundamental structural prerequisites for sustained online learning behavior (Almaiah et al., 2020; Venkatesh et al., 2016). Deficiencies in hardware and service provision directly break the transformation from usage intention to consistent behavior (Naidoo & Singh-Pillay, 2025). Without complete supporting infrastructure, even students with strong learning intentions fail to maintain long-term platform engagement (Bervell et al., 2021).

3.2 Stratified Heterogeneity Among Student Groups

3.2.1 Grade differences

Freshmen prioritize effort expectancy when making usage decisions, whereas upper-year students attach greater weight to performance expectancy and autonomous learning value.

3.2.2 Disciplinary differences

STEM majors exhibit stronger sensitivity to tool utility and social influence; arts students pay more attention to interface complexity and content matching. A meta-analysis by Saihi et al. (2025) verifies that discipline only exerts a weak moderating effect without fundamental behavioral divides.

3.2.3 Digital literacy stratification

Students with high digital proficiency focus solely on functional value of learning platforms and operate independently without auxiliary guidance (Van Deursen & Van Dijk, 2014; Zheng et al., 2018), while learners with limited technical skills are highly dependent on external infrastructure, device access guarantees, and real-time instructional scaffolding to complete online learning tasks (Hanny et al., 2023; OECD, 2022).

3.3 Inherent Theoretical Deficiencies of the Original UTAUT

Synthesizing post-digital critical reviews and meta-analyses published in top journals, the original framework suffers from four core drawbacks. First, its theoretical foundation is rooted in instrumental rationality, presuming uniform evaluative standards for digital technologies and ignoring divergences in individual cognition and value orientations (Rasa, 2025). Second, it excludes

variables of cognitive consumption and emotional burnout, failing to explain the widespread phenomenon of “recognizing utility yet abandoning voluntary usage”. Third, the model overlooks structural variables related to infrastructure and resource distribution, making it hard to address digital divide and educational equity issues. Fourth, it only addresses short-term adoption intention and lacks a complete logical chain linking initial acceptance to long-term learning habits.

4. UTAUT2 EXPANSION AND LOCALIZED VARIABLE CONSTRUCTION FOR EDUCATIONAL SCENARIOS

4.1 Adaptation Boundaries of UTAUT2 Derived Constructs

Venkatesh et al. (2012) extended UTAUT to consumer scenarios by adding hedonic motivation, price value and habit. Their predictive power varies markedly across educational research contexts. Hedonic motivation shows significant effects only in gamified simulation and short-video learning tools, with negligible predictive power for standardized curriculum platforms. Price value is mostly non-significant in Chinese universities where digital learning resources are provided free of charge, yet positively correlated with usage intention in overseas paid course samples. Habit has emerged as a core outcome variable in recent studies, serving as the critical indicator distinguishing temporary adoption from long-term routine usage.

4.2 Positive Extended Variables

4.2.1 Learning self-efficacy / digital proficiency

This stands as the most widely adopted localized variable in existing scholarship. Bond & Buntine (2024) offer quantitative evidence that students with high self-efficacy are 2.3 times more likely to sustain online learning than low-efficacy counterparts. Self-efficacy buffers the negative impacts of cognitive load and mitigates avoidance behaviours triggered by operational difficulties (Saihi et al., 2025).

4.2.2 Perceived content quality

Well-structured, curriculum-aligned and timely updated online resources strengthen long-term participation willingness, while fragmented, irrelevant materials drastically reduce sustained engagement (Chen et al., 2022).

4.2.3 Autonomous learning control

Platforms without mandatory check-in rules and flexible learning schedules reduce student resistance and alleviate academic burnout (Hardey & Pimblett, 2026).

4.3 Negative Restraining Extended Variables

4.3.1 Cognitive load

Rooted in Cognitive Load Theory, frequent platform switching and excessive information overload consume limited working memory, generating extrinsic cognitive burdens. Empirical data from Bond & Buntine (2024) demonstrate that each unit increase in cognitive load reduces continuous usage

intention by 28.3%, rendering it the most potent negative predictor. Hardey & Pimblett (2026) further propose the concept of affective load, rigid mandatory learning schedules compound cognitive strain and jointly suppress sustained participation.

4.3.2 Academic burnout

Repetitive compulsory online tasks and meaningless attendance requirements induce psychological fatigue and generate aversion to digital learning, cutting off sustained behavioral chains (Maslach & Leiter, 2016).

Perceived digital injustice. Unequal access to equipment, mobile data and premium learning resources creates implicit digital divides, discouraging voluntary digital participation among disadvantaged students (Naidoo & Singh-Pillay, 2025).

4.3.3 Ethical concerns over AI tools

A unique construct for generative AI research; worries about academic plagiarism, algorithmic bias and personal data leakage significantly lower students' willingness to adopt large language learning tools.

4.4 Comparison of Model Explanatory Power

The original UTAUT yields an R^2 ranging from 0.30 to 0.39 for continuous usage intention. After incorporating cognitive load, self-efficacy and burnout variables, integrated extended models generally reach an explanatory variance of 0.50–0.58, which empirically validates the irreplaceable theoretical value of cognitive and emotional constructs (Bond & Buntine, 2024).

CONSENSUS AND DIVERGENCE IN MEDIATING AND MODERATING MECHANISMS

5.1 Core Mediating Consensus

Standard sequential mediation path: Performance expectancy, effort expectancy and other antecedents cannot directly generate persistent usage behavior; continuous usage intention acts as the mandatory transmission mediator, a conclusion unanimously validated by nearly all empirical papers (Bhattacharjee, 2001).

Multi-layer chained mediation: Self-efficacy and cognitive load frequently function as secondary mediators. A representative path is facilitating conditions → learning self-efficacy → continuous usage intention.

Supplementary mediation from a post-digital perspective: Perceived digital justice and technological dissensus form independent mediating chains that reshape usage attitudes and subsequent sustained willingness (Rasa, 2025).

5.2 Frequently Adopted Moderating Variables

Scholarly inquiries on UTAUT-based digital learning mechanisms have identified three layered clusters of moderating predictors encompassing individual indicators such as digital proficiency grade gender and academic discipline environmental factors including campus digital infrastructure

and sustained faculty technical guidance as well as contextual variables covering digital tool typology and mandatory intensity of online coursework assignments (Eur et al., 2024; Mancao & Dequito, 2022), and the comprehensive meta-analysis conducted by Saihi et al. (2025) alongside parallel empirical evidence from Fajaruddin et al. (2024) collectively verifies that digital proficiency stands as the most stable and statistically salient moderating construct within such nomological networks which simultaneously amplifies the positive nomological pathways originating from performance expectancy and mitigates the detrimental predictive repercussions generated by extraneous and intrinsic cognitive load across student learning samples.

Table5.1 Frequently Adopted Moderating Variables

SORT	Adopted Moderating Variables
Individual level	digital proficiency, grade, gender, academic discipline
Environmental level	campus digital infrastructure, faculty technical guidance
Contextual level	tool category, mandatory degree of online assignments

5. EVOLUTIONG RESEARCH CONTEXTS AND DEFICIENCIES IN METHODOLOGY

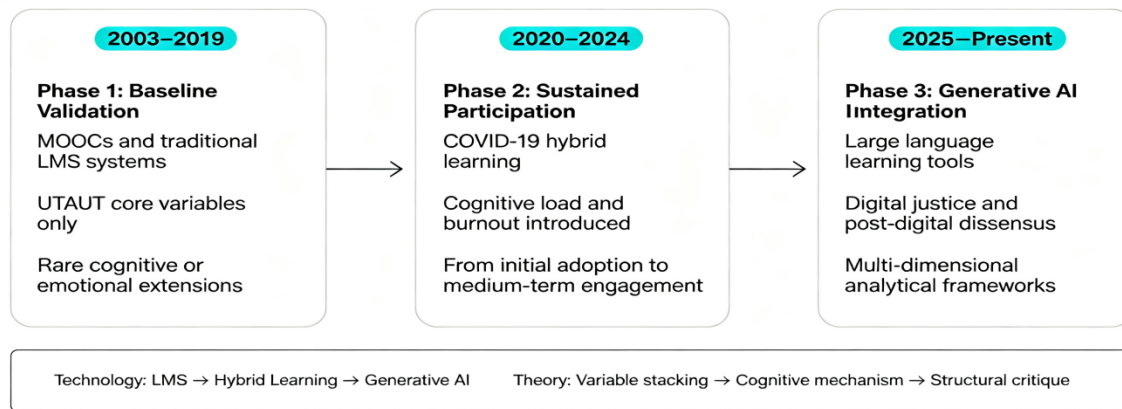
6.1 Three Stages of Contextual Development

Phase 1 (2003–2019) is research centred on MOOCs and traditional LMS systems, limited to simple validation of UTAUT baseline variables without cognitive or emotional extensions. Phase 2 (2020–2024) is the COVID-19 pandemic popularized hybrid learning. Scholars gradually introduced cognitive load and burnout variables to investigate medium-term sustained participation. Phase 3 (2025–present) is Generative AI becomes the mainstream research subject. Studies integrate digital justice and post-digital dissensus to form multi-

dimensional analytical frameworks.

Figure6.1 Phase of UTAUT-Based Digital Learning Research

Phases of UTAUT-Based Digital Learning Research



6.2 Systematic Drawbacks of Current Research Methods

Single-shot questionnaires only capture behavioral snapshots at one time point, failing to track dynamic shifts in usage willingness across semesters and technological iterations. Qualitative interviews and mixed-method designs remain scarce, making it difficult to excavate deep-rooted value conflicts behind students' abandonment of digital tools. Most studies directly adopt foreign mature items with minimal revisions, ignoring domestic institutional features such as mandatory online attendance and uneven regional internet resources, which impairs measurement validity. Most surveys target urban comprehensive universities, with inadequate data from rural colleges, vocational schools and low-income student groups, resulting in weak empirical support for digital equity discussions.

6. CORE THEORETICAL AND EMPIRICAL LIMITATIONS OF EXTANT LITERATURE

Existing UTAUT-centred digital learning research is constrained by a narrow analytical vision confined to instrumental rational reasoning. The bulk of relevant empirical works simply superimpose supplementary latent variables onto baseline structural models yet fail to engage in substantive theoretical dialogue with postdigital critical perspectives and digital justice scholarship. Such research tends to frame digital learning technologies as value-neutral instrumental artefacts while neglecting the structural institutional power relations and unequal distribution of learning resources that fundamentally reshape students' digital engagement trajectories (Naidoo & Singh-Pillay, 2025; Rasa, 2025). Methodologically, the field remains entrenched in static cross-sectional research designs, which lack the capacity to disentangle clear causal chronological chains and fail to capture the divergent nomological mechanisms operating across distinct behavioural phases including initial tool uptake, medium-term learning maintenance and long-term habitual usage. When it comes to generative AI learning instruments, current theoretical construction remains overly superficial; prevailing scholarship mechanically borrows measurement scales developed for conventional digital platforms rather than designing dedicated latent constructs that capture unique risks such as academic integrity violations, algorithmic prejudice and the erosion of learners' autonomous critical thinking capacities. Furthermore, empirical investigations targeting digitally

vulnerable student subgroups remain scarce, with minimal comparative analyses conducted across cohorts distinguished by household economic conditions and personal digital hardware endowments, rendering most discussions of digital equity abstract and empirically unsubstantiated. Last but not least, domestic studies in this field suffer from homogenized model expansion practices: numerous local empirical papers merely replicate Western extended UTAUT architectures without developing context-specific measurement dimensions tailored to the centralized online administration and mandatory assessment regimes prevalent within Chinese tertiary institutions.

7. FORWARD RESEARCH AGENDA

8.1 Theoretical Integration and Innovation

Future theoretical advancement ought to transcend the dominant instrumental rational paradigm prevailing in existing UTAUT scholarship by integrating postdigital dissensus theory (Rasa, 2025) and the social justice-oriented digital justice analytical framework proposed by Naidoo and Singh-Pillay (2025), two critical perspectives that expose the structural power inequities concealed by simplistic instrumental technological assumptions (Feenberg, 2017; Knox, 2019). Rather than engaging in superficial mechanical stacking of isolated latent variables, subsequent research should construct integrated composite UTAUT models capable of simultaneously incorporating three interwoven analytical dimensions: learners' subjective instrumental perceptions of digital tools, internal cognitive and affective emotional dynamics, as well as structural resource inequalities shaped by institutional digital governance and socioeconomic stratification (Jandrić et al., 2019). Such multi-layered theoretical integration can remedy the longstanding defect of conventional extended UTAUT frameworks, which separate technical perceptions from social structural contexts and fail to interpret divergent usage patterns stemming from unequal learning resource allocation.

8.2 Renewal of Research Methodologies

Methodological limitations rooted in static cross-sectional designs have long hampered the capacity of UTAUT scholarship to unpack dynamic shifts in digital learning trajectories (Liu & Wang, 2025). To remedy this deficiency, subsequent empirical inquiries ought to advocate multi-wave longitudinal tracking schemes comprising two-wave or three-wave sequential questionnaires, which can be triangulated with qualitative evidence drawn from semi-structured interviews and in-situ classroom observations to realize mixed-method corroboration of behavioural evolutions (Ding et al., 2025; McKell & Thonmai, 2026). Beyond longitudinal mixed-method designs, researchers should launch comparative subgroup analyses centering on urban and rural student cohorts, with stratified sampling deliberately covering participants suffering insufficient digital hardware and unstable internet access, so as to supplement insufficient empirical data on digitally disadvantaged populations and enrich evidence-based discussions regarding digital equity (Lyngdoh et al., 2025; Zhao et al., 2022). Such multi-source, stratified data collection strategies can mitigate sample bias prevalent in prior single-shot questionnaire studies and yield more robust conclusions for institutional digital pedagogy optimization.

8.3 Customized UTAUT Expansion for Generative AI

Existing UTAUT extensions designed for conventional digital learning platforms lack targeted latent constructs that capture unique risks accompanying large language model learning tools (Bakari et al., 2025; Matto, 2024). Subsequent theoretical refinement should prioritize developing dedicated,

validated measurement dimensions centering on three core generative AI-specific domains: academic ethics and integrity risks, multi-faceted algorithmic trust covering output accuracy and data privacy, as well as cognitive offloading-induced erosion of learners' independent critical and creative autonomy (Gerlich, 2026; Nazaretsky et al., 2022). By integrating these context-specialized latent variables into the canonical UTAUT nomological network, scholars can construct differentiated, specialized analytical frameworks exclusively tailored to generative AI learning agents, which remedy the theoretical superficiality of current GenAI research that mechanically borrows scale items designed for traditional online systems (Kundu et al., 2025; Obenza et al., 2024).

8.4 In-depth Exploration of Moderated Chained Mediation

Subsequent longitudinal inquiries ought to partition learners' digital engagement into three sequential developmental phases consisting of initial tool adoption, medium-term learning maintenance and long-term habitual formation, then conduct comparative tests on differentiated path coefficients across distinct behavioural stages to unpack dynamic shifts of nomological linkages over time (Ding et al., 2025; Venkatesh et al., 2012). Beyond phase-wise trajectory analysis, future scholarship should prioritize excavating the complex moderated mediation mechanisms embedded within the research framework, with special attention devoted to two pivotal boundary variables: individual digital literacy and institutional campus digital governance systems, whose interactive conditioning effects on the whole causal chain remain insufficiently elaborated in

existing cross-sectional empirical works (Zhao et al., 2024; Liu, 2025).

8.5 Practice-Oriented Stratified Research

From the lens of digital justice advocated by Naidoo and Singh-Pillay (2025), scholars ought to launch targeted stratified questionnaire surveys cantering on undergraduates characterized by inadequate digital literacy and limited household digital hardware and stable internet access, which can systematically capture multilayered barriers restricting their consistent digital learning engagement (Dyantyi & Mkabile-Masebe, 2025). Based on empirical evidence derived from such differentiated surveys, institutions are supposed to formulate tiered digital skill training programs and hierarchical digital resource allocation schemes tailored to learners' varying technical foundations and material conditions, thereby narrowing structural digital participation gaps rooted in socioeconomic disparities and providing actionable policy reference for institutional digital pedagogy reform (Traxler, 2021).

9. CONCLUSIONS

The UTAUT framework lays a foundational analytical architecture for investigating college students' digital learning behaviors. Over the past two decades, domestic and international scholars have fully validated its four baseline constructs and extended the model with cognitive load, learning self-efficacy, academic burnout and digital justice variables, greatly boosting explanatory power for long-term learning engagement. Nevertheless, existing research suffers from multiple flaws including narrow theoretical horizons, over-reliance on static cross-sectional data, underdeveloped AI-specific theories and insufficient sampling of disadvantaged learners. Future inquiries ought to transcend simple quantitative verification routines, incorporate post-digital critical and equitable perspectives, adopt longitudinal mixed-method designs, and focus on emerging generative AI tools. More localized frameworks matching Chinese higher education realities can be established to deliver rigorous

theoretical and empirical evidence for optimizing campus digital learning ecosystems and fostering students' autonomous long-term digital learning habits.

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