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Technology Acceptance Model in Digital Higher Education (2015-2025): A Bibliometric Analysis of Theoretical Evolution and Collaboration Patterns

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Abstract. The technology acceptance model (TAM) has been central to understanding technology adoption in higher education (HE) for decades. However, a comprehensive decade-scale synthesis of its evolution in digital learning contexts has remained absent. This bibliometric review systematically mapped TAM research in digital HE from 2015 to 2025. PRISMA guidelines were followed. A total of 429 Scopus-indexed articles were analyzed using VOSviewer for co-authorship, keyword co-occurrence, and co-citation analyses. The literature review confirmed that prior studies were largely qualitative, domain-specific, or limited in time span. Three salient findings emerged. First, publication output grew steadily, with a sharp acceleration during the COVID-19 pandemic. Second, the field shifted from core TAM constructs (perceived usefulness, perceived ease of use) toward affective, social, and contextual variables such as enjoyment, self-efficacy, and social influence. Third, research was geographically concentrated. Malaysia (62), Saudi Arabia (41), and China (38) led output. Collaboration networks showed strong regional clustering but weak intercontinental ties. Structural holes thus limited cross-cultural validation. Keyword analysis further revealed an emerging emphasis on artificial intelligence (AI), ChatGPT, and immersive technologies. It was concluded that TAM remained highly adaptable but faced challenges in geographic dispersion and theoretical generalization. Future research should prioritize international collaboration, culturally adaptable extensions, and deeper investigation of AI-driven learning systems. Educational institutions are recommended to use the identified collaboration patterns to form international consortia and faculty exchanges. This review provides a structured baseline for cross-cultural and collaborative research on technology acceptance in HE.

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1. Introduction

In the past decade, digitalization has reshaped higher education. The COVID-19 pandemic accelerated online and blended learning, forcing institutions to rely on digital tools and intensifying the need to understand technology acceptance (Alqahtani et al., 2022; Cheung et al., 2023). The technology acceptance model (TAM) (Davis, 1989) was widely used in HE to explain behavioral intention through perceived usefulness and perceived ease of use, often extended with affective, social, and contextual factors (Alalwan et al., 2018; Alyoussef, 2022; Dahri et al., 2024). TAM publications in online learning grew from 65 in 2018 to 168 in 2021 (Abuhassna et al., 2023), confirming a marked proliferation. Despite this large volume of empirical studies, a comprehensive bibliometric synthesis of TAM in HE over the past decade has remained absent.

Earlier reviews advanced the field but had several limitations. Granić and Marangunić (2019) qualitatively summarized TAM in education up to 2018 but did not quantify the temporal emergence of affective or social clusters. Alsharida et al. (2021) and Rosli et al. (2022) focused only on mobile learning or the pandemic period, missing longer-term evolution and AI-related trends. Abuhassna et al. (2023) used bibliometric methods but stopped at 2020 and did not analyze collaboration networks or cross-cultural patterns. A decade-long (2015–2025) bibliometric study that mapped thematic shifts, international collaboration, emerging technologies, and cross-cultural differences was still lacking.

To address these gaps, this study analyzed TAM research in HE from 2015 to 2025. The temporal boundary covered two phases: pre-pandemic consolidation (2015–2019) and pandemic-accelerated transformation (2020–2025), allowing for a comparison of the stability and changes in themes. Unlike traditional systematic reviews, bibliometric methods quantitatively mapped publication corpora, detected thematic shifts, and revealed collaboration patterns (Donthu et al., 2021). This approach was well suited for a mature field such as TAM and could identify "structural holes", which were gaps in collaboration networks that limit knowledge flow (Bizzi, 2013).

This study aimed to provide a descriptive baseline by depicting the quantity and growth trends of publications and identifying influential authors, institutions, and countries. Secondly, it went beyond description by examining how TAM extensions evolved, thereby making theoretical contributions. Thirdly, it introduced methodological innovation by applying co-citation and co-authorship network analysis to TAM research, thereby assessing research quality and collaboration dynamics. Fourthly, it provided actionable recommendations for different stakeholders.

Guided by these aims, the review addressed the following research questions:

1. What thematic clusters appeared in TAM research on digital HE between 2015 and 2025?
2. What was the structure of the international collaboration network among TAM scholars, including density, regional concentration, and bridging nodes?
3. What methodological approaches and emerging technologies (e.g., AI, VR/AR) were represented in the TAM literature?
4. What differences in cultural or contextual factors were observed across regions in TAM studies?
5. What implications for researchers, educators, and policymakers could be drawn from this bibliometric synthesis?

By answering these questions, this review provided an evidence-based portrait of TAM research to inform digital learning adoption in HE. The next section reviews the relevant literature to set the context for this study.

2. Literature Review

Davis (1989) proposed the TAM, which was derived from the theory of reasoned action (Fishbein & Ajzen, 1975). TAM posited that perceived usefulness (PU) and perceived ease of use (PEOU) were the primary drivers of user acceptance. Researchers widely applied TAM in HE to explain the acceptance of digital learning and AI-assisted systems (Dahri et al., 2024; Rehman et al., 2025; Zhao & Dong, 2025).

Despite its popularity, TAM also faced criticism (Venkatesh et al., 2003). Its overly simplistic model overlooked institutional, cultural, and pedagogical complexities (Dalle et al., 2024). In digital learning, technology acceptance was not instantaneous, but a dynamic process shaped by peer norms and digital literacy (Sayaf et al., 2022; Shonfeld et al., 2021). Cultural factors further limited TAM's cross-cultural applicability (Dalle et al., 2024). Methodologically, most TAM studies relied on self-reported surveys and cross-sectional designs (Al-Adwan et al., 2023; Bhattarai & Maharjan, 2020), raising concerns about common method bias.

These limitations prompted several extensions. Venkatesh et al. (2003) proposed the unified theory of acceptance and use of technology (UTAUT), which added facilitating conditions and social influence as direct predictors. They later extended it to UTAUT2, incorporating hedonic motivation and habit (Venkatesh et al., 2012). Abdullah and Ward (2016) developed the general extended technology acceptance model for E-learning (GETAMEL), compiling commonly used external factors. Other studies introduced variables such as self-efficacy, enjoyment, and trust (Alalwan et al., 2018; To & Trinh, 2021). Meanwhile, digital learning in HE expanded to include online platforms, mobile apps, blended learning, virtual reality (VR), augmented reality (AR), and AI-driven systems (Enyoojo et al., 2024; Huang, 2020; Mulenga & Shilongo, 2025; Mutambara & Bayaga, 2021).

Studies applying TAM to digital learning consistently showed that PU and PEOU predicted behavioral intention (Ajibade et al., 2022; Shonfeld et al., 2021). Recent extensions added enjoyment, self-efficacy, and trust (Alalwan et al., 2018; Ferdousi, 2022). However, the proliferation of extended variables raised concerns about conceptual fragmentation. Prior reviews summarized external factors but were largely qualitative, domain-specific, or limited in time span, thus failing to explain when or why specific variables gained prominence (Al-Emran et al., 2018; Rosli et al., 2022). The field lacked a longitudinal, quantitative synthesis tracking the temporal evolution of affective, social, and contextual clusters.

This gap motivated the present bibliometric review, guided by two propositions. First, TAM extensions co-evolved with technological disruptions (e.g., pandemic-driven online learning) and pedagogical shifts. Second, the centrality of affective and social variables increased over time, reflecting a maturation beyond cognitive-instrumental explanations. This review filled a gap by providing a bibliometric analysis of thematic evolution, collaboration patterns, and emerging technologies over the past decade.

The following section presents the methodology used to address this gap.

3. Methodology

3.1 Research Approach

This review adopted bibliometric analysis to map TAM) research systematically within digital learning in HE. Bibliometric analysis offered a quantitative lens to evaluate large publication corpora, and trace intellectual structures, collaboration patterns, and emergent themes (Donthu et al., 2021). Building on established practices, this study combined descriptive indicators with network analyses to identify key themes, influential authors and sources, and country and institutional contributions.

3.2 Literature Search and Screening Process

Bibliographic data were retrieved from Scopus, selected for its broad multidisciplinary coverage and reliable indexing in education and social sciences (Pranckutė, 2021). The search was conducted on January 5, 2026, covering publications from January 2015 to December 2025. The year 2015 was chosen as the start because it aligned with the widespread adoption of mobile learning and learning analytics in HE (Al-Emran et al., 2018; Rosli et al., 2022).The Boolean query (applied to title–abstract–keywords) was as follows:

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(TITLE-ABS-KEY("digital learning" OR "e-learning" OR "online learning" OR "mobile learning"))
  AND (TITLE-ABS-KEY("higher education" OR "university"))
  AND (TITLE-ABS-KEY("Technology Acceptance Model" OR "TAM"))
  AND PUBYEAR >= 2015 AND PUBYEAR <= 2025
  AND (LIMIT-TO(SUBJAREA, "SOCI"))
  AND (LIMIT-TO(DOCTYPE, "ar") OR LIMIT-TO(DOCTYPE, "re"))
  AND (LIMIT-TO(SRCTYPE, "j"))
  AND (LIMIT-TO(LANGUAGE, "English"))
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Inclusion and exclusion criteria (Table 1) were applied during screening, which followed PRISMA guidelines (Page et al., 2021). The initial search yielded 1,022 articles. After filtering by subject area, document type, and language, and removing duplicates, book chapters, and non-relevant studies (e.g., those not focused on HE or TAM), 488 articles remained. Careful screening left 429 studies. The screening was performed by a single author. To mitigate potential selection bias, a second author independently reviewed a random 10% sample of both included and excluded studies, and any disagreements were resolved through discussion. Although conference proceedings, non-English publications, and regionally indexed sources were excluded, the dataset was comprehensive. A random check of 20 excluded records from Google Scholar showed no substantial thematic difference from the included studies, confirming the robustness of the core trends.

Table 1: Inclusion and exclusion criteria

Category	Inclusion Criteria	Exclusion Criteria
Publication Type	Peer-reviewed journal articles (2015—2025)	Conference papers, book chapters, dissertations, editorials, and non-peer-reviewed
Language	English	Non-English
Research Context	HE institutions (universities/colleges)	K–12, vocational training, corporate learning
Research Focus	Digital learning: e-learning, online learning, mobile learning, virtual learning	Non-digital learning or system engineering without learning context
Theoretical Framework	TAM or extensions (PU, PEOU, enjoyment, trust, self-efficacy)	Unrelated theories (e.g., UTAUT, TPB, DOI) without TAM core
Empirical Scope	Quantitative/qualitative/ mixed method on acceptance, intention, or outcomes	Purely technical studies without behavioral/acceptance variables
Study Quality	Clear description of sample, data collection, and analysis	Missing essential methodological details
Availability	Full-text accessible via Scopus	No full-text or incomplete metadata

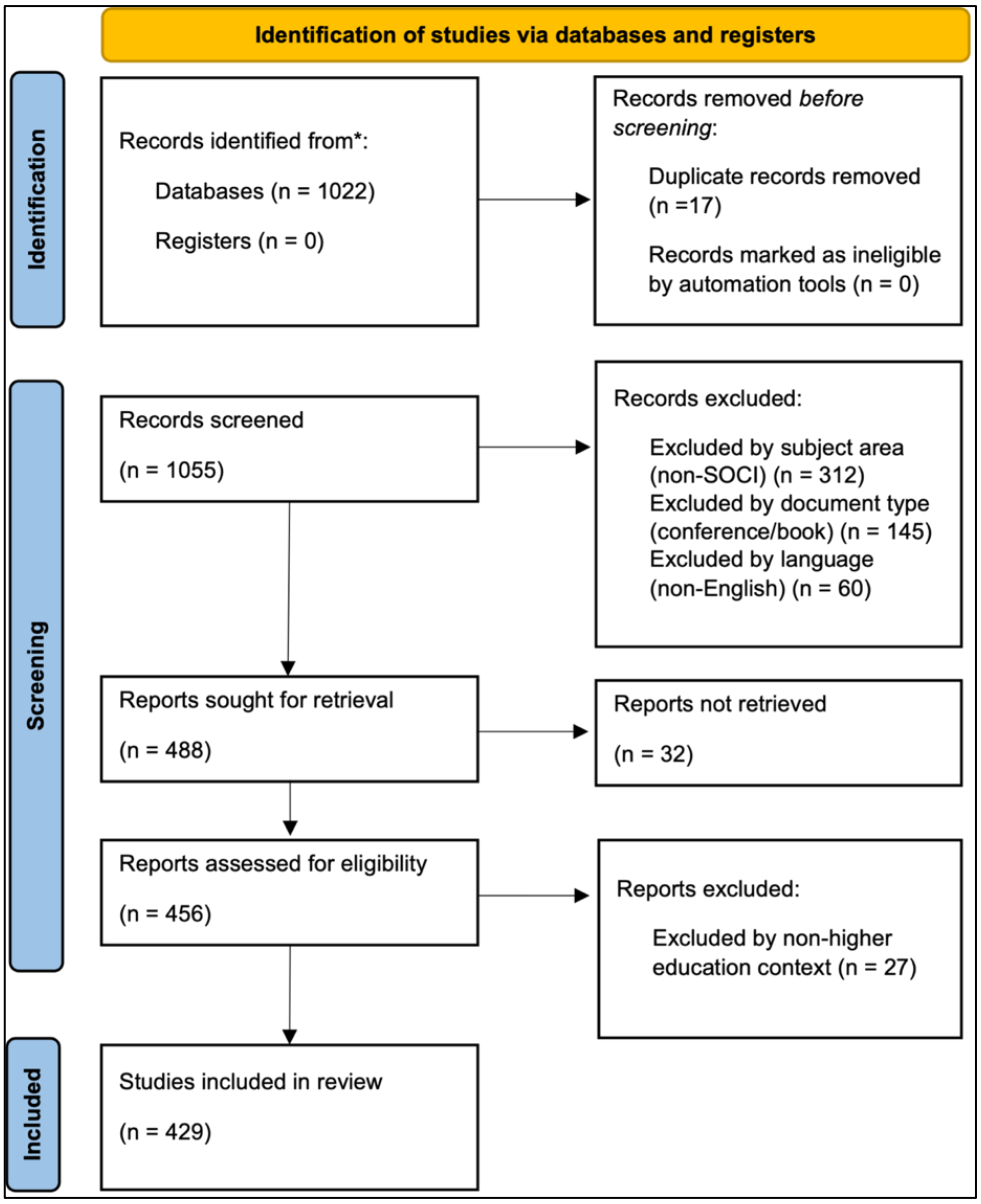

Figure 1: PRISMA flow diagram

3.3 Bibliometric and Network Analysis

The analysis used VOSviewer (version 1.6.20). Five areas were examined: publication trends, geographic and institutional distribution, author productivity and collaboration, keyword co-occurrence and thematic clusters, and co-citation and source analysis. Retrieved records were exported in CSV format, and duplicates were removed manually. For keyword analysis, synonyms were merged (e.g., "TAM" and "Technology Acceptance Model"), and generic terms (e.g., "study", "paper") were deleted. The keyword cleaning and standardization process was independently reviewed by two researchers to ensure consistency and reduce subjective bias. A minimum threshold of five keyword occurrences was set, which produced 48 keywords. The resulting thematic clusters were validated through an iterative examination of cluster contents, including high-

frequency keywords and representative publications within each cluster, to ensure conceptual coherence and meaningful interpretation.

For co-authorship analysis, the full counting method was applied, with thresholds of two for authors and one for countries. For co-citation analysis, the cited reference threshold was set to 15. Normalization used the association strength method. Conference proceedings, books, and non-English publications were excluded to ensure quality control and comparability (Donthu et al., 2021). Visualizations used default layout parameters (attraction = 2, repulsion = 0). The software reported network indicators such as total link strength and modularity, which were used to assess the robustness of collaboration and thematic structures (Orduña-Malea & Costas, 2021). Visual maps revealed the field's intellectual structure. With the search and analysis procedures established, the results are presented next.

4. Results

4.1 Publication Trends (2015–2025)

The annual publication trend of TAM-based digital learning research in HE showed sustained growth across the decade. From modest output in 2015, publications increased year on year. Total publications rose from 81 in the pre-pandemic period (2015–2019) to 156 during the acute pandemic period (2020–2022) and further to 192 in the post-pandemic period (2023–2025). A linear regression confirmed a significant upward trend ($R^2 = 0.89$, $\beta = 4.67$, $p < 0.01$).

The mean annual output increased from 16.2 (SD = 4.1) in 2015–2019 to 52.0 (SD = 8.7) in 2020–2022, with a sharp surge during 2020–2022 (Figure 2) coinciding with the COVID-19 pandemic (Turnbull et al., 2021). This suggested that exogenous shocks could accelerate research activity in technology acceptance, though pandemic-driven studies might transiently focus on emergency remote teaching rather than long-term transformation. The observed volatility also pointed to potential publication bias, as journals might have preferentially accepted COVID-related manuscripts.

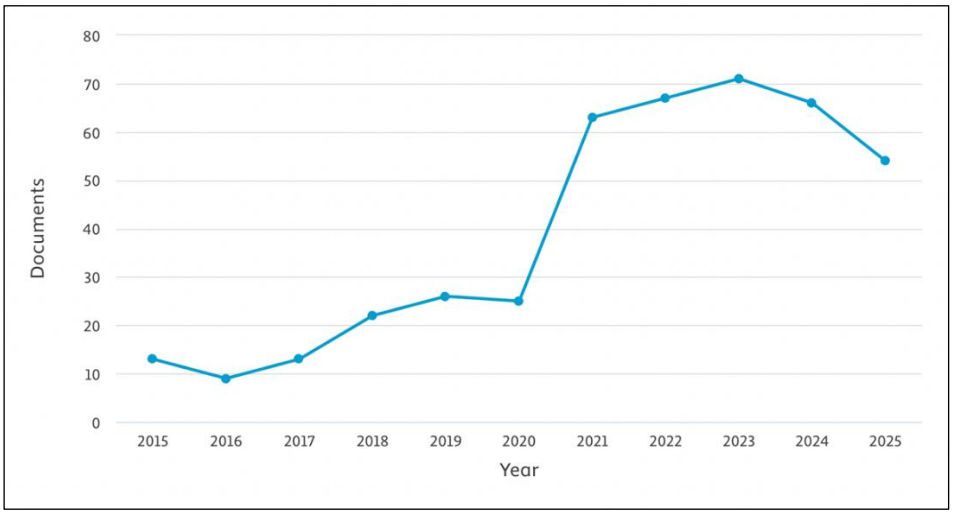

Figure 2: Annual number of TAM-based digital learning publications (2015–2025)

The journal distribution (Figure 3) indicated sharp increases in publications in *Sustainability (Switzerland)* during 2021 and 2023, and peaks in *Education and Information Technologies* in 2021. This concentration partly reflected the open-access publishing model and rapid review processes of these journals during the pandemic, which might have introduced a temporal publication bias. Nevertheless, it also underscored TAM's theoretical utility for educational digital transformation under urgent demand.

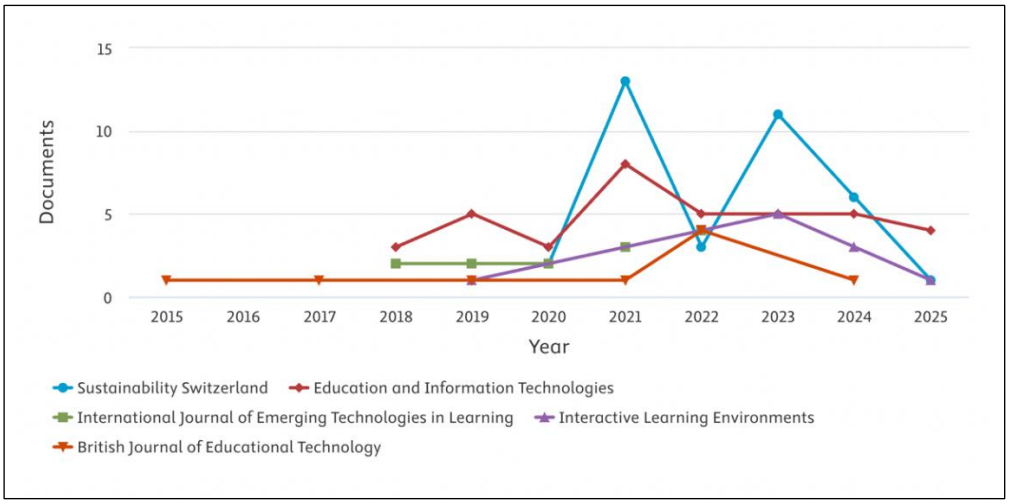

Figure 3: Annual publication counts per journal source for TAM research (2015–2025)

4.2 Geographic and Institutional Distribution

Publication output showed distinct regional concentrations, with Asian and Middle Eastern countries leading. Table 2 showed Malaysia with 62 documents, followed by Saudi Arabia (41), China (38), Jordan (27), and the United Arab Emirates (26). These patterns were likely explained by national investments in educational technologies and policies promoting digital transformation, as well as by cultural factors such as collectivism that aligned with TAM's social influence constructs. However, a critical caveat is that our exclusion of non-English publications might have over-represented English-producing regions (e.g., Malaysia, Saudi Arabia) while entirely omitting relevant studies from non-English-speaking countries (e.g., those in Latin America or continental Europe).

Table 2: Top 10 countries by publications and link strength

Rank	Countries	Documents	Total link strength
1	Malaysia	62	37.00
2	Saudi Arabia	41	25.00
3	China	38	8.00
4	Jordan	27	15.00
5	Turkey	27	7.00
6	United Arab Emirates	26	18.00
7	United States	26	11.00
8	Indonesia	25	11.00
9	United Kingdom	23	16.00
10	India	22	6.00

Countries' co-authorship networks (Figure 4) revealed a multi-polar structure. Two dense clusters dominated: a Southeast Asian cluster anchored by Malaysia (with strong ties to Indonesia and neighbors) and a Middle Eastern cluster centered on Saudi Arabia, Jordan, and the United Arab Emirates. High total link strength within clusters reflected strong intra-regional relationships. Meanwhile, China, the United States, and the United Kingdom often appeared as relatively isolated nodes with few weak ties to the main clusters, suggesting substantial but less connected outputs. This fragmentation limits cross-cultural validation of TAM constructs.

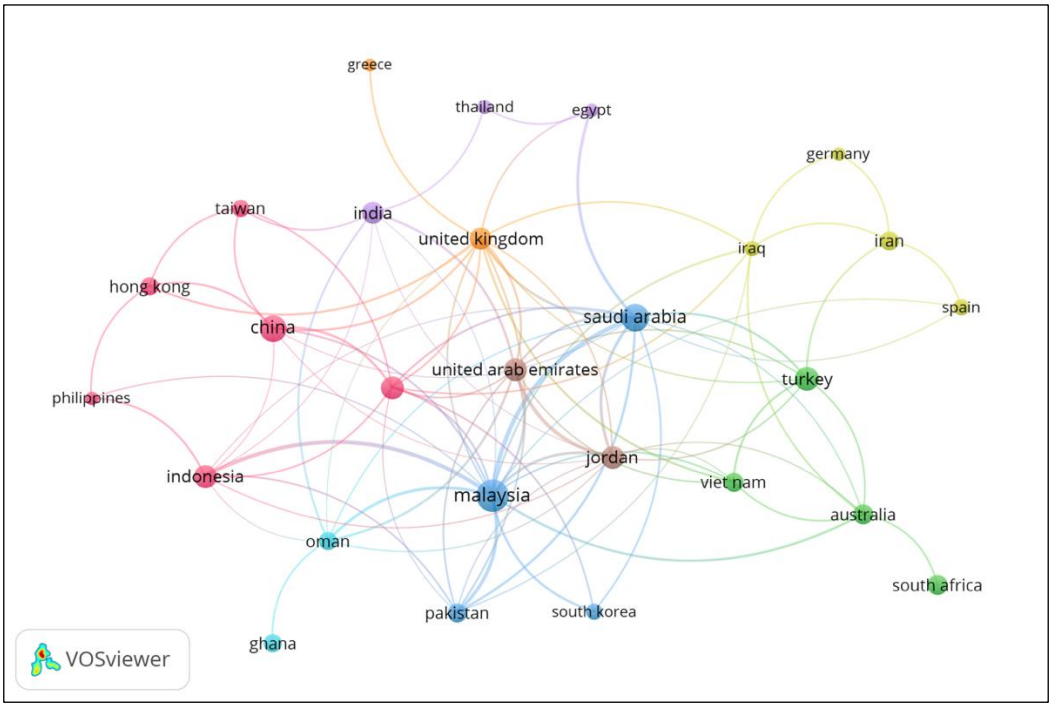

Figure 4: Co-authorship network of countries publishing TAM research

At the institutional level (Table 3), output was concentrated in universities across these hubs. Universiti Teknologi Malaysia (UTM) and King Faisal University led with five documents each, followed by the University of Sharjah and University of Salford with four. Notably, institutions with high publication counts also displayed moderate total link strength, suggesting that productivity alone does not guarantee centrality in collaboration networks. Units such as the Faculty of Social Sciences and Humanities (UTM) and the Department of Information Systems (University of Sharjah) showed both high publication counts and notable total link strengths, indicating active roles in collaboration networks. Institutional collaboration (Figure 5) remained mostly regional, with limited intercontinental ties, suggesting scope to strengthen cross-cultural collaborations for greater global relevance.

Table 3: Top 10 institutions by publications and link strength

Rank	Institution	Documents	Total link strength
1	Faculty of Social Sciences and Humanities, Universiti Teknologi Malaysia	5	4.00
2	Education Technology Department, King Faisal University	5	2.00
3	Department of Information Systems, University of Sharjah	4	3.00
4	Department of Engineering, University of Salford	4	3.00
5	Educational Technology Department, King Saud University	4	3.00
6	Research Institute of Sciences and Engineering, University of Sharjah	4	3.00
7	Department of Special Education, Ağrı İbrahim Çeçen University	4	0.00
8	Faculty of Business and Management, Universiti Teknologi MARA	4	0.00
9	Department of Business Administration, Hashemite University	3	3.00
10	Department of Management, College of Business Administration	3	3.00

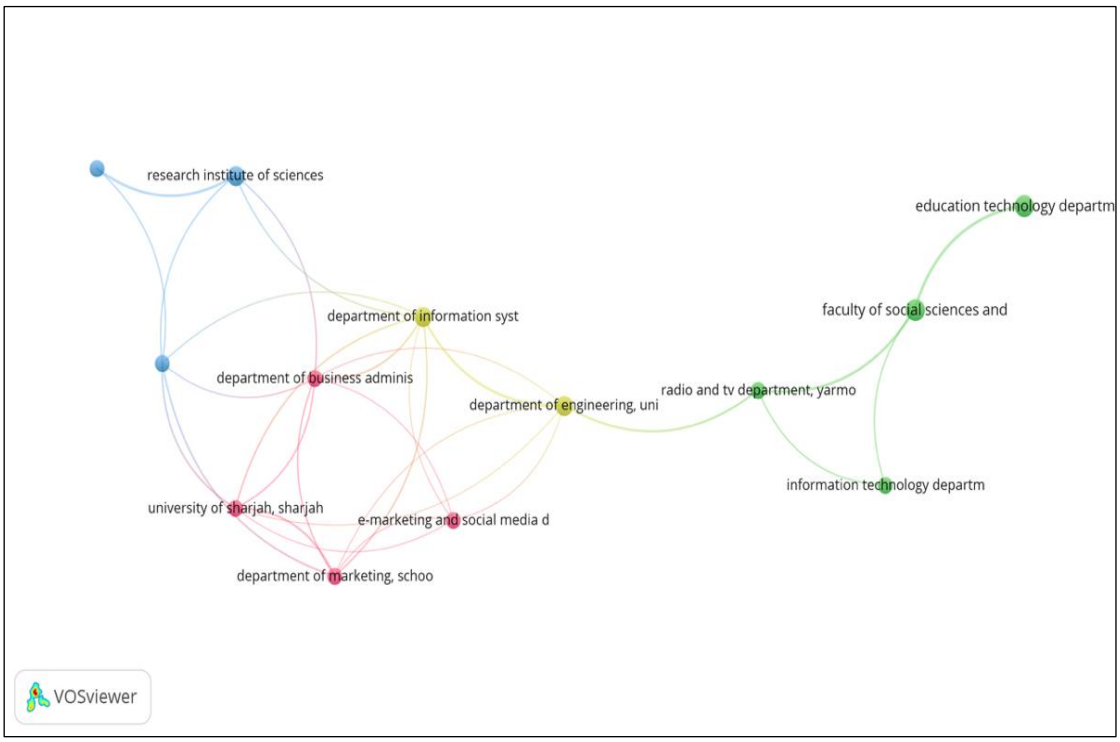

Figure 5: Geographic distribution of TAM publications by country

4.3 Author Productivity and Collaboration

A distinct group of authors shaped the intellectual landscape of TAM-based digital learning. Table 4 listed the leading contributors: Waleed Mugahed Al-Rahmi (9 publications), Said A. Salloum (8 publications), and Mostafa

Al-Emran (5 publications). Their works have accrued substantial citations (e.g., 815 and 774), reflecting high impact. However, the concentration of productivity among a small group of authors based in similar geographic regions (Malaysia, UAE, Jordan) indicated a regional research network rather than a globally distributed community.

Table 4: **Top 10 authors by publications, citations, and link strength**

Rank	Authors	Documents	Citations	Total link strength
1	Waleed Mugahed Al-Rahmi	9	815	4.00
2	Said A. Salloum	8	774	5.00
3	Fikrettin Şahin	6	45	0.00
4	Ahmad Samed Al-Adwan	5	777	3.00
5	Mostafa Al-Emran	5	611	3.00
6	Barween Al Kurdi	5	459	5.00
7	Muhammad Alshurideh	5	459	5.00
8	Uthman Alturki	5	401	4.00
9	Ahmed Aldriweesh	4	401	4.00
10	Charles Buabeng-Andoh	4	230	0.00

Co-authorship networks (Figure 6) showed tightly-linked clusters, often within the same institutions or regions, and a shortage of bridge authors connecting clusters. The absence of authors with high betweenness centrality suggested that knowledge flowed mainly within regional clusters, limiting the diffusion of novel constructs across different educational systems. Strengthening interdisciplinary and international collaboration could foster a more integrated ecosystem (Haidegger et al., 2024).

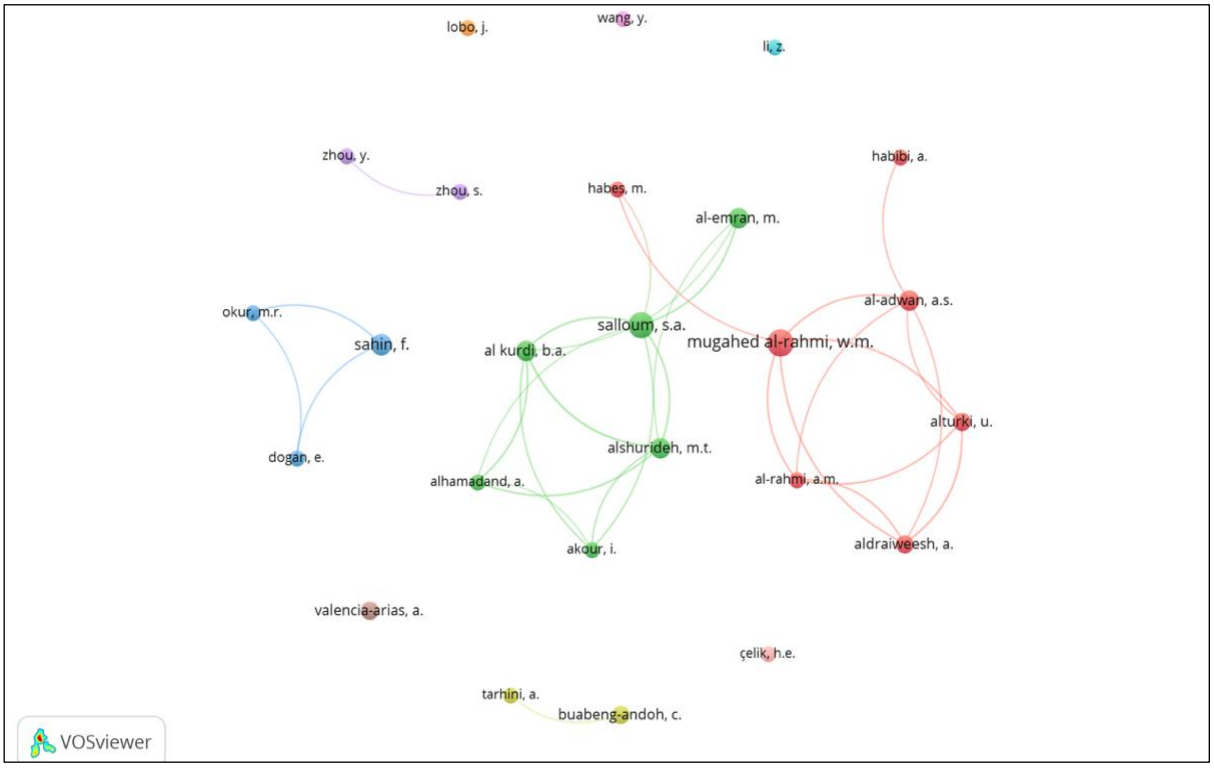

Figure 6: Author co-authorship network, colored by regional cluster

4.4 Keyword Co-occurrence and Thematic Clusters

Keyword co-occurrence analysis revealed the field's conceptual structure. Table 5 shows that core TAM terms dominated: "Technology Acceptance Model" (120 occurrences), "E-Learning" (108), and "Higher Education" (73), with total link strengths of 107.00, 100.00, and 69.00, respectively. "Online learning" (69) and "mobile learning" (45) highlighted modality-specific interests, while "COVID-19" (49) reflected pandemic-era concerns. Methodologically, "structural equation modeling" (17) appeared frequently. The constructs "perceived usefulness" (18) and "perceived ease of use" (14) also remained central, indicating contextual adaptation without losing theoretical core.

Table 5: Top 10 keywords by occurrence and link strength

Rank	Keywords	Occurrences	Total link strength
1	Technology Acceptance Model	120	107.00
2	E-Learning	108	100.00
3	Higher Education	73	69.00
4	Online Learning	69	67.00
5	TAM	62	60.00
6	COVID-19	49	45.00
7	Mobile Learning	45	41.00
8	Perceived Usefulness	18	18.00
9	Structural Equation Modeling	17	16.00
10	Perceived Ease of Use	14	13.00

The overlay visualization (Figure 7) showed that the average publication year of keywords ranged approximately from 2018 to 2024. This temporal gradient indicated that affective (enjoyment) and social (social influence) variables became prominent only after 2018, while AI and ChatGPT emerged as the most recent cluster (post-2022). These shifts were not merely descriptive. They suggested a field-wide maturation from a purely cognitive-instrumental view toward a holistic model that integrated learner emotions and social contexts. Keywords with earlier average publication years (closer to 2018) included basic concepts such as "perceived ease of use" and "behavioral intention", while newer keywords (closer to 2024) included "perceived enjoyment", "artificial intelligence" and "ChatGPT".

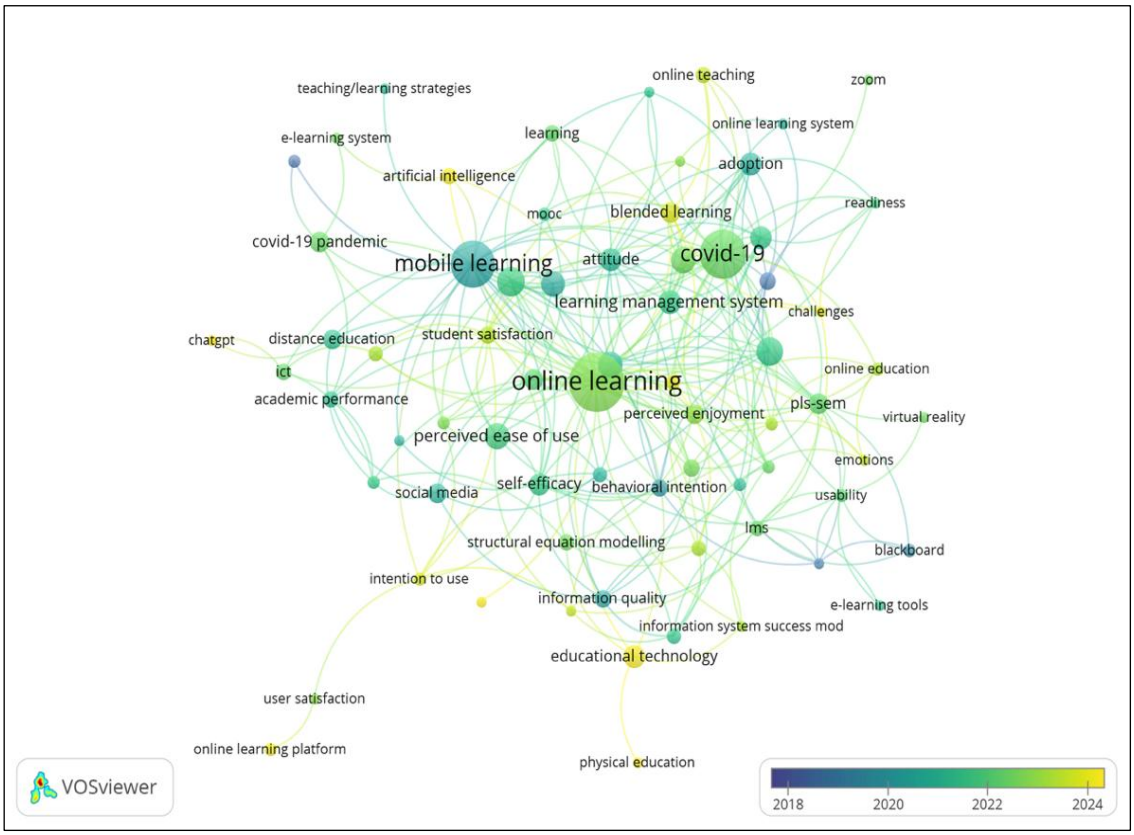

Figure 7: Overlay visualization of keyword co-occurrence

4.5 Co-citation and Source Analysis

Core theoretical works by Ajzen (1991) and Davis (1989) remained dominant. Abdullah and Ward (2016)'s GETAMEL extension and Al-Emran's (2018) m-learning review were highly integrated into recent studies. The persistent co-citation of foundational TAM papers alongside recent methodological reviews (e.g., PLS-SEM guidelines) suggested that the field valued both theoretical parsimony and methodological rigor.

Table 6 (in Appendix 1) summarized the top sources by total citations, illustrating the field's reliance on foundational theories revised through empirical investigations in evolving digital learning contexts. Co-citation network visualization (Figure 8) depicted the intellectual structure and knowledge flow within the research domain. Notably, the network showed a tight cluster around Davis (1989) and Ajzen (1991), with peripheral branches representing applied extensions. This suggested that theoretical progress was primarily incremental rather than disruptive.

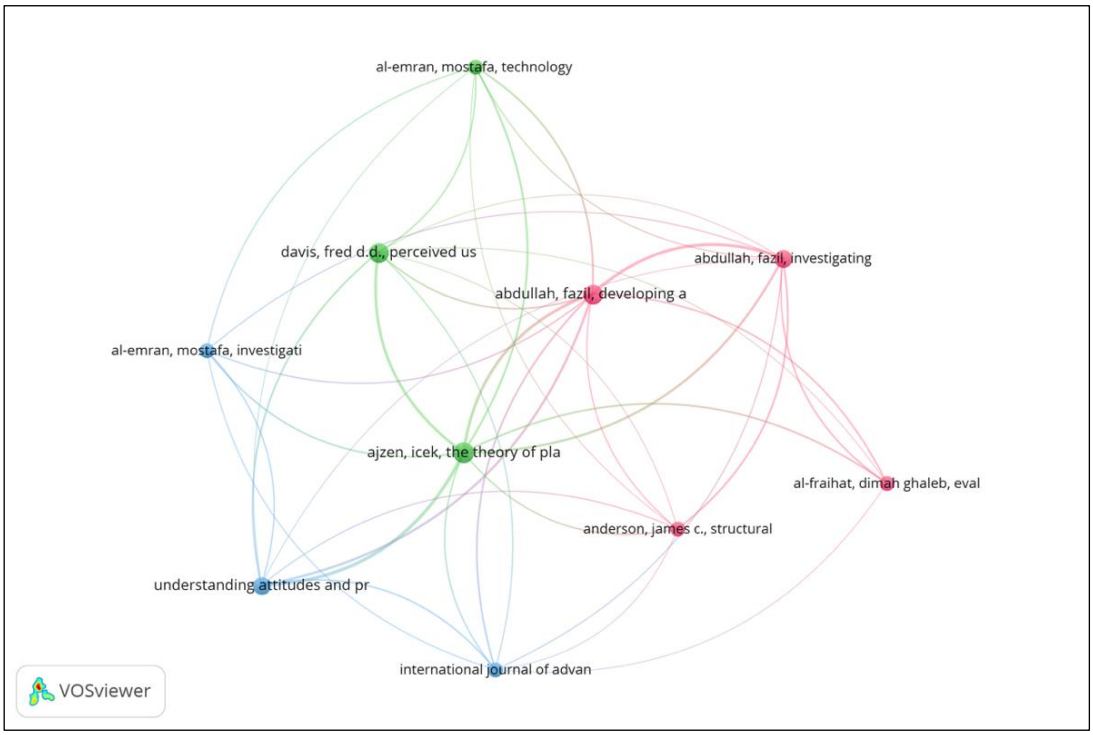

Figure 8: Co-citation network of cited references

Table 7 (in Appendix 2) listed the top journals by co-citation count and total link strength, reflecting their roles in anchoring and integrating research streams. The dominance of *MIS Quarterly* and *Computers & Education* suggested that TAM research in digital HE was anchored at the intersection of information systems and educational technology, with relatively less influence from pure educational psychology journals. Journal co-citation analysis (Figure 9) identified the key publication venues that connect technology acceptance, educational technology, and behavioral psychology.

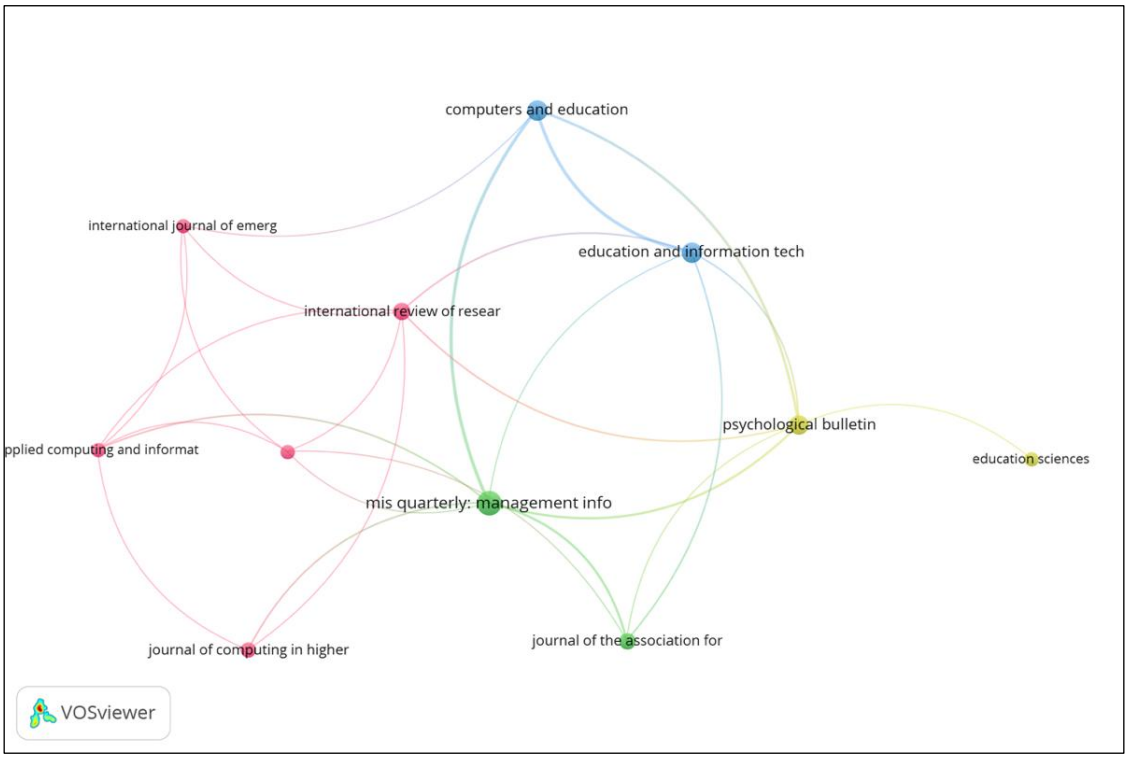

Figure 9: Co-citation network of journals

Taken together, the geographic concentration (Asia and Middle East) aligned with the thematic preference for social influence and collectivist constructs, while the temporal shift toward AI and enjoyment correlated with the post-pandemic surge in publications. The structural holes in collaboration networks mirrored the limited cross-regional validation of TAM extensions, highlighting a systemic gap that future research needs to address. The next section explains these research trends and collaborative networks and discusses their implications.

5. Discussion

5.1 Findings

This bibliometric review delineated the knowledge structure and evolution of TAM-based digital learning research in HE over the past decade. Three interlinked macro-trends emerged: sustained output growth, conceptual diversification, and geographically clustered institutions. These trends were not merely descriptive. They demonstrated TAM's theoretical adaptability to shifting digital education contexts.

The publication surge during 2020–2022 (Rosli et al., 2022) was interpreted as an immediate empirical response to an exogenous shock. However, beyond numeric expansion, the field deliberately moved from validating core TAM constructs (perceived usefulness and perceived ease of use) toward examining their interactions with environmental, affective, and social variables (Bhattarai & Maharjan, 2020; Dahri et al., 2024; Saidi et al., 2022). This reorientation signified a theoretical maturation. Researchers recognized that technology acceptance in complex learning settings could not be reduced solely to cognitive utility.

Thematic analyses further confirmed this shift (Alyoussef, 2023; Ferdousi, 2022; Yunior & Augustine, 2024), reflecting a deepening understanding of TAM in HE, moving beyond a purely cognitive examination of user attitudes towards technology. This was because contemporary online learning environments were inherently social, emotional, and increasingly personalized. The emergence of research surrounding AI-driven education and immersive technologies (Dahri et al., 2024; Geddam et al., 2024; Rehman et al., 2025) not only signified an innovative trend but also foreshadowed the inevitable convergence of theory and practice.

Geographically, Asian and Middle Eastern countries, represented by Malaysia, Saudi Arabia, and China, dominated in terms of output. The UTM and the University of Sharjah, as regional hubs, built local knowledge clusters through intersectoral and interdisciplinary collaboration. However, international cooperation remained limited. Strong regional clusters (Bergman & Feser, 2020) and core-periphery structures (Shen, 2025) persisted. These results might be influenced by different national contexts. Performance-based research funding systems in Malaysia and Saudi Arabia were more conducive to local collaboration, while differences in English proficiency and national journal priorities might reduce cross-regional visibility and incentives. Structural gaps between regions hinder cross-regional knowledge flows (Bizzi, 2013).

More importantly, it limited the cross-cultural validation of the TAM. This suggested a theoretical risk: TAM extensions validated in collectivist, rapidly digitalizing environments might not be applicable to individualistic or structurally different education systems. Therefore, strengthening global connections was not only a practical suggestion but also a theoretical necessity for developing a universal TAM.

5.2 Implications

The findings offered two theoretical implications for TAM research. One was the empirically validated shift away from a purely cognitive-instrumental TAM toward an integrated cognitive-affective-social model over the past decade. Keyword co-occurrence overlay analysis placed affective (enjoyment, self-efficacy), social (social influence), and contextual (facilitating conditions) clusters at the center only after 2018, with a sharp rise during 2020–2022. That timing challenged any static view of TAM extensions. They co-evolved with technological disruptions (e.g., pandemic-driven online learning) and pedagogical changes.

Based on cross-cultural psychology literature (Hofstede, 2001) and earlier comparative TAM work (Al-Emran et al., 2018; Rosli et al., 2022), two testable propositions emerged. In collectivist settings (e.g., Malaysia, Saudi Arabia), social influence moderated the relationship between perceived usefulness and behavioral intention more strongly than in individualist settings (e.g., the USA, UK). For AI-based learning systems, recent studies on AI in education (Chiu, 2025; Pillai et al., 2024) pointed to transparency and anthropomorphism as possible additional predictors beyond perceived usefulness and perceived ease of use, which in turn mediated how self-efficacy affects behavioral intention.

The findings also led to the learner-centric TAM (LC-TAM). It treated perceived usefulness and ease of use as necessary but not sufficient. Three higher-order constructs were added: Affective Readiness (self-efficacy, enjoyment, computer anxiety), Social Embeddedness (social influence, facilitating conditions), and AI-driven System Adaptability (transparency, anthropomorphism). Unlike GETAMEL (Abdullah & Ward, 2016), which merely listed external factors, LC-TAM organized them around the learner's psychology. Unlike UTAUT2 (Venkatesh et al., 2012), which treated hedonic motivation as a direct predictor, LC-TAM considered affective and social variables as moderating factors between perceived usefulness and behavioral intention. This design reflected a recent keyword shift. Such variables did not directly drive acceptance but amplified the effect of perceived usefulness and ease of use on behavioural intention.

The findings have clear implications for other regions. For Western institutions (such as those in the US and UK), the identified collaboration gaps provide a roadmap for working with productive Asian partners, thus enriching the cross-cultural validation of the TAM. For underrepresented regions such as Latin America and sub-Saharan Africa, key trending keywords (e.g., a shift towards emotion and AI-related variables) provide a benchmark for aligning local research agendas with global developments.

On the practical side, three direct implications followed from the findings. The persistent centrality of PU and PEOU meant that user-centered design with rigorous usability testing remained essential (Bhattacharya et al., 2024). The collaboration gaps identified suggested that universities should push for international research consortia and faculty exchanges to fill structural holes (Shonfeld et al., 2021). The growing visibility of AI and immersive technologies as keyword clusters pointed policymakers toward funding pilot studies and developing ethical guidelines for these new tools (Pellegrini & Vivanet, 2021).

5.3 Limitations

Several limitations were acknowledged. Reliance on English-language Scopus-indexed literature may have introduced selection bias. The exclusion of non-English research and regionally indexed journals (e.g., CNKI, SciELO) might have under-represented certain contextual factors. Bibliometric methods also could not capture micro-level methodological nuances. Moreover, the expansion of TAM carried a risk of conceptual redundancy. The review identified over 30 external variables, some overlapping with existing concepts (e.g., enjoyment vs. intrinsic motivation). Nevertheless, post-2018 trends showed that affective and social variables gained centrality as moderators, not mere additions. Meaningful progress thus requires theoretical pruning, not uncontrolled proliferation.

6. Conclusion

This bibliometric review assessed TAM applications in digital HE from 2015 to 2025. Three main conclusions emerged: sustained output growth (accelerated by COVID-19 pandemic), a theoretical shift from core perceived usefulness and perceived ease of use toward affective and social variables, and a geographic concentration in Asia and the Middle East with weak intercontinental

collaboration. AI and immersive environments also emerged as key thematic clusters. The review empirically validated a decade-long shift from a purely cognitive-instrumental TAM toward an integrated cognitive-affective-social model. It proposed two testable cross-cultural propositions and a learner-centric TAM (LC-TAM) that treats affective and social variables as moderators rather than direct predictors. These contributions move beyond descriptive bibliometrics toward hypothesis-driven theory building.

Future research should pursue several directions. Within two years, cross-cultural validation using existing datasets from collectivist and individualist countries is recommended. For technology-specific studies (1–3 years), researchers should examine transparency and anthropomorphism for AI, presence for VR/AR, and trust for blockchain, using mixed methods. Methodologically, the field needs longitudinal designs, experimental manipulations, and routine reporting of common method bias and power analysis.

To address geographic disparities (2–4 years), establishing regional hubs with joint funding and low-cost virtual exchange programs is a moderately feasible step requiring institutional commitment. National research councils should prioritize international consortia with dedicated budgets for cross-cultural TAM studies, and journals could mandate data sharing. Researchers are encouraged to adopt LC-TAM, test the two propositions, and collaborate through open science.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Appendix 1

Table 6: Top 10 sources by total citations

Rank	Authors	Title / Source / Year	Citations	Total Link Strength
1	Icek Ajzen	The theory of planned behaviour, organizational behaviour and *Human Decision Processes*, 50(2), 179-211, (1991)	71	51.00
2	Fred D. Davis	Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly*, 13(3), 319-339 (1989)	60	22.00
3	Fazil Abdullah; Rupert Ward	Developing a general extended technology acceptance model for E-learning (GETAMEL) by analysing commonly used external factors, *Computers in Human Behavior*, 56, pp. 238-256 (2016)	55	40.00
4	Icek Ajzen	Understanding attitudes and predicting social behavior, *Prentice Hall* (1980)	41	30.00
5	Fazil Abdullah	Investigating the influence of the most commonly used external variables of TAM on students' PEOU and PU of e-portfolios, *Computers in Human Behavior,* 63, 75-90 (2016)	36	26.00
6	Mostafa Al-Emran	Technology Acceptance Model in M-learning context: a systematic review, *Computers and Education*, 125, 389-412 (2018)	21	15.00
7	Dimah Ghaleb Al-Fraihat	Evaluating e-learning systems success: an empirical study, *Computers in Human Behavior*, 102, 67-86 (2020)	21	11.00
8	James C. Anderson	Structural equation modeling in practice: a review and recommended two-step approach, *Psychological Bulletin*, 103(3), 411-423 (1988)	20	12.00
9	Saleh Alharbi	Using the technology acceptance model in understanding academics' behavioural intention to use learning management systems, *IJACSA* (2014)	18	13.00
10	Mostafa Al-Emran	Investigating attitudes towards the use of mobile learning in higher education, *Computers in Human Behavior*, 56, 93-102 (2016)	18	10.00

Appendix 2

Table 7: Top 10 journals by co-citation count

Rank	Source	Citations	Total Link Strength
1	MIS Quarterly: Management Information Systems	72	19.00
2	Education and Information Technologies	38	13.00
3	Computers and Education	33	18.00
4	Psychological Bulletin	28	13.00
5	International Review of Research in Open and Distributed Learning	18	8.00
6	Journal of the Association for Information Systems	14	7.00
7	Journal of Computing in Higher Education	12	4.00
8	Applied Computing and Informatics	10	5.00
9	Computers in Human Behavior	10	4.00
10	International Journal of Emerging Technologies in Learning	10	3.00