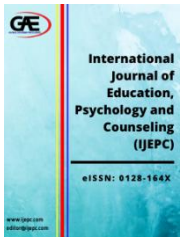
International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217



INTERNATIONAL JOURNAL OF EDUCATION, PSYCHOLOGY AND COUNSELLING (IJEPC)
https://gaexcellence.com/ijepc

RAPID GROWTH, NARROW FOCUS: A BIBLIOMETRIC REVIEW OF TECHNOLOGY ACCEPTANCE RESEARCH ON GENERATIVE ARTIFICIAL INTELLIGENCE IN WEB OF SCIENCE (2023–2026)

Jiaxing Zhou[1], Tse Guan Tan[2*], Heng Yao[3]

[1]Chengdu Academy of Fine Arts, Ziyang, Sichuan, China; Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, Bachok, Kelantan, Malaysia
1345177714@qq.com https://orcid.org/0009-0007-5173-8557
[2]Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan, Bachok, Kelantan, Malaysia
tan.tg@umk.edu.my https://orcid.org/0000-0002-9334-0041
[3]Chengdu Academy of Fine Arts, Ziyang, Sichuan, China
dr.yao@126.com https://orcid.org/0009-0001-4667-6079
[*]Corresponding Author

Article Info:

Article history:
Received date: 03.08.2026
Revised date: 17.08.2026
Accepted date: 30.08.2026
Published date: 22.09.2026

To cite this document:

Jiaxing, Z., Tse, T. G., & Heng, Y. (2026). Rapid Growth, Narrow Focus: A Bibliometric Review of Technology Acceptance Research on Generative Artificial Intelligence in Web of Science (2023–2026). *International Journal of Education, Psychology and Counselling, 11*(64), 1202-1217.

Abstract:

Within three years of the release of ChatGPT, generative artificial intelligence (GenAI) has moved into classrooms, clinics, and counselling rooms, and its acceptance is now a research question in its own right. This literature is now large and scattered, yet few bibliometric studies have systematically mapped the intersection of technology acceptance and GenAI as a distinct research domain. This study aims to map the intellectual, thematic, geographic, and publication structure of research on technology acceptance of GenAI. A topic search of the Web of Science Core Collection on 7 August 2026 returned 644 records; refinement to English-language Articles and Early Access items excluded 72, leaving 572, and eligibility screening removed 2 more, giving 570 articles. Performance analysis indicators covering publication counts, citations, source titles, subject categories, countries, highly cited papers, and term-family frequencies were compiled in Microsoft Excel. Annual output grew from 5 articles in 2023 to 49 in 2024 and 225 in 2025, with 290 carrying a 2026 issue date; the 2026 figure covers records indexed to the search date and is not a full-year total. As of 7 August 2026 the corpus had accumulated 7,113 citations (mean of 12.48 per article; h-index of 40). Education and Information Technologies led the journals (25), Education and Educational Research the categories (224; 39.3%), and China the countries (194; 34.0%), ahead of the United States (75; 13.2%) and

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

South Korea (42; 7.4%); Malaysia ranked seventh (23; 4.0%). The most cited work developed an expectancy value instrument for student perceptions of GenAI (417 citations), indicating an early emphasis on measuring psychological and motivational responses to emerging AI. Survey or questionnaire terminology appears in 54.4% of records, longitudinal terminology in 2.5%, and counselling terminology in 0.5%. The boundaries are a single database and a search defined by acceptance vocabulary.

DOI: 10.35631/IJEPC.1164064

Keyword:

Bibliometric Analysis, Generative Artificial Intelligence, Higher Education, Technology Acceptance Model, Web of Science

© The authors (2026). This is an Open Access article distributed under the terms of the Creative Commons Attribution (CC BY NC) (http://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact ijepc@gaexcllence.com.

Introduction

Within three years of the public release of ChatGPT in November 2022, generative artificial intelligence (GenAI) moved from a specialist research topic into classrooms, clinics, and counselling rooms. GenAI systems produce novel text, images, and other content from natural language prompts, and their conversational interfaces lower the entry barrier that constrained earlier educational technologies. Capability, however, does not settle adoption. Decades of information systems research show that use depends on how people perceive a technology, and the technology acceptance model (TAM) remains the most widely applied lens for that judgement (Davis, 1989; Davis et al., 1989). TAM holds that perceived usefulness and perceived ease of use shape attitudes and behavioural intention, and its lineage runs through TAM2 (Venkatesh & Davis, 2000) to the unified theory of acceptance and use of technology (UTAUT) and its consumer variant UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012).

The bottleneck is no longer a shortage of evidence but its volume and dispersion. Instruments for measuring student perceptions of GenAI appeared within months of ChatGPT (Chan & Zhou, 2023), and validated acceptance scales followed (Yilmaz et al., 2024). Others modelled ChatGPT usage among university students (Duong et al., 2023; Shahzad et al., 2024), or compared acceptance across countries (Strzelecki & ElArabawy, 2024). Newer constructs such as artificial intelligence (AI) literacy have since been folded into the models (Wang et al., 2025). This output is scattered across education, psychology, information systems, and management journals, and narrative reading can no longer provide a reliable overview of where the field stands.

Bibliometric analysis addresses exactly this problem: it profiles a field systematically and reproducibly from its publication and citation records (Donthu et al., 2021; Pritchard, 1969; Zupic & Čater, 2015), complementing narrative and systematic reviews that synthesise study

content (Booth et al., 2016; Efron & Ravid, 2019). Bibliometric studies have already profiled ChatGPT research within particular domains, notably medical education (Zhang et al., 2025) and higher education (T. Ma, 2025). Few bibliometric studies, however, have systematically mapped the intersection of technology acceptance research and GenAI as a distinct research domain. A verification search in August 2026, which combined the two search blocks reported below with the term "bibliometric" in the Web of Science (WoS) Core Collection, located no such study. That search covers a single database and a single vocabulary, so the claim advanced here is one of scarcity rather than of absence: the intersection has not been profiled as a defined WoS corpus, and no equivalent mapping was located in the sources consulted.

This review addresses that scarcity. Its objective is to map the intellectual, thematic, geographic, and publication structure of research on technology acceptance of GenAI, and it pursues that objective through five research questions: (RQ1) how have publications and citations on TAM-GenAI research developed between 2023 and 2026; (RQ2) which journals, subject categories, and countries lead the field; (RQ3) which publications are the most influential; (RQ4) which theories, methods, and constructs dominate its keyword landscape; and (RQ5) which populations and contexts remain under-researched. The paper sets out the theoretical background, then the search and indicator methodology, before turning to the findings and to what they mean for the education, psychology, and counselling communities this journal serves. Following bibliometric practice, explicit Methodology and Findings sections carry the generalisation of the main statements that the journal expects of a review article.

Literature Review

The Technology Acceptance Model and Its Extensions

TAM endures because it is parsimonious and extensible. Davis (1989) established perceived usefulness and perceived ease of use as reliable predictors of usage intention, and Davis et al. (1989) showed that this compact model explained intention roughly as well as the more elaborate theory of reasoned action. Building on this base, TAM2 added social influence and cognitive instrumental processes (Venkatesh & Davis, 2000), UTAUT unified eight competing models into four determinants, namely performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), and UTAUT2 added hedonic motivation, price value, and habit for consumer settings (Venkatesh et al., 2012). Reviews of the tradition document both longevity and adaptability: Marangunić and Granić (2015) traced TAM applications from 1986 to 2013, and Granić and Marangunić (2019) found TAM still dominant in educational technology adoption research, typically extended with context-specific antecedents. Both reviews, however, closed before GenAI existed, so the shape of acceptance research on GenAI itself remains unmapped.

Acceptance Research on Generative Artificial Intelligence

GenAI confronted acceptance researchers with a technology that converses, generalises across tasks, and sometimes fabricates content. One early response was measurement. Chan and Zhou (2023) developed an expectancy value instrument for student perceptions of GenAI, and Yilmaz et al. (2024) validated a GenAI acceptance scale grounded in the acceptance tradition. A second response extended the models themselves. Duong et al. (2023) added knowledge sharing to a modified TAM to explain ChatGPT usage among Vietnamese students. Trust recurs

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

across this work; Shahzad et al. (2024) made it the cornerstone of adoption in higher education, and core TAM paths were confirmed again by Shahzad et al. (2025). Wang et al. (2025) brought AI literacy into the theory of planned behaviour, while X. Ma and Huo (2023) went outside the TAM lineage altogether, drawing on the artificial intelligence device use acceptance framework. Other studies asked how far acceptance travels. UTAUT2 held up within an academic community (Strzelecki et al., 2024), and a Poland-Egypt comparison found gender and study-level moderation (Strzelecki & ElArabawy, 2024). Reddy (2024) took the question into healthcare implementation, and Christensen et al. (2025) into tourism, where GenAI hallucination complicates decision-making. Rich as this work is at the study level, no single study can reveal the structure of the field: its growth rate, its geography, its outlets, or the balance of its theories and methods.

The Need for a Bibliometric Review

Review methodology explains what such a field-level account requires. Review types differ in how systematically they search, appraise, synthesise, and analyse evidence (Booth et al., 2016), and a defensible review of a fast-moving field needs an explicit, reproducible search and screening record (Hempel, 2020; Page et al., 2021) organised as an argued case rather than an annotated list (Hart, 1998; Machi & McEvoy, 2022). Bibliometric indicators meet the reproducibility requirement by quantifying output, impact, and structure directly from the citation index (Donthu et al., 2021; van Eck & Waltman, 2010). What remains missing is precisely that quantified account for the TAM-GenAI corpus, and supplying it is the contribution of this review.

Methodology

A bibliometric review treats the publication record itself as data (Donthu et al., 2021; Zupic & Čater, 2015). Records were retrieved from the WoS Core Collection (Clarivate Analytics) on 7 August 2026. The search used the Web of Science Topic field tag (TS=), which queries the article title, abstract, author keywords, and Keywords Plus, and combined two concept blocks: TS=("technology acceptance" OR "technology acceptance model") AND ("generative artificial intelligence" OR "generative ai" OR "genai" OR "gen-ai" OR "gen ai" OR "gai"). No publication-year restriction was applied, so the timespan is the full coverage of the subscribed Core Collection editions and the 2023 lower bound of the retrieved set is an empirical result rather than a filter. The search returned 644 records. Because substantive research articles contain whole research ideas and results, the records were refined to the document types of Article and Early Access and to the English language. English was required because the term-family indicators depend on reading titles, author keywords, and abstracts in a single language, and the three non-English records were too few to form a separate language stratum; the restriction is carried forward as a stated limitation. The refinement excluded 72 records, namely 51 proceedings papers, 16 reviews, 3 non-English articles (Malay, Spanish, and Icelandic), 1 correction, and 1 meeting abstract, leaving 572 records. Manual eligibility screening then excluded 2 further records: one classified by WoS as Review with Early Access, which the early access filter had admitted despite the document-type criterion, and one off-topic record that matched the GenAI block only through the standalone token "gai", which there abbreviates the Geriatric Anxiety Inventory in a digital cognitive behavioural therapy study. The final dataset holds 570 articles. Table 1 summarises the search and Figure 1 presents the screening flow in the transparent reporting spirit of PRISMA 2020 (Page et al., 2021). One note applies to the retained set: one early access article carries the publication year 2027 at the search date.

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

Table 1: Search Strategy and Dataset

Item	Specification
Database	Web of Science Core Collection (Clarivate Analytics)
Indexes	Web of Science Core Collection editions
Search field	Topic (TS=): title, abstract, author keywords, and Keywords Plus
Search string	TS=("technology acceptance" OR "technology acceptance model") AND ("generative artificial intelligence" OR "generative ai" OR "genai" OR "gen-ai" OR "gen ai" OR "gai")
Search date	7 August 2026
Timespan	No publication-year restriction applied; earliest retrieved record 2023
Initial records	644
Refinement	Document type: Article or Early Access; Language: English
Language rationale	English required for consistent term-family reading of titles, keywords, and abstracts; 3 non-English records excluded
Excluded	72 (51 proceedings papers; 16 reviews; 3 non-English articles; 1 correction; 1 meeting abstract)
Eligibility screening	Excluded 2 (1 review-classified record admitted by the early access filter; 1 off-topic record in which GAI denotes the Geriatric Anxiety Inventory)
Final dataset	570 articles (2023–2026, including one early access record dated 2027)
Analysis approach	Performance analysis (publication, citation, source, category, country, and keyword indicators). Science mapping (co-occurrence, co-citation, bibliographic coupling, collaboration, thematic mapping) not performed
Software	Web of Science interface for retrieval; Microsoft Excel for indicator computation. No science mapping software (e.g. VOSviewer, Bibliometrix, CiteSpace) used

Source: Authors' compilation from Web of Science Core Collection (2026)

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

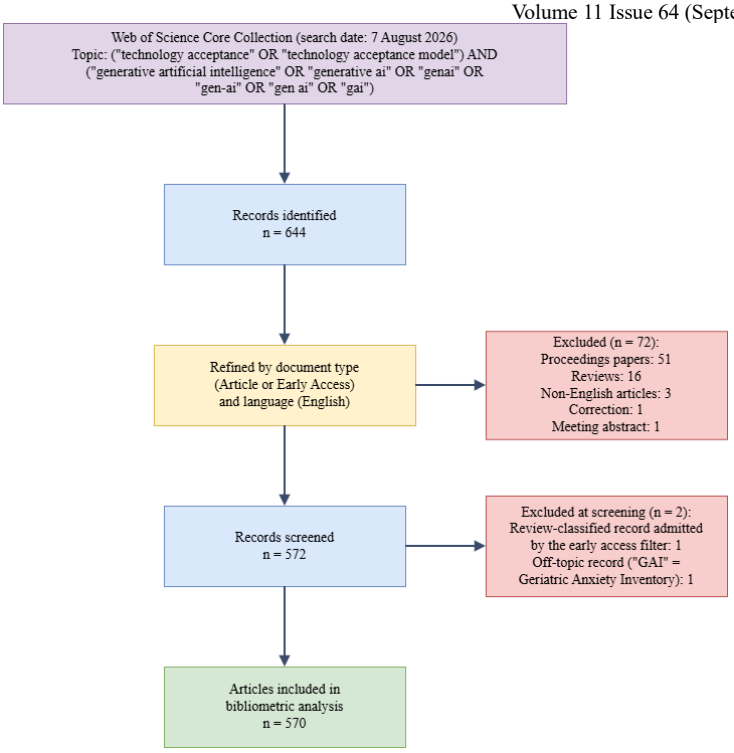


Figure 1: Screening Flow of the Bibliometric Dataset

Source: Authors' compilation from Web of Science Core Collection (2026)

Donthu et al. (2021) separate bibliometric analysis into two families. Performance analysis measures the productivity and impact of research constituents, that is authors, institutions, countries, and journals, while science mapping reconstructs the relational structure of a field through co-citation, bibliographic coupling, co-word, and collaboration networks. This review is a performance analysis, and the choice follows from the research questions: RQ1 to RQ5 ask how much has been published, by whom, where, with what visibility, and with what vocabulary, and these are the questions that performance indicators answer directly and reproducibly. The bibliographic records, comprising the full record and cited references for each article, were downloaded and compiled in Microsoft Excel. Four indicator groups were computed. First, total publications (TP) and total citations (TC) by year, with citations per publication (CPP = TC/TP). Each record was assigned to the publication year recorded by Web of Science, which is the year of the journal issue; early access records carry the issue year they held at the search date, so a record that first appeared online in an earlier calendar year is counted in its issue year here. Second, productivity rankings of source titles, WoS categories, and countries, with country productivity computed by full counting, whereby an article is credited once to every country appearing among its author affiliations. Third, the ten most cited articles by TC. Fourth, the frequency distribution of author keywords, with spelling and abbreviation variants merged during interpretation. Merging was confined to variant forms of the same term, so that the generative artificial intelligence family, for example, combines its spelled-out, abbreviated, and parenthetical forms, while compound keywords built on a term were left uncounted in that family. The h-index of the corpus was computed following Hirsch (2005). In addition, to verify prevalence claims about methods and study contexts beyond the author keyword frequencies, term-family searches were run across the combined titles, author keywords, and abstracts of the 570 records, with each article counted once per term family regardless of how often a term appeared within it. Term-family prevalence records the presence

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

of terminology in a record rather than a coded study design, so an article that discusses, criticises, or proposes a method counts the same as one that uses it; the reported percentages are therefore upper-bound proxies for design prevalence. All retrieval was performed in the Web of Science interface and all indicator computation in Microsoft Excel; no science mapping software was used, so the review reports no VOSviewer, Bibliometrix, or CiteSpace output. The list of the 570 accession numbers is available from the authors on request. It follows that the relational techniques of science mapping, namely keyword co-occurrence, co-citation analysis, bibliographic coupling, co-authorship and country collaboration networks, and thematic mapping (van Eck & Waltman, 2010), lie outside the scope of this review. They are not an oversight but a deliberate boundary: the intellectual structure they would reveal is a different question from the profile reported here, it requires the full cited-reference network rather than the indicator set compiled for this study, and it is set out in the Conclusion as the first priority for extending this map. Where the Discussion draws on these indicators, the limits of what they can carry are stated with the claim itself.

Findings

Publication Output and Citation Impact

In under four years the field went from five papers a year to several hundred. Table 2 and Figure 2 show 5 articles in 2023, 49 in 2024, 225 in 2025, and 290 carrying a 2026 issue date. The 2026 figure needs two cautions. It covers only records indexed up to the search date of 7 August 2026. It is therefore a partial-year count, and reading it as a full-year total, or setting it directly against the complete 2025 figure, would overstate the growth. Nor is an annualised rate projected from it here: indexing within a partial year is not spread evenly across the months, so any such projection would be arbitrary. The safe statement is the weaker one. Output in the first seven months of 2026 already exceeded the combined output of 2023, 2024, and 2025. Citation indicators are time-dependent and are therefore reported at a fixed observation date. As of 7 August 2026, the 570 articles had accumulated 7,113 citations in the WoS Core Collection, a mean of 12.48 citations per publication, and an h-index of 40, meaning 40 articles had each been cited at least 40 times. Any later re-run of the same search will return higher counts. As expected for a young field, citation impact runs opposite to output: the 5 articles from 2023 averaged 178.20 citations each, the 2024 cohort 53.90, the 2025 cohort 13.95, and the 2026 cohort only 1.52, while 195 articles (34.2%) had not been cited at the search date.

Table 2: Annual Publications and Citations, 2023–2026

Year	TP	TP (%)	TC	CPP
2023	5	0.9	891	178.20
2024	49	8.6	2,641	53.90
2025	225	39.5	3,139	13.95
2026	290	50.9	442	1.52
2027*	1	0.2	0	0.00
Total	**570**	**100.0**	**7,113**	**12.48**

Note: TP = total publications; TC = total citations; CPP = citations per publication. The 2026 row covers records indexed up to the search date of 7 August 2026, includes early access items, and is a partial-year count. All citation figures are as at that date. Percentages are rounded to one decimal place, so the column sums to 100.0 after rounding. *One early access article carried the publication year 2027 at the search date. Source: Authors' compilation from Web of Science Core Collection (2026)

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

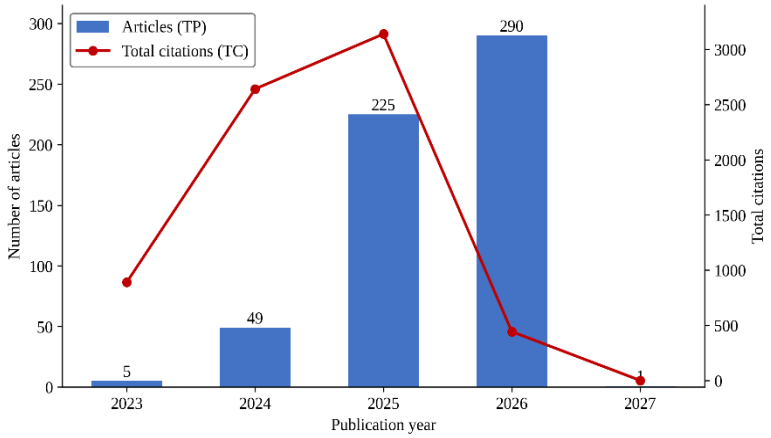


Figure 2: Annual Publication Output and Citations

Note: The 2026 bar covers publications indexed up to 7 August 2026. The declining citation line for recent years reflects the shorter citation window of newer cohorts, not falling impact; the two axes use different scales. Source: Authors' compilation from Web of Science Core Collection (2026)

Journals and Subject Categories

TAM-GenAI research lives primarily in education journals, with psychology and human-computer interaction as its second homes. Table 3 lists the ten most productive outlets: Education and Information Technologies ranked top with 25 articles (4.4% of 570), followed closely by Frontiers in Psychology with 24 (4.2%) and Education Sciences with 23 (4.0%), then the International Journal of Human–Computer Interaction (21; 3.7%), Frontiers in Education (16; 2.8%), and Acta Psychologica (14; 2.5%). The category profile mirrors the outlets: Education and Educational Research led with 224 articles (39.3%), followed by Psychology, Multidisciplinary (54; 9.5%), Computer Science, Information Systems (41; 7.2%), and Management (30; 5.3%).

Table 3: Top 10 Most Productive Journals

Rank	Journal	TP	TP (%)
1	Education and Information Technologies	25	4.4
2	Frontiers in Psychology	24	4.2
3	Education Sciences	23	4.0
4	International Journal of Human–Computer Interaction	21	3.7
5	Frontiers in Education	16	2.8
6	Acta Psychologica	14	2.5
7	Computers and Education: Artificial Intelligence	11	1.9
7	IEEE Access	11	1.9
9	Sustainability	10	1.8
10	Behavioral Sciences	8	1.4
10	Interactive Learning Environments	8	1.4

Source: Authors' compilation from Web of Science Core Collection (2026)

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

Country/Region Contributions

Productivity is led by China at a distance. Authors from 90 countries and regions contributed to the corpus, and Table 4 reports the most productive based on all author affiliations. China led with 194 articles (34.0% of 570), followed distantly by the United States (75; 13.2%), South Korea (42; 7.4%), and Türkiye (32; 5.6%). England and Saudi Arabia contributed 27 articles each (4.7%). Malaysia ranked seventh with 23 (4.0%), ahead of Australia (21; 3.7%), India (19; 3.3%), and Spain and Taiwan (18 each; 3.2%). Earlier TAM research was led from the United States. This corpus is not, and Asian and Middle Eastern systems hold seven of the eleven places in Table 4.

Table 4: Most Productive Countries and Regions

Rank	Country/Region	TP	TP (%)
1	China	194	34.0
2	United States	75	13.2
3	South Korea	42	7.4
4	Türkiye	32	5.6
5	England	27	4.7
5	Saudi Arabia	27	4.7
7	Malaysia	23	4.0
8	Australia	21	3.7
9	India	19	3.3
10	Spain	18	3.2
10	Taiwan	18	3.2

Note: Counts are based on all author affiliations, so an article can be credited to several countries or regions. Names follow Web of Science indexing, which records the United Kingdom by constituent country and lists Taiwan as a separate entry; England and Taiwan are reported as indexed. Source: Authors' compilation from Web of Science Core Collection (2026)

Highly Cited Articles

Table 5 lists the ten most cited articles. Chan and Zhou's (2023) expectancy value instrument study leads with 417 citations. Reddy's (2024) implementation science pathway for GenAI in healthcare follows at 321, then X. Ma and Huo's (2023) AIDUA-based ChatGPT acceptance study at 259. What the list contains matters more than the order. Instrument development and model extension dominate it, and seven of the ten papers concern education or student populations. The work at the top is an expectancy value instrument, not a theoretical statement and not an application study. That tells us where the early effort went. GenAI arrived without acceptance instruments of its own, so the first shared need was a way to measure users' psychological and motivational responses to it, and whoever supplied that measure was going to be cited by everyone who came next. A second validated acceptance scale sits lower in the same list. The trust-centred and AI-literacy studies beside it show the other move available at the time: take an established model and add one construct to it. The speed of uptake also stands out. Wang et al. (2025) reached 254 citations and Liu et al. (2025) 218 within two to two and a half years of first appearing online, a mark of how quickly influential work is absorbed in this field.

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

Table 5: Top 10 Most Cited Articles

Rank	TC	Source	Title	Journal
1	417	Chan and Zhou (2023)	An expectancy value theory (EVT) based instrument for measuring student perceptions of generative AI.	Smart Learning Environments
2	321	Reddy (2024)	Generative AI in healthcare: An implementation science informed translational path on application, integration and governance.	Implementation Science
3	259	X. Ma and Huo (2023)	Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework.	Technology in Society
4	254	Wang et al. (2025)	Factors influencing university students' behavioral intention to use generative artificial intelligence: Integrating the theory of planned behavior and AI literacy.	International Journal of Human–Computer Interaction
5	218	Liu et al. (2025)	Exploring AI-mediated informal digital learning of English (AI-IDLE): A mixed-method investigation of Chinese EFL learners' AI adoption and experiences.	Computer Assisted Language Learning
6	188	Strzelecki and ElArabawy (2024)	Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt.	British Journal of Educational Technology
7	170	Christensen et al. (2025)	Understanding the role and impact of generative artificial intelligence (AI) hallucination within consumers' tourism decision-making processes.	Current Issues in Tourism
8	159	Duong et al. (2023)	Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator.	The International Journal of Management Education
9	156	Yilmaz et al. (2024)	Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study.	International Journal of Human–Computer Interaction
10	143	Shahzad et al. (2024)	ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone.	International Journal of Educational Technology in Higher Education

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

Note: TC = total citations in the Web of Science Core Collection at 7 August 2026. Source: Authors' compilation from Web of Science Core Collection (2026)

Author Keyword Landscape

After merging spelling and abbreviation variants, generative artificial intelligence terms appeared 347 times and technology acceptance model terms 179 times; that much restates the search design. The co-travelling keywords say more. Higher education (91 occurrences) and ChatGPT (87) mark the dominant context and the dominant tool. University students (12) and pre-service teachers (11) recur as populations. The 50 combined appearances of UTAUT and UTAUT2 point to a live rivalry with the TAM lineage. Behavioural intention (27) leads the extension constructs, with artificial intelligence literacy (23), trust (18), self-efficacy (13), perceived usefulness (12), motivation (10), and self-determination theory (10) behind it. Method keywords are sparser: partial least squares structural equation modelling (21) and structural equation modelling (17) top a short list. Most articles tag no method keyword at all, so prevalence was checked against the full titles, keywords, and abstracts of the 570 records. Survey or questionnaire terms turn up in 310 records (54.4%), and structural equation modelling or partial least squares terms in 223 (39.1%). Qualitative terms appear in 93 (16.3%), interview terms in 81 (14.2%), mixed-methods terms in 57 (10.0%), and experimental terms in 33 (5.8%). Longitudinal terms appear in just 14 records (2.5%). Taken together, the profile is of student acceptance of ChatGPT-type tools in higher education, examined through extended acceptance models, with survey terminology outweighing qualitative and longitudinal terminology many times over.

Discussion

TAM-GenAI research has grown rapidly, and the growth has concentrated its focus rather than widened it. Annual output moved from 5 articles to 290 in four years, in step with the public diffusion of ChatGPT-type systems from late 2022. Citation impact runs the other way, and the reason is mechanical: older cohorts have simply had longer to be cited, and the early instrument papers, Chan and Zhou (2023) above all, became obligatory references for the wave that followed. That is how a five-paper 2023 cohort comes to average 178.20 citations per article. Meanwhile an h-index of 40, in a corpus barely four years old, shows that a stable core of reference works already exists.

Where the field lives has shifted even as what it studies has not. The journal and category profiles show an education-led field with psychology and human-computer interaction as strong secondary homes, consistent with the educational concentration Granić and Marangunić (2019) documented before GenAI. The geography, in contrast, has moved: where classic TAM research was led by North American information systems scholarship (Davis, 1989; Venkatesh et al., 2003), the TAM-GenAI corpus is led clearly by China, with the United States second, South Korea and Türkiye next, and England and Saudi Arabia tied in fifth place, while Malaysia stands seventh. This redistribution matches the highly cited list, in which comparative and non-Western samples are prominent (Duong et al., 2023; Strzelecki & ElArabawy, 2024). For Malaysian and regional researchers, the finding is encouraging: the field is young and regional work is highly visible, although China's 34.0% share means that Chinese samples and contexts weigh heavily in what the field collectively learns.

International Journal of Education, Psychology and Counseling
IJEPC
EISSN : 0128-164X
Volume 11 Issue 64 (September 2026) PP. 1202-1217

Three patterns define the intellectual content, and each carries a caution. First, theory use is extensive but centripetal, a reading that must respect the corpus definition: because the search required the technology acceptance vocabulary, UTAUT studies that never use those terms fall outside this dataset, so the TAM-UTAUT balance reported here describes the acceptance-labelled literature rather than the adoption literature at large. Within that scope, most studies extend TAM or UTAUT2 with one or two GenAI-specific constructs, notably trust (Shahzad et al., 2024), AI literacy (Wang et al., 2025), and self-efficacy, rather than proposing new models, with the AIDUA application of X. Ma and Huo (2023) a rare exception. Second, the method vocabulary of the corpus is dominated by the cross-sectional survey toolkit: survey or questionnaire terms appear in over half of the records and longitudinal terms in barely one in forty. Even read as an upper bound on design prevalence, that distribution leaves little room for causal and developmental claims about how acceptance forms and changes, and it echoes the pattern reviews identified in the pre-GenAI acceptance literature (Marangunić & Granić, 2015). Third, the contexts are narrower than the technology itself. Across the titles, keywords, and abstracts of the 570 records, higher education or university terms appear in 297 records (52.1%). School terms appear in 32 (5.6%) and workplace or employee terms in 23 (4.0%). Therapy or mental health terms fall to 8 (1.4%), and counselling terms to only 3 records (0.5%). The three are a Delphi study of GAI's benefits and future potential for mental health (Oo et al., 2026), a study of mental health professionals confronting AI's promise and ethical perils (Demir et al., 2026), and a study of counsellors' views on ChatGPT's role in pregnancy termination counselling (Kubitza & Degen, 2026). Healthcare (Reddy, 2024) and tourism (Christensen et al., 2025) are present but thin. For this journal's readership the counselling figure is the one that matters, and it is now a number: 3 articles out of 570. GenAI chatbots are already being consulted for emotional support. Acceptance research has barely followed them there.

How far these readings can be pushed depends on the method behind them. A spreadsheet-based performance analysis (Donthu et al., 2021) answers profile questions well. It cannot expose intellectual structure, which needs co-citation or keyword co-occurrence mapping (van Eck & Waltman, 2010; Zupic & Čater, 2015). Nor can it judge the quality of individual studies; that requires the appraisal apparatus of systematic review methodology (Booth et al., 2016; Hempel, 2020).

Conclusion

This review set out to map technology acceptance research on GenAI as a defined WoS corpus, and the map now exists, with a search record transparent enough for others to update as the field grows. The evidence comes from 570 verified English-language articles published between 2023 and 2026. Output rose from 5 to 290 annual articles. The corpus holds 7,113 citations with an h-index of 40. Education and Information Technologies is the leading journal, China leads the countries by a wide margin with Malaysia seventh, and Chan and Zhou's (2023) instrument study is the most cited anchor. The keyword and term-family profile shows a field focused on student acceptance of ChatGPT-type tools in higher education, theorised through TAM and UTAUT extensions featuring trust, AI literacy, and self-efficacy, with survey and structural equation modelling terminology dominant in its records and longitudinal terminology scarce.

The implication follows directly: educators and policymakers now know where mature evidence on GenAI acceptance can be found, and researchers know where it cannot. Future

work should first extend this map with science mapping, applying keyword co-occurrence, co-citation, bibliographic coupling, collaboration network, and thematic mapping techniques in VOSviewer, Bibliometrix, or CiteSpace to the same corpus, meta-analyse the accumulated structural model estimates, pursue the longitudinal and qualitative designs the current method base lacks, and carry acceptance research into school, workplace, and especially counselling settings, where the acceptance of GenAI support tools remains almost unexamined. For practitioners, the map has an immediate use: validated GenAI acceptance instruments already exist (Chan & Zhou, 2023; Yilmaz et al., 2024) and can be adopted by educators and counsellors who wish to assess readiness before introducing GenAI tools in their own settings. The boundaries are those of the design: a single database, a short and uneven citation window, a search defined by acceptance vocabulary, and performance indicators that cannot judge study quality.

Acknowledgements:	This work was supported by the Science, Technology, Engineering, and Mathematics (STEM) Research Group at the Faculty of Creative Technology and Heritage, Universiti Malaysia Kelantan (UMK).
Funding Statement:	No Funding
Conflict of Interest Statement:	The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the International Journal of Education, Psychology and Counselling (IJEPC).
Ethics Statement:	This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
Author Contribution Statement:	All authors contributed significantly to the development of this manuscript. Tse Guan Tan and Heng Yao jointly conceptualized the study, designed the methodology, and provided overall supervision throughout the research process. Jiaxing Zhou was responsible for the data collection, formal analysis, and interpretation of the results, as well as drafting the original manuscript. Tse Guan Tan and Heng Yao further contributed to the critical revision of the manuscript for important intellectual content and provided continuous guidance during the literature review and writing stages. All authors have read and approved the final version of the manuscript prior to submission.

References

Booth, A., Sutton, A., & Papaioannou, D. (2016). *Systematic approaches to a successful literature review* (2nd ed.). SAGE.

Chan, C. K. Y., & Zhou, W. (2023). An expectancy value theory (EVT) based instrument for measuring student perceptions of generative AI. *Smart Learning Environments*, *10*(1), Article 64. https://doi.org/10.1186/s40561-023-00284-4

Christensen, J., Hansen, J. M., & Wilson, P. (2025). Understanding the role and impact of generative artificial intelligence (AI) hallucination within consumers' tourism decision-making processes. *Current Issues in Tourism*, *28*(4), 545–560. https://doi.org/10.1080/13683500.2023.2300032

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Demir, M., Aydoğdu, F., Alabay, M. B., Yaşar, H. K., & Bozkurt, A. (2026). More than an algorithm: Mental health professionals confront the promise and ethical perils of artificial intelligence. *Universal Access in the Information Society*, *25*(1), Article 24. https://doi.org/10.1007/s10209-025-01297-1

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Duong, C. D., Vu, T. N., & Ngo, T. V. N. (2023). Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator. *The International Journal of Management Education*, *21*(3), Article 100883. https://doi.org/10.1016/j.ijme.2023.100883

Efron, S. E., & Ravid, R. (2019). *Writing the literature review: A practical guide*. Guilford Press.

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, *50*(5), 2572–2593. https://doi.org/10.1111/bjet.12864

Hart, C. (1998). *Doing a literature review: Releasing the social science research imagination*. SAGE.

Hempel, S. (2020). *Conducting your literature review*. American Psychological Association.

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United States of America*, *102*(46), 16569–16572. https://doi.org/10.1073/pnas.0507655102

Kubitza, E., & Degen, J. L. (2026). AI as a sparring partner in professional settings: Counselors' views on ChatGPT's role and potential in pregnancy termination counseling. *Archives of Sexual Behavior*. Advance online publication. https://doi.org/10.1007/s10508-026-03437-x

Liu, G. L., Darvin, R., & Ma, C. (2025). Exploring AI-mediated informal digital learning of English (AI-IDLE): A mixed-method investigation of Chinese EFL learners' AI adoption and experiences. *Computer Assisted Language Learning*, *38*(7), 1632–1660. https://doi.org/10.1080/09588221.2024.2310288

Ma, T. (2025). Systematically visualizing ChatGPT used in higher education: Publication trend, disciplinary domains, research themes, adoption and acceptance. *Computers and Education: Artificial Intelligence*, *8*, Article 100336. https://doi.org/10.1016/j.caeai.2024.100336

Ma, X., & Huo, Y. (2023). Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society*, *75*, Article 102362. https://doi.org/10.1016/j.techsoc.2023.102362

Machi, L. A., & McEvoy, B. T. (2022). *The literature review: Six steps to success* (4th ed.). Corwin.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Oo, C. T. L., Wider, W., Pang, N. T. P., Koh, E. B. Y., Vasanthi, R. K., Thet, K. Z. Z., Ramalho, R., Özdemir, B. N., & Mahboob, K. (2026). The benefits and future potential of generative artificial intelligence (GAI) on mental health: A Delphi study. *International Journal of Qualitative Studies on Health and Well-being*, *21*(1), Article 2621802. https://doi.org/10.1080/17482631.2026.2621802

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., . . . Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, Article n71. https://doi.org/10.1136/bmj.n71

Pritchard, A. (1969). Statistical bibliography or bibliometrics? *Journal of Documentation*, *25*(4), 348–349.

Reddy, S. (2024). Generative AI in healthcare: An implementation science informed translational path on application, integration and governance. *Implementation Science*, *19*(1), Article 27. https://doi.org/10.1186/s13012-024-01357-9

Shahzad, M. F., Xu, S., & Asif, M. (2025). Factors affecting generative artificial intelligence, such as ChatGPT, use in higher education: An application of technology acceptance model. *British Educational Research Journal*, *51*(2), 489–513. https://doi.org/10.1002/berj.4084

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*(1), Article 46. https://doi.org/10.1186/s41239-024-00478-x

Strzelecki, A., & ElArabawy, S. (2024). Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology*, *55*(3), 1209–1230. https://doi.org/10.1111/bjet.13425

Strzelecki, A., Cicha, K., Rizun, M., & Rutecka, P. (2024). Acceptance and use of ChatGPT in the academic community. *Education and Information Technologies*, *29*(17), 22943–22968. https://doi.org/10.1007/s10639-024-12765-1

van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Wang, C., Wang, H., Li, Y., Dai, J., Gu, X., & Yu, T. (2025). Factors influencing university students' behavioral intention to use generative artificial intelligence: Integrating the theory of planned behavior and AI literacy. *International Journal of Human–Computer Interaction*, *41*(11), 6649–6671. https://doi.org/10.1080/10447318.2024.2383033

Yilmaz, F. G. K., Yilmaz, R., & Ceylan, M. (2024). Generative Artificial Intelligence Acceptance Scale: A Validity and Reliability Study. *International Journal of Human–Computer Interaction*, *40*(24), 8703–8715. https://doi.org/10.1080/10447318.2023.2288730

Zhang, Y., Xie, X., & Xu, Q. (2025). ChatGPT in medical education: Bibliometric and visual analysis. *JMIR Medical Education*, *11*, Article e72356. https://doi.org/10.2196/72356

Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. *Organizational Research Methods*, *18*(3), 429–472. https://doi.org/10.1177/1094428114562629