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MAPPING THE LANDSCAPE OF GENERATIVE AI ACCEPTANCE IN ACADEMIC WRITING: A BIBLIOMETRIC REVIEW OF THE EXTENDED TAM RESEARCH

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Abstract:

Academic writing in higher education has been reshaped within a remarkably short period by ChatGPT and comparable large language models (LLMs). This review asks how that shift has been studied: what the scholarly record so far reveals about university students' willingness to take up such tools, and how the Technology Acceptance Model (TAM) has been stretched to account for it. Fifteen peer-reviewed studies appearing between 2023 and 2025 were assembled and examined through bibliometric profiling alongside qualitative content analysis, each article coded against a shared set of extraction fields. Output rose steeply across the three-year window, mirroring the wave of interest that followed ChatGPT's public release. TAM proved the framework of choice, frequently merged with the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) or the Theory of Planned Behaviour (TPB). Constructs recurring across the corpus were Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioural Intention (BI) and, distinctively for this domain, Academic Integrity Concern (AIC). Among the ten most cited papers the prevailing design was a cross-sectional survey analysed with Partial Least Squares Structural Equation Modelling (PLS-SEM), with authorship concentrated in Malaysia, the United States, Norway, Poland, Turkey and China. Two patterns stand out. Growth in output has outpaced growth in methodological variety, and AIC behaves less like a fixed construct than one contingent on institutional policy. The review therefore offers postgraduate researchers, educators and policymakers a mapped starting point for governing how GenAI enters academic writing.

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Keyword:

Academic Writing, Bibliometric Analysis, Generative Artificial Intelligence, Higher Education, Technology Acceptance.

Introduction

Generative Artificial Intelligence (GenAI) has disrupted the higher education landscape at an unprecedented pace. Within a short span of two years, platforms such as OpenAI's ChatGPT, Claude, Google Gemini, QuillBot and various Large Language Models (LLMs) have evolved from technological novelties into ubiquitous writing assistants. University students now routinely leverage these tools to summarise, edit, draft and structure their academic manuscripts(Dwivedi et al., 2023a). Academic writing remains one of the most rigorous and complex challenges in higher education, demanding that students synthesise intricate literature, construct logical arguments and maintain authentic scholarly authorship (Chan & Hu, 2023). Consequently, although these tools markedly optimise drafting efficiency, they simultaneously obscure the boundary between genuine student authorship and automated assistance. This raises serious concerns regarding academic integrity, ethical compliance and the long-term erosion of critical thinking skills among students (Bittle & El-Gayar, 2025).

Although the volume of empirical research addressing student GenAI adoption has grown rapidly, literature remains fragmented and unmapped. To date, no comprehensive bibliometric study has systematically evaluated the evolutionary trajectory, core conceptual boundaries or methodological weight of this emerging field. This study addresses that gap by using the Scopus database to construct a systematic bibliometric map of GenAI acceptance in academic writing among university students. Specifically, this paper charts publication trends, identifies high-impact contributions and evaluates the dominant theoretical frameworks and methods, thereby providing postgraduate researchers, educators and institutional policymakers with a rigorous baseline understanding of the current state of the domain.

Literature Review

The review that follows is organised around the adoption theories on which this body of work rests. It begins with the frameworks researchers have most often applied, then situates recent Malaysian scholarship against the wider international picture.

The Technology Acceptance Model (TAM) and Its Extensions

Why some students take up GenAI tools while others hold back has become a recurring question in the educational literature. Most of that work traces back to(Fred D. Davis, 1989), whose Technology Acceptance Model (TAM) remains the reference point against which newer explanations are measured. The model rests on a straightforward proposition: two judgements

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about a technology, namely whether it is useful (Perceived Usefulness, PU) and whether it is easy to work with (Perceived Ease of Use, PEOU), together shape Behavioural Intention (BI), which in turn predicts actual use. GenAI, however, raises ethical and cognitive questions that the original formulation was never built to handle, and researchers have responded by widening it. Variables with no counterpart in early adoption theory now appear routinely, among them Academic Integrity Concern (AIC), social influence and AI self-efficacy(Strzelecki 2024)(Grassini et al., 2024a). Others have turned to different frameworks altogether. The Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) and the Theory of Planned Behaviour (TPB) each bring socio-environmental and motivational factors into view that a strict reading of TAM leaves out (Ivanov et al., 2024).

GenAI Acceptance in the Malaysian Higher Education Context

In Malaysia, the pedagogical implications of GenAI have become increasingly prominent across diverse tiers of higher education, spanning undergraduate, postgraduate and diploma programmes. Tools such as Grammarly, ChatGPT, Gemini and QuillBot have become deeply embedded in student writing workflows at all academic levels. A distinct localised research pattern has emerged, in which researchers frequently employ an extended TAM framework that integrates AIC alongside the traditional PU and PEOU constructs. These studies, typically deployed via cross-sectional surveys within public and private universities, evaluate how these determinants simultaneously drive usage intentions among the wider Malaysian university student population.

To synthesise these theoretical strands, Figure 1 outlines the integrated conceptual framework derived from the literature, which directly corresponds to the model structure in this study. Moving away from the traditional mediated configuration, this framework establishes a parallel direct path where Perceived Usefulness (PU) H1, Perceived Ease of Use (PEOU) H2, and Academic Integrity Concern (AIC) H3, as simultaneous, independent predictors shaping students' Behavioural Intention (BI) to use GenAI in academic writing.

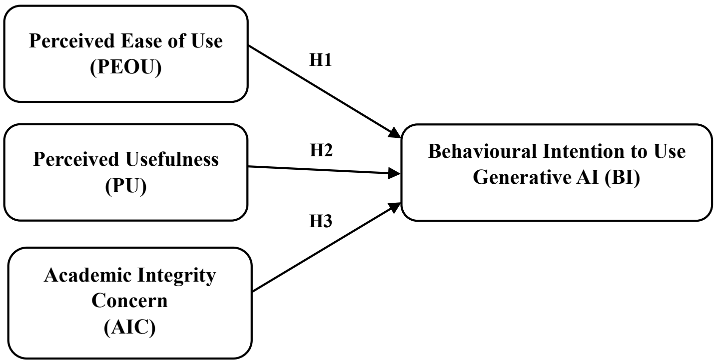

Figure 1: Integrated Conceptual Framework Synthesised from the Reviewed Literature.
Source: Adapted and extended from the Technology Acceptance Model (Davis, 1989).

Taken as a whole, this body of work is theoretically productive but unsettled: no agreement has formed on how the extended TAM should best be specified. Constructs such as AIC, social pressure and technology literacy enter and leave different models, and the coefficients reported for them frequently point in opposite directions. Most of the evidence, moreover, comes from a single institution surveyed at one point in time, which limits what can be claimed beyond that setting. Mapping publication trajectories, theoretical configurations and methodological

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choices bibliometrically is one way of bringing these scattered results into a single view, and that is the task taken up here.

Research Questions

1. RQ1: What are the evolutionary trajectories and publication trends of scholarly literature concerning GenAI acceptance in academic writing among university students?
2. RQ2: What are the ten most impactful scholarly articles examining GenAI acceptance in this domain, and what are their defining structural and conceptual characteristics?
3. RQ3: What is the nature of international authorial collaboration and methodological diversity within this research domain?

Methodology

Two complementary approaches were combined here: bibliometric analysis, which describes the literature as a body, and qualitative content analysis, which reads individual studies closely. The first is well established for questions of the kind asked in this review, since counting and mapping published output makes visible patterns of productivity, influence and thematic structure that are difficult to see one paper at a time (Abdullah, 2022).Work proceeded in four phases: formulating the search string, retrieving and de-duplicating records, mapping the resulting corpus bibliometrically, and reading the high-impact articles in detail.

To ensure transparency and replicability, the review protocol was defined in advance and reported in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles, adapted to a bibliometric context. Three categories of information were extracted from every retained record: bibliographic metadata (authors, year, journal and country of affiliation), theoretical metadata (framework adopted and constructs measured), and methodological metadata (research design, analytical technique, sampling frame and sample size).

Data Search Strategy

Scopus served as the single source for retrieval. It was chosen because its coverage of peer-reviewed work spans the fields this review straddles, namely education, the social sciences, computer science and the humanities, and because its indexing is applied consistently enough for metadata to be compared across records. Table 1 sets out the advanced search string. At the extraction stage neither date nor language limits were imposed, the intention being to see the domain in full before narrowing it with the criteria in Table 2.

The search was confined to the TITLE-ABS-KEY field so that only studies in which GenAI acceptance formed a substantive focus, rather than an incidental mention, were captured. Retrieved records were imported into Mendeley, which was used for reference management, de-duplication and storage of the corresponding full texts. Because the corpus is drawn from a single database, the design prioritises indexing consistency and metadata completeness over exhaustive coverage; this trade-off is revisited in the limitations.

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Table 1: The Search String

Database	Search String
Scopus	TITLE-ABS-KEY (("generative artificial intelligence" OR "generative AI" OR "ChatGPT" OR "large language model*" OR "LLM*") AND ("academic writing" OR "academic literacy" OR "writing assistance") AND ("technology acceptance model" OR "TAM" OR "extended TAM" OR "technology acceptance" OR "acceptance") AND ("university student*" OR "higher education" OR "tertiary education"))

Following data extraction, the inclusion and exclusion criteria presented in Table 2 were applied to ensure that the final corpus focused specifically on student acceptance and use of GenAI within academic writing contexts. Following manual screening through a PRISMA-style workflow (Figure 2), a final sample of 15 papers was retained for bibliometric and content analysis. Notably, the final dataset spans exclusively from 2023 to 2025, reflecting the emerging and rapidly evolving nature of the field.

Screening proceeded in two stages, as summarised in Figure 2. Titles and abstracts were assessed first against the criteria in Table 2, and full texts were then retrieved for every record that passed that stage and assessed for empirical or conceptual engagement with TAM or AIC constructs. The extracted data for the retained articles were compiled into a single Excel matrix, which functioned as the master record for the review, so that every figure reported in the following section can be traced back to an identifiable source.

Table 2: The Selection Criteria

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2023-2025	<2023
Subject relevance	Directly examines students' acceptance or use of GenAI in academic writing	Not directly related to GenAI acceptance in academic writing
Literature type	Peer-reviewed journal articles	Conference papers, Editorials, Review Papers and other document types.

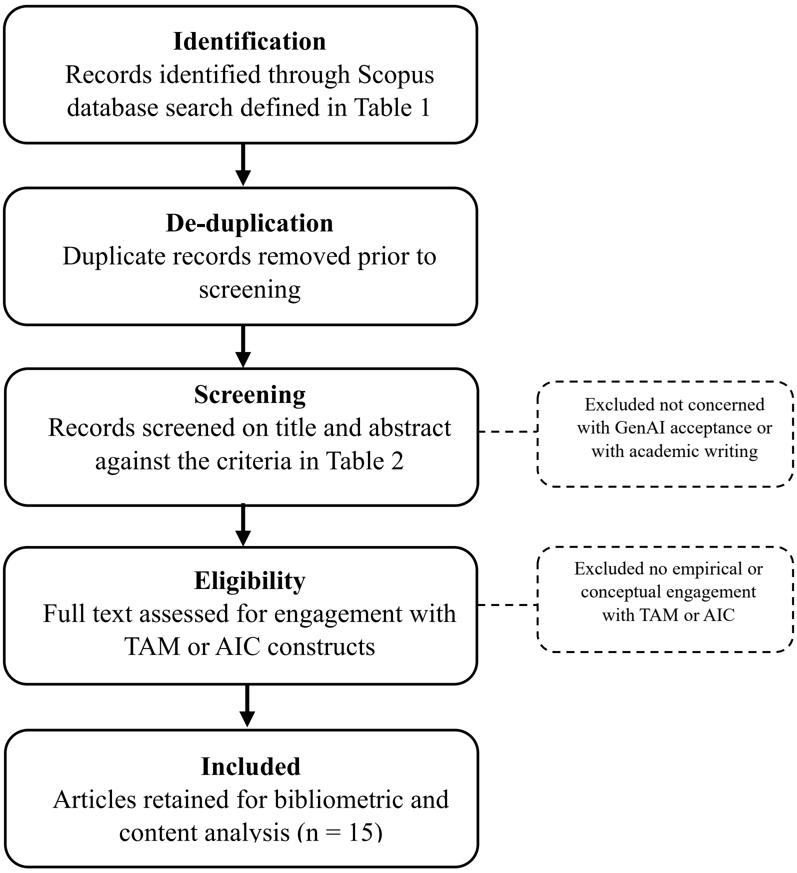

Figure 2: PRISMA-Style Flow Diagram of Study Selection

The complete corpus is enumerated in Table 3, so that the basis of every subsequent analysis is fully traceable. Listing the corpus in full allows readers to verify the year distribution reported under RQ1 and to reproduce the profiling reported in Tables 4 and 5.

Table 3: The Final Corpus of Fifteen Articles Analysed

No.	Author (Year)	Article Title	Source Journal
1	(Chan & Hu, 2023a)	Students' voices on generative AI: perceptions, benefits, and challenges in higher education	International Journal of Educational Technology in Higher Education
2	(Dwivedi et al., 2023b)	“So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI	International Journal of Information Management
3	(Meyer et al., 2023a)	ChatGPT and large language models in academia: opportunities and challenges	BioData Mining
4	(Farrokhnia et al., 2024)	A SWOT analysis of ChatGPT: implications for educational practice and research	Innovations in Education and Teaching International

5	(Grassini et al., 2024b)	Understanding university students' acceptance of ChatGPT: insights from the UTAUT2 model	Applied Artificial Intelligence
6	(Ivanov et al., 2024a)	Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour	Technology in Society
7	(Strzelecki, 2024b)	Students' acceptance of ChatGPT in higher education: an extended Unified Theory of Acceptance and Use of Technology	Innovative Higher Education
8	(Bittle & El-Gayar, 2025)	Generative AI and academic integrity in higher education: a systematic review and research agenda	Information (Switzerland)
9	(Cao et al., 2025a)	Will human-like features affect the adoption of generative AI tools? A study in Chinese university students	Frontiers in Education
10	(Kim et al., 2025)	Students–generative AI interaction patterns and its impact on academic writing	Journal of Computing in Higher Education
11	(Maxwell et al., 2025a)	Generative AI in higher education: demographic differences in student perceived readiness, benefits, and challenges	TechTrends
12	(Nelson et al., 2025a)	Students' perceptions of generative artificial intelligence (GenAI) use in academic writing in English as a foreign language	Education Sciences
13	(Sousa & Cardoso, 2025a)	Use of generative AI by higher education students	Electronics (Switzerland)
14	(Türk et al., 2025)	What makes university students accept generative artificial intelligence? A moderated mediation model	BMC Psychology
15	(Vieriu & Petrea, 2025)	The impact of artificial intelligence (AI) on students' academic development	Education Sciences

Note: Articles are ordered by year of publication. The distribution is 2023 (n = 3), 2024 (n = 4) and 2025 (n = 8).

Data Analysis

Three tools carried the analysis. Keyword co-occurrence and the term networks built from it were mapped in VOSviewer. Citation figures, comprising totals and an annualised rate, were drawn through Publish or Perish (PoP) and used to rank the papers by impact. Microsoft Excel handled cleaning and frequency distributions. The ten highest-ranked papers were then read

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and coded for theoretical framework, methodology and core variables, following the profiling protocol set out by (Abdullah, 2022).Figure 3 presents the four stages as a mind map.

Three families of indicator were derived from these tools. Productivity was captured as the annual distribution of publications; impact was captured through total citations and citations per year, the latter included so that recently published work is not penalised relative to older records; and intellectual structure was captured through term co-occurrence mapping of the abstracts. For the qualitative component, the ten highest-ranked articles were coded against a common profiling sheet covering theoretical framework, research design, analytical technique, database, sample and internal reporting structure. The resulting profiles are presented in Tables 4 and 5.

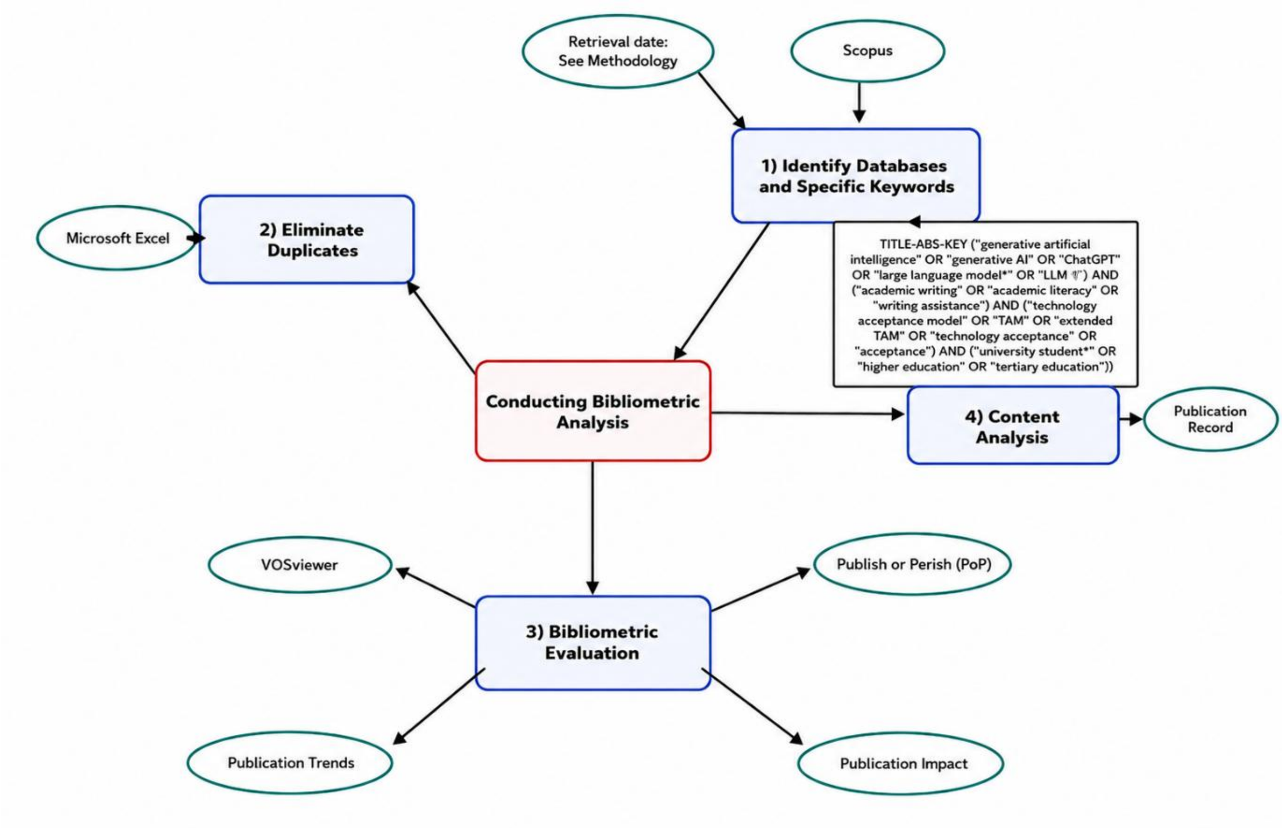

Figure 3: Mind Map of the Bibliometric Evaluation Workflow

Findings and Discussion

Publication Trajectory and Trend Analysis (RQ1)

Publication dates in this corpus track a technological event rather than an academic one. Nothing appears before 2023: no peer-reviewed empirical study had yet framed GenAI use in academic writing as a research problem. ChatGPT was released publicly in late 2022, and the first papers follow within months. The three that appeared in 2023 were largely conceptual, mapping early educational consequences and ethical limits rather than testing them(Chan & Hu, 2023b; Dwivedi et al., 2023a; Meyer et al., 2023a). The four published in 2024 mark a turn towards measurement, most of them survey-based and analysed with PLS-SEM (Farrokhnia et al., 2024; Grassini et al., 2024c; Ivanov et al., 2024b; Strzelecki, 2024).

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The year 2025 represents the peak of publication density (n = 8), introducing advanced methodological configurations including moderated mediation models (Türk et al., 2025), demographic comparative analyses (Maxwell et al., 2025), and comprehensive systematic reviews (Bittle & El-Gayar, 2025). This progression marks a rapid evolution from exploratory conceptualisation to advanced statistical model testing.

Text mining analysis reveals an expanding scholarly vocabulary. Early nomenclature focused tightly on ‘generative AI’, ‘ChatGPT’ and ‘academic integrity’. By 2024 and 2025, keywords had expanded to include ‘responsible AI’, ‘cognitive offloading’, ‘AI literacy’ and ‘large language models.

VOSviewer term co-occurrence analysis of the abstracts (Figure 4) revealed four prominent thematic clusters:

1. The TAM Core (Red): Centred on ‘study’, ‘model’ and ‘acceptance’.
2. The Technology Dimension (Green): Focused on ‘generative AI’ and ‘ChatGPT’.
3. The Methodological Cluster (Blue): Comprising ‘SEM-PLS’, ‘survey’ and ‘quantitative’.
4. The Contextual and Ethical Boundary (Yellow): Linking ‘academic writing’, ‘higher education’ and ‘academic integrity’.

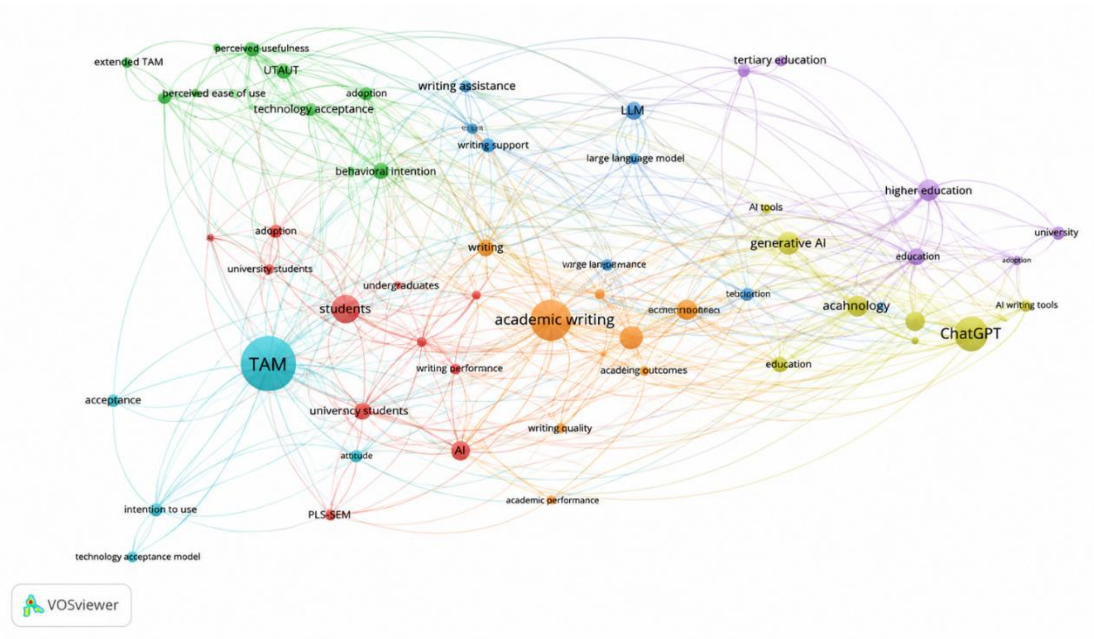

Figure 4: Network Visualisation of Term Co-Occurrence in Abstracts

Crucially, the term ‘gap’ was located in close spatial proximity to ‘model’, ‘context’ and ‘ethics. This pattern aligns with the findings of (Abdullah, 2022) and confirms that researchers in this domain are preoccupied with two specific gaps: adapting established technology models to novel AI interfaces, and evaluating the ethical friction generated by automated writing tools.

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Analysis of High-Impact Scholarly Articles (RQ2)

Table 4 ranks the ten most impactful documents based on citation metrics, theoretical contribution and direct relevance to the extended TAM domain.

Table 4: Top Ten Most Impactful Documents on GenAI Acceptance in Academic Writing

Rank	Reference	Article Title	Journal / Field	Methodology	Key Variables
1	(Chan & Hu, 2023)	Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education	Education & Technology	Survey; Likert; Thematic Analysis	TAM PEOU, PU, AIC
2	(Dwivedi et al., 2023a)	“So, what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy	Information Management	Conceptual; Opinion Paper	GenAI; LLMs; Academic Integrity
3	(Meyer et al., 2023a)	ChatGPT and Large Language Models in Academia: Opportunities and Challenges	BioData Mining	Conceptual; Literature Analysis	LLMs; Authorship; AI Ethics
4	(Grassini et al., 2024c)	Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model	Education Sciences	Quantitative; SEM-PLS; Survey	UTAUT2; TAM; Performance Expectancy
5	(Strzelecki, 2024a)	Students' Acceptance of ChatGPT in Higher Education: An Extended UTAUT	Innovations in Education & Teaching	Quantitative; SEM; Survey	UTAUT; ChatGPT; Behavioural Intention

6	(Farrokhnia et al., 2024)	A SWOT Analysis of ChatGPT: Implications for Educational Practice and Research	British Journal of Educational Technology	SWOT; Conceptual; SLR	ChatGPT; Cognitive Offloading; Ethics
7	(Ivanov et al., 2024b)	Drivers of Generative AI Adoption in Higher Education Through TPB	Computers & Education	Quantitative; SEM; Survey	TPB; Subjective Norms; Attitude
8	(Türk et al., 2025)	What Makes University Students Accept Generative Artificial Intelligence? A Moderated Mediation Model	Education & Information Technologies	Quantitative; PLS-SEM	TAM; Moderated Mediation; BI
9	(Bittle & El-Gayar, 2025)	Generative AI and Academic Integrity in Higher Education: A Systematic Review	Journal of Academic Ethics	PRISMA; Systematic Review	Academic Integrity; Plagiarism; AI Policy
10	(Sousa & Cardoso, 2025b)	Use of Generative AI by Higher Education Students	Education Sciences	Quantitative; Descriptive; Regression	TAM; PU; Behavioural Intention

Note: Selection based on citation impact, theoretical contribution and relevance to TAM-based GenAI acceptance research.

Read across, these ten papers converge on one methodological choice: a quantitative survey analysed with PLS-SEM. Of the 2023 entries, (Chan & Hu, 2023) attracted the most citations, while (Dwivedi et al., 2023)and (Meyer et al., 2023)supplied the multidisciplinary and conceptual groundwork that later work builds on. Wherever a model was estimated, the same variable came out strongest: Perceived Usefulness, or performance expectancy where UTAUT supplied the structure (Grassini et al., 2024b; Strzelecki, 2024) predicted students' intention to adopt GenAI more reliably than any other construct.

To evaluate structural reporting practices, Table 5 profiles the internal organisation of the six most comprehensive studies.

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Table 5: Structural Profiling of Key High-Impact Documents

Publication	Main Content Structure	Schematic Diagram	Database	Sample	Period
(Chan & Hu, 2023)	1. Introduction 2. Methodology 3. Results 4. Discussion 5. Conclusion	Survey instrument	Not specified	Not specified	2020–2023
(Grassini et al., 2024)	1. Introduction 2. Related Work 3. Research Method 4. Findings 5. Discussion 6. Conclusion	None data retrieval table	Google Scholar, Scopus	126 responses	2022–2023
(Strzelecki, 2024)	1. Introduction 2. Background 3. Review Method 4. Results 5. Discussion 6. Conclusion	None structured questionnaire	Scopus, WoS	752 respondents	2022–2024
(Bittle & El-Gayar, 2025)	1. Introduction 2. Theoretical Framework 3. Method 4. Results 5. Discussion 6. Conclusion	PRISMA flowchart	Scopus, WoS, ERIC	47 articles	2020–2024
(Türk et al., 2025)	1. Introduction 2. Literature Review 3. Methodology 4. Results 5. Discussion 6. Conclusion	None structured questionnaire	Scopus, Google Scholar	382 respondents	2022–2024
(Sousa & Cardoso, 2025)	1. Introduction 2. Literature Review 3. Method 4. Results 5. Discussion 6. Conclusion	None online questionnaire	Not specified	312 respondents	2023–2025

Structurally these studies are conventional, nearly all of them following IMRAD. Objectives are stated up front, and findings are tied back to the questions that prompted them. Sample sizes differ widely from 126 respondents at one institution (Grassini et al., 2024) to 752 drawn

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across several universities (Strzelecki, 2024). For a field barely three years old, the consistency of reporting is notable.

Collaboration Pattern and Methodological Diversity (RQ3)

Authorship is spread widely. Contributions come from the United States, Norway, Poland, Turkey, China, the Netherlands, Portugal, the United Arab Emirates, Saudi Arabia and Malaysia. The methodological picture (Figure 5) is narrower: just over half the corpus (53%) rests on quantitative designs using PLS-SEM or SPSS regression, a third (33%) on conceptual frameworks and systematic reviews, and the remaining 14% on mixed methods. Several of the empirical papers name the same weakness in their own designs, namely that a single cross-sectional survey cannot show change over time and call for longitudinal and experimental work as GenAI tools settle into routine use (Kim et al., 2025; Sousa & Cardoso, 2025).

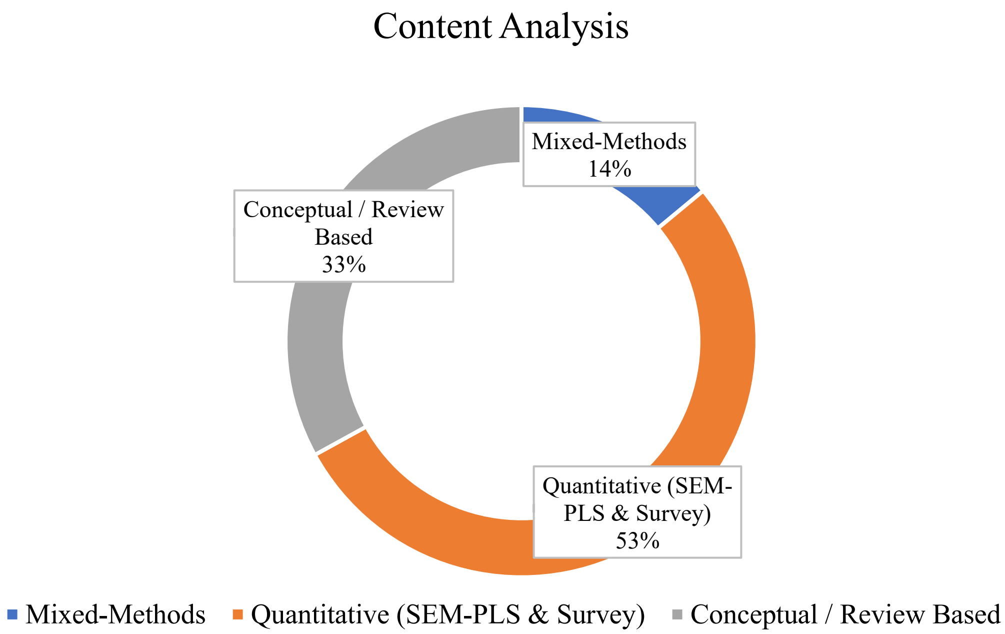

Figure 5: Methodological Distribution of the 15 Analysed Publications

TAM underpins nine of the fifteen papers in one form or another, so theoretically the field has a clear centre. The more consequential development is what has been added to it. At least four of the 2025 models treat Academic Integrity Concern as a measurable variable in its own right rather than a background worry (Bittle & El-Gayar, 2025; Cao et al., 2025).What AIC captures is specific: fear of being accused of plagiarism, unease about leaning too heavily on automation, the prospect of losing skills through disuse, and the possibility of disciplinary action (Bittle & El-Gayar, 2025; Dwivedi et al., 2023). Placing that inside TAM changes what the model is for, since acceptance in a graded environment turns partly on consequences rather than on the tool alone. (Maxwell et al., 2025) add a further qualification: digital literacy and disciplinary background both moderate acceptance, which suggests that a single institution-wide AI policy is unlikely to fit every cohort equally.

Synthesis Across the Three Research Questions

Read together, the three strands of evidence describe a field whose growth has outpaced its consolidation. The publication curve (RQ1) shows near-vertical expansion within a thirty-six-

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month window, yet the structural profiling (RQ2) shows that this expansion has been achieved largely by replicating a single design template: a cross-sectional survey of one student cohort, analysed with PLS-SEM, testing a lightly modified TAM. Volume has therefore increased faster than methodological variety, which accounts for the apparent paradox in the collaboration data (RQ3), namely a domain that is geographically broad but methodologically narrow. It is also notable that the most cited studies are not those with the most elaborate models but those, such as Chan and Hu (2023), that reported transparently and spoke directly to classroom practice.

The theoretical implication follows from the trajectory of Academic Integrity Concern. In classical TAM, adoption is explained by two appraisals of the technology itself, namely whether it is useful and whether it is easy to use (Davis, 1989). AIC introduces an appraisal of the consequences of being seen to use it, which is a categorically different judgement because it is governed by institutional rules rather than by the artefact. This distinction helps explain why AIC behaves inconsistently across the corpus: where institutional policy is explicit, it operates as a constraint on intention, whereas where policy is ambiguous its effect attenuates (Bittle & El-Gayar, 2025; Vieriu & Petrea, 2025) Treating AIC as a stable construct with a single expected coefficient therefore risks misreading it. The evidence assembled here suggests that it is more defensibly modelled as policy-contingent, which in turn implies that the moderating effects reported by (Maxwell et al., 2025) for digital literacy and disciplinary background warrant testing alongside a measure of policy clarity rather than in isolation.

The practical implication concerns where institutional effort is best directed. Because Perceived Usefulness is the consistently strongest predictor across the empirical subset (Grassini et al., 2024c; Sousa & Cardoso, 2025b; Strzelecki, 2024) interventions that merely make GenAI tools available are unlikely to alter behavior that is already established. The more consequential lever is the one implied by the pairing of cognitive offloading (Gerlich, 2025) with AI literacy (Kim et al., 2026; Nelson et al., 2025) which is to shape how the tool is used rather than whether it is used. For Malaysian faculties in particular, this reframes the policy question from detection towards disclosure, since a transparent declaration of AI assistance addresses the integrity concern that students themselves report while leaving the productivity benefit intact.

Limitations of the Review

Three limitations qualify for these conclusions. First, the corpus is confined to Scopus, so conference proceedings, ERIC-indexed education research and non-English scholarship fall outside the frame; the geographical spread reported under RQ3 should accordingly be read as the spread of Scopus-indexed output rather than of the field as a whole. Second, a corpus of fifteen articles supports close reading but is too small to sustain co-citation or bibliographic coupling analysis, so the intellectual structure reported here rests on term co-occurrence alone. Third, because the field is only three years old, citation counts remain heavily influenced by publication date, and the impact ranking in Table 4 therefore favours 2023 publications and should be treated as provisional. These constraints inform the recommendations set out in conclusion.

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Conclusion

This study set out to map the scholarly literature on Generative AI acceptance in academic writing among university students, drawing on 15 Scopus-indexed publications from 2023 to 2025 and guided by three research questions on publication trends, high-impact contributions and patterns of collaboration and methodology. The analysis describes a field that emerged almost overnight after the public release of ChatGPT in late 2022 and matured quickly, moving from conceptual papers in 2023 to model-based empirical work by 2025. Across this body of work, the Technology Acceptance Model remains the dominant framework, with Perceived Usefulness consistently the strongest predictor of students' intention to adopt GenAI, while Academic Integrity Concern has emerged as the key domain-specific extension that sets this literature apart from earlier technology adoption research. Methodologically, quantitative survey designs analysed with PLS-SEM prevail, and the most influential studies are those that report systematically and connect theory with classroom practice. Authorship is markedly international, spanning the United States, Norway, Turkey, China, Poland and Malaysia, among others.

These patterns carry practical weight. The recurring warning that habitual reliance on large language models may lead to cognitive offloading (Gerlich, 2025b) suggests that the educational response should shift from prohibition towards the deliberate cultivation of AI literacy and critical prompt engineering skills (Nelson et al., 2025c). For Malaysian institutions working within the National AI Roadmap and the Malaysia Education Blueprint, the steady influence of Perceived Ease of Use points to a clear role for structured training that lowers the friction of these tools (Grassini et al., 2024c), while the weight of Academic Integrity Concern calls for transparent, culturally grounded integrity guidelines that students can genuinely internalise (Vieriu & Petrea, 2025). The same logic extends to postgraduate research in Malaysian faculties of education, where extended TAM designs that pair AIC with PU and PEOU, tested through cross-sectional surveys and SPSS or PLS-SEM analysis, are becoming a standard template at universities such as Universiti Kebangsaan Malaysia (UKM) and Universiti Teknologi Malaysia (UTM). In these studies, PU tends to remain the primary driver of adoption, while the influence of AIC varies with the clarity and enforcement of institutional policy.

Overall, this review offers an evidence-based picture of how GenAI acceptance in academic writing has taken shape over a very short span and provides a baseline against which later studies can be positioned. Subject to the limitations set out above, future bibliometric work should widen the net to include Web of Science, ERIC and Google Scholar, and apply tools such as VOSviewer or Bibliometrix to a larger corpus for richer co-citation and thematic mapping. Longitudinal and experimental designs are also needed to establish whether the acceptance patterns observed here persist as GenAI tools become routine infrastructure rather than novelties. Even within these bounds, the study provides a structurally rigorous and current foundation for researchers, educators and academic leaders seeking to understand and responsibly manage the integration of Generative Artificial Intelligence into academic writing.

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