International Journal of Modern Education IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

INTERNATIONAL JOURNAL OF MODERN EDUCATION (IJMOE)
www.gaexcellence.com/ijmoe

GLOBAL ACADEMIC EXCELLENCE

VOLUNTARY ADOPTION OF GENERATIVE ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION AND TVET: A DIAGNOSTIC SYSTEMATIC REVIEW OF STUDENT-CENTRED ADOPTION MODELS

Mohd Badli Ramli[1]*, Suhaizal Hashim[2], Mohd Zulfadli Rozali[2], Aida Aisyah Moktar Abdullah[2]

[1]Department of Mechanical Engineering, Politeknik Ibrahim Sultan ,81700 Pasir Gudang Johor, Malaysia
mohdbadliramli@gmail.com https://orcid.org/0009-0009-9257-9366

[2]Faculty of Technical and Vocational Education, Universiti Tun Hussein Onn, 86400 Parit Raja, Johor, Malaysia
suhaizal@uthm.edu.my https://orcid.org/0000-0002-0236-1892
mzulfadli@uthm.edu.my https://orcid.org/0000-0002-5163-7437
aydaaisyah94@yahoo.com https://orcid.org/0009-0004-6764-2275

Article Info:

Article history:
Received date: 28.12.2025
Revised date: 15.01.2026
Accepted date: 12.02.2026
Published date: 03.03.2026

To cite this document:

Ramli, M. B., Hashim, S., Rozali, M. Z., Abdullah, A. A. M. (2026). Voluntary Adoption of Generative Artificial Intelligence in Higher Education And TVET: A Diagnostic Systematic Review of Student-Centred Adoption Models. *International Journal of Modern Education, 8*(29), 164-183.

Abstract:

The rapid diffusion of generative artificial intelligence (GenAI), particularly tools such as ChatGPT, has led to growing voluntary adoption among higher education students. However, within Technical and Vocational Education and Training (TVET) contexts, educational success is ultimately evaluated based on demonstrable competence rather than favourable attitudes or intentions. Despite an expanding body of empirical research on GenAI adoption, existing studies remain predominantly intention-centric, offering limited insight into actual use and sustained engagement that are critical for competence development. This study presents a diagnostic systematic literature review that maps empirical evidence on students' voluntary adoption of GenAI in higher education and TVET contexts, with explicit attention to outcome boundaries along the intention–use continuum. Guided by PRISMA 2020, a systematic search of Scopus and Web of Science identified 143 records published between 2023 and 2025. Following screening and eligibility assessment, 23 student-only empirical studies were retained for core synthesis. Data were analysed using a descriptive, counting-based evidence-mapping approach focusing on adoption models, construct presence, structural relationships, and outcome categories. The results reveal a strong concentration of studies grounded in UTAUT and UTAUT2 model families, with behavioural intention overwhelmingly positioned as the primary outcome variable. Performance expectancy and social influence consistently emerge as significant predictors of intention, while effort expectancy and

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

facilitating conditions show mixed patterns. Although fewer studies examine downstream outcomes, behavioural intention is generally associated with actual use or continuance when such outcomes are included. However, evidence on sustained and habitual GenAI use remains sparse. By systematically exposing the imbalance between intention-focused and use-oriented evidence, this review contributes a diagnostic empirical map rather than a model extension. The findings underscore the need for future TVET-oriented research to move beyond intention as a proxy for readiness and to prioritise competence-building, repeated, and practice-oriented engagement with GenAI technologies.

DOI: 10.35631/IJMOE.829011

Keyword:

ChatGPT; Generative Artificial Intelligence; Higher Education; Intention - Behavior Gap; Technology Adoption; TVET; Voluntary Adoption;

Introduction

In technical and vocational education and training (TVET), educational success is ultimately judged by demonstrable competence, not by favourable attitudes toward technology. Students may express strong willingness to use a tool, yet still fail to translate that willingness into repeated, task-focused practice that builds measurable skills. This distinction is particularly consequential for generative artificial intelligence (GenAI). The central risk is not whether students recognise GenAI's potential, but whether intention is mistakenly interpreted as readiness, and readiness is then assumed to indicate competence. In TVET settings, such an assumption can inflate perceptions of work preparedness while masking gaps in hands-on performance and sustained practice.

A defining characteristic of student GenAI engagement is voluntariness. GenAI tools are often accessed through self-initiated, discretionary use rather than formal institutional mandates. This voluntary context resembles real workplace conditions, where the availability of digital tools does not guarantee consistent, competence-building utilisation. Competence emerges through repeated use, deliberate practice, and application in authentic tasks, not through initial adoption decisions alone. Therefore, voluntary use is not merely a contextual descriptor. It is a diagnostic condition that reveals whether students move beyond exploratory engagement to sustained utilisation patterns that could plausibly support skill acquisition and work readiness.

Despite the rapid growth of GenAI adoption research in higher education, the evidence base remains largely intention-centric. Many empirical studies, grounded in established adoption frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, prioritise behavioural intention as the primary outcome (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). While these models are valuable for explaining adoption decision-making, behavioural intention is frequently treated as a proxy for actual use, even though intention does not consistently translate into sustained behaviour (Venkatesh et al., 2016). As a result, what the literature can legitimately claim about readiness and competence remains constrained when actual use, continuance, or habit are not measured with clear boundaries.

This review addresses that constraint by positioning the intention–behavior gap as the central analytical lens. Specifically, it interrogates the outcome boundary problem in GenAI adoption studies, where intention-related outcomes and use-related outcomes are sometimes conflated or unevenly represented. For TVET, this boundary is not a technical detail but a validity issue. If most evidence stops at intention, then claims about competence-oriented readiness are necessarily limited. Conversely, when outcomes include actual use or continuance, the literature becomes more informative for understanding whether voluntary GenAI engagement is likely to support repeated practice, mastery progression, and competence development.

Accordingly, this study conducts a systematic literature review of empirical research on the voluntary adoption and use of GenAI among higher education students, with particular relevance to TVET's competence-based objectives. Rather than proposing a new adoption model or extending existing frameworks, the review is designed as a diagnostic evidence-mapping exercise. Guided by PRISMA 2020, it synthesises student-only empirical studies published between 2023 and 2025 and applies a structured outcome mapping protocol to distinguish behavioural intention, actual use, and continuance-related outcomes (Page et al., 2021). Through this diagnostic mapping and outcome boundary clarification, the review aims to prevent intention-centric overinterpretation and to refocus the field toward a competence-relevant question, namely how voluntary GenAI use translates into sustained utilisation that can support skill acquisition and work readiness.

Conceptual Framework

Generative artificial intelligence (GenAI) has entered students' learning environments primarily through self-initiated and discretionary engagement. In higher education and TVET contexts, students often decide independently whether to try, continue, or abandon GenAI tools, frequently outside formal instructional requirements. This voluntary context matters because it exposes a fundamental boundary problem in the adoption literature: what is being measured as "adoption" is frequently behavioural intention, while what is often assumed in practice is sustained utilisation and competence-relevant engagement. When intention is treated as equivalent to readiness, and readiness is implicitly taken as evidence of competence, the resulting claims become particularly fragile for TVET, where competence is produced through repeated practice and observable performance.

In this review, the conceptual framing is therefore anchored in outcome boundary clarification rather than construct-level exposition of adoption theories. Adoption research commonly distinguishes between an initial decision orientation, subsequent utilisation, and post-adoption persistence. However, empirical studies do not always maintain clear boundaries in how these outcomes are operationalised and interpreted. To support a diagnostic synthesis, outcomes in GenAI adoption studies are framed across three boundary-consistent categories. The first category is adoption decision, operationalised as behavioural intention or intention to use. The second category is actual utilisation, operationalised as use behaviour, actual use, or reported usage frequency and extent. The third category is continuance or habit, operationalised as continuance intention, continuance behaviour, or habit-related measures indicating persistence

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182
beyond initial trial. This framing does not introduce a new theoretical model. It clarifies what outcomes represent, and what they do not represent, when interpreting evidence in voluntary use settings.

Voluntariness is central to this boundary framing because discretionary engagement increases the likelihood that intention and behaviour diverge. In mandatory systems, usage can be partially sustained by institutional requirements, assessment rules, or infrastructural integration. In voluntary contexts, usage must be repeatedly chosen, which makes persistence and habit more informative indicators of meaningful engagement than intention alone. This does not mean intention is irrelevant. Instead, it means intention has limited interpretive power if it is not accompanied by evidence of actual utilisation or continuance. For TVET, this distinction is not merely conceptual. If research evidence stops at intention, it cannot credibly speak to competence building or work readiness, because competence requires sustained and purposeful application rather than willingness in principle.

Most empirical studies on GenAI adoption have been anchored in established adoption models, commonly including TAM, UTAUT, UTAUT2, and hybrid configurations (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). These models have been widely used to explain adoption decision-making and to identify antecedents associated with intention to use emerging technologies. In GenAI research, they have similarly guided the selection of predictors and the specification of relationships surrounding behavioural intention. The core limitation is not the presence of these models, but the imbalance in outcomes tested and reported. Across many studies, behavioural intention functions as the primary dependent variable, while actual use and continuance outcomes are comparatively less examined, inconsistently defined, or excluded altogether (Venkatesh et al., 2016; Chopra et al., 2025). As a consequence, the literature becomes intention-centric, and the empirical basis for claims about sustained utilisation remains incomplete.

A second constraint concerns fragmentation in operationalisation and outcome labelling. Studies employ different terminology for outcomes such as behavioural intention, intention to use, use behaviour, actual use, and continuance, sometimes using them interchangeably despite their distinct implications. This variation weakens comparability across studies and encourages overgeneralisation, particularly when intention measures are implicitly used to imply actual engagement. In voluntary GenAI use, such conflation is especially problematic because the central diagnostic question is precisely whether intention is followed by utilisation and persistence. Without consistent outcome boundaries, synthesis risks aggregating findings that are not equivalent in meaning, thereby obscuring the intention–behavior gap rather than clarifying it.

Accordingly, this review adopts a diagnostic evidence-mapping stance that privileges outcome clarity over construct elaboration. Rather than re-describing adoption theories in textbook form, the review maps how student-only GenAI adoption studies, conducted in voluntary contexts, have operationalised outcomes across intention, actual use, and continuance. This outcome boundary framing enables the review to identify what the evidence base can support and, importantly, what it cannot support. Specifically, where outcomes remain predominantly intention-based, claims about competence-relevant engagement and work readiness must be treated as limited and conditional. Where utilisation and continuance outcomes are measured, the evidence becomes more informative for TVET-oriented interpretation because it better

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

approximates repeated engagement, practice continuity, and the conditions under which competence can plausibly develop (Page et al., 2021).

Research Questions

Research questions play a central role in shaping the scope, logic, and synthesis strategy of a systematic literature review. In a diagnostic-oriented review, research questions are not only used to delimit the literature but also to clarify what the existing evidence can and cannot substantiate. In the context of voluntary adoption of generative artificial intelligence (GenAI) among students, well-defined research questions are essential to avoid overinterpreting intention-based findings as indicators of sustained use or competence development, particularly in higher education and TVET settings.

In this review, the formulation of research questions is guided by the PICo framework to ensure alignment between the review objectives, search strategy, inclusion criteria, and analytical focus. The population of interest comprises students in higher education and Technical and Vocational Education and Training contexts. The phenomenon of interest concerns the voluntary adoption and use of GenAI technologies examined through adoption-based theoretical models. The context is limited to empirical studies conducted in voluntary use settings within higher education and TVET. The application of PICo in this review serves a scoping and boundary-setting function rather than a theory-building purpose. Guided by this framework and by the diagnostic aim of examining the intention–behavior gap, this systematic literature review addresses the following research questions:

RQ1. What are the empirical characteristics, research contexts, and outcome measures of studies examining students' voluntary adoption and use of generative artificial intelligence in higher education and TVET?
RQ2. How have adoption-based theoretical models been applied in empirical studies on students' voluntary engagement with generative artificial intelligence, and to what extent do these studies distinguish between behavioural intention, actual use, and continuance-related outcomes?

Material and Methods

This study adopted a systematic literature review design to synthesise empirical evidence on students' voluntary adoption and use of generative artificial intelligence in higher education and Technical and Vocational Education and Training contexts. The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure transparency, methodological rigour, and reproducibility across all stages of the review process. Consistent with the positioning of this study as a diagnostic evidence-mapping review, the synthesis focuses on documenting how adoption-related outcomes have been operationalised and reported in the literature, rather than estimating pooled effects or proposing new theoretical extensions.

Several methodological boundaries were specified a priori to preserve analytical coherence. The population was restricted to student-only samples for core synthesis. The context was limited to voluntary use settings, reflecting discretionary engagement rather than institutionally mandated technology use. The theoretical scope was confined to adoption-based frameworks, including the Technology Acceptance Model, the Unified Theory of Acceptance and Use of

International Journal of Modern Education IJMOE EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182
Technology, UTAUT2, and explicitly stated hybrid adoption models. Adoption-related outcomes were limited to behavioural intention, actual use, and continuance-related measures. These boundaries guided the search strategy, study selection, and data abstraction processes.
Identification

A systematic literature search was conducted using Scopus and Web of Science, selected for their extensive coverage of peer-reviewed journals in education, information systems, and technology adoption research. Search strategies were developed to capture four key elements: generative artificial intelligence technologies, student populations in higher education or TVET settings, adoption-based theoretical framing, and adoption-related outcomes.

In Scopus, the search was implemented using the TITLE-ABS-KEY field, while an equivalent Topic search strategy was applied in Web of Science. Database filters were applied to restrict results to journal articles published in English between 2023 and 2025. Although the final set of included studies was published between 2024 and 2025, the extended search window was intentionally adopted to ensure coverage of early empirical studies following the public release of ChatGPT in late 2022. All database searches were conducted on 1 December 2025.

The complete search strategies and applied filters are presented in Table 1. The identification stage yielded records from both databases, which were subsequently consolidated for screening.

Table 1: Search Strategy and Database Filters

Database	Search field	Search string	Filters applied	Date of access
Scopus	TITLE-ABS-KEY	("ChatGPT" OR "generative AI" OR "generative artificial intelligence" OR "large language model*") AND (UTAUT OR UTAUT2 OR TAM OR "technology adoption") AND (student* OR "higher education" OR TVET) AND ("behavioural intention" OR "behavioural intention" OR "use behavior" OR "use behaviour" OR continuance OR adoption)	Year: 2023–2025; Document type: Article; Language: English	1 December 2025
Web of Science	Topic (TS)	("ChatGPT" OR "generative AI" OR "generative artificial intelligence" OR "large language model*") AND (UTAUT OR UTAUT2 OR TAM OR "technology adoption") AND (student* OR "higher education" OR TVET) AND ("behavioural intention" OR "behavioural intention" OR "use behavior" OR "use behaviour" OR continuance OR adoption)	Year: 2023–2025; Document type: Article; Language: English	1 December 2025

Source: Author’s Own Work

International Journal of Modern Education IJMOE EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

Screening

All records retrieved from the two databases were exported and consolidated. Duplicate records were identified and removed prior to screening. Title and abstract screening were then conducted to assess the relevance of each record against the predefined methodological boundaries.

At this stage, records were excluded if they clearly met one or more of the following conditions: focus on non-educational contexts, inclusion of non-student populations, examination of mandatory or institutionally enforced technology use, outcomes unrelated to adoption or use behaviour, or non-empirical study designs such as conceptual papers, reviews, or bibliometric analyses. Screening decisions were applied consistently to preserve the intended scope of a student-focused, voluntary-use, adoption-model review. Records retained after title and abstract screening proceeded to full-text assessment.

Table 2: Inclusion and Exclusion Criteria with Coding Scheme

Component	Inclusion (Core Synthesis)	Inclusion (Discussion Only)	Exclusion Code
Publication year	2023–2025	2023–2025	Outside range (E3)
Document type	Journal article	Journal article	Conference paper, book chapter, review, editorial (E3)
Language	English	English	Non-English (E3)
Context	Higher education / TVET	Higher education / TVET	Non-education context
Population	Student-only	Mixed sample (student + non-student)	Non-student population
Technology focus	Generative AI / ChatGPT	Generative AI / ChatGPT	Non-GenAI technology
Theoretical model	TAM / UTAUT / UTAUT2 / Hybrid adoption model	Same	No adoption-based model
Outcome measure	Behavioural intention, use, actual use, continuance	Same	Non-adoption outcome
Study type	Empirical quantitative	Empirical	Conceptual, review, bibliometric
Usage context	Voluntary use	Voluntary use	Mandatory or enforced use

Source: Author’s Own Work

Eligibility

Full texts of the retained articles were examined to determine their eligibility for inclusion in the core synthesis. To be included, studies were required to focus on higher education or TVET contexts, employ student-only samples, examine voluntary use of generative artificial

International Journal of Modern Education IJMOE EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182
intelligence technologies, apply an adoption-based theoretical framework, and report adoption-related outcomes in the form of behavioural intention, actual use, or continuance-related measures.

Articles were excluded at this stage if they involved mixed populations without separable student data, examined outcomes or usage contexts misaligned with voluntary adoption, or lacked an explicit adoption-model framing. Eligibility decisions were documented using a small set of exclusion categories to support auditability without inflating methodological complexity. Following full-text assessment, studies meeting all eligibility criteria were retained as core studies for synthesis. The overall flow of records across identification, screening, eligibility, and inclusion stages is illustrated in the PRISMA flow diagram.

Data Abstraction and Analysis

Data abstraction was conducted through full-text examination of the studies included in the core synthesis. A structured extraction protocol was applied to ensure consistency across studies. Only information explicitly reported in the original articles was recorded, and no additional interpretation or imputation was introduced at the extraction stage.

Extracted information was organised to capture three analytical dimensions: study characteristics, adoption-model family and reported constructs, and outcome category. Study characteristics included geographical context, education level, sample size, and generative artificial intelligence tool examined. Adoption-model information captured the theoretical framework applied and the type of adoption-related outcome reported. Outcomes were categorised into behavioural intention, actual use, or continuance-related measures to support outcome boundary clarity.

The synthesis employed a counting-based analytical approach to summarise recurring patterns in model usage and outcome operationalisation across studies. This approach preserves the integrity of the original empirical evidence while enabling systematic identification of concentration and gaps within the literature. Importantly, the analysis prioritised outcome boundary distinction rather than path-level comparison or effect-size estimation, ensuring alignment with the diagnostic aim of the review.

Quality Appraisal

Following established guidelines for systematic literature reviews, a quality appraisal process was conducted after the final set of primary studies had been identified (Kitchenham & Charters, 2007). Primary studies refer to the original empirical research articles that constitute the core evidence base of the review. The purpose of the quality appraisal was to assess the overall clarity, methodological soundness, and reporting transparency of the included studies.

In this review, quality appraisal was applied as an audit layer rather than as a strict exclusion mechanism. All studies that satisfied the predefined inclusion and eligibility criteria were retained for synthesis. The appraisal results were used to contextualise the strength and limitations of the existing evidence base and to support a balanced interpretation of findings, consistent with diagnostic and mapping-oriented systematic reviews.

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

The quality appraisal framework was adapted from prior systematic literature reviews in technology-related research (e.g., Abouzahra et al., 2023). Six appraisal criteria (QA1–QA6) were applied to evaluate key aspects of study design, execution, and reporting. Each criterion was assessed using a three-point scale: Yes (Y), indicating that the criterion was fully met; Partly (P), indicating that the criterion was partially met with minor limitations; and No (N), indicating that the criterion was not met.

The appraisal criteria were defined as follows. QA1 assessed whether the purpose and objectives of the study were clearly stated and aligned with the research focus. QA2 examined whether the relevance and contribution of the study were adequately justified in relation to existing literature. QA3 evaluated the clarity and appropriateness of the research methodology, including study design, data collection, and analytical procedures. QA4 assessed whether key concepts, variables, and theoretical constructs were clearly defined and operationalised. QA5 examined the suitability of data analysis techniques and outcome measures for investigating technology adoption phenomena, including behavioural intention, actual use, or continuance-related outcomes. QA6 evaluated whether the study explicitly acknowledged its limitations, whether methodological, contextual, or analytical.

Quality appraisal was conducted consistently across all included studies using the same criteria and scoring scheme. Individual criterion scores were not used to exclude studies but were aggregated to provide an overall indication of methodological robustness across the evidence base. This approach enhances transparency while avoiding undue exclusion bias and is consistent with recommended practices for systematic literature reviews that aim to synthesise and diagnose patterns in empirical adoption research (Kitchenham & Charters, 2007).

PRISMA Flow Diagram

The study selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The flow of records through identification, screening, eligibility assessment, and inclusion is illustrated in Figure 1. During the identification stage, a total of 143 records were retrieved from the selected databases, comprising 72 records from Scopus and 71 records from Web of Science. After duplicate removal, 139 unique records remained for screening. Title and abstract screening resulted in the exclusion of 109 records that did not meet the predefined scope of the review. Subsequently, 30 full-text reports were assessed for eligibility. Of these, seven reports were excluded following full-text assessment due to population mismatch, misalignment with voluntary adoption contexts, or the absence of adoption-based theoretical framing. As a result, 23 empirical studies met all eligibility criteria and were included in the systematic review. These studies constituted the final dataset for results, synthesis, and discussion.

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

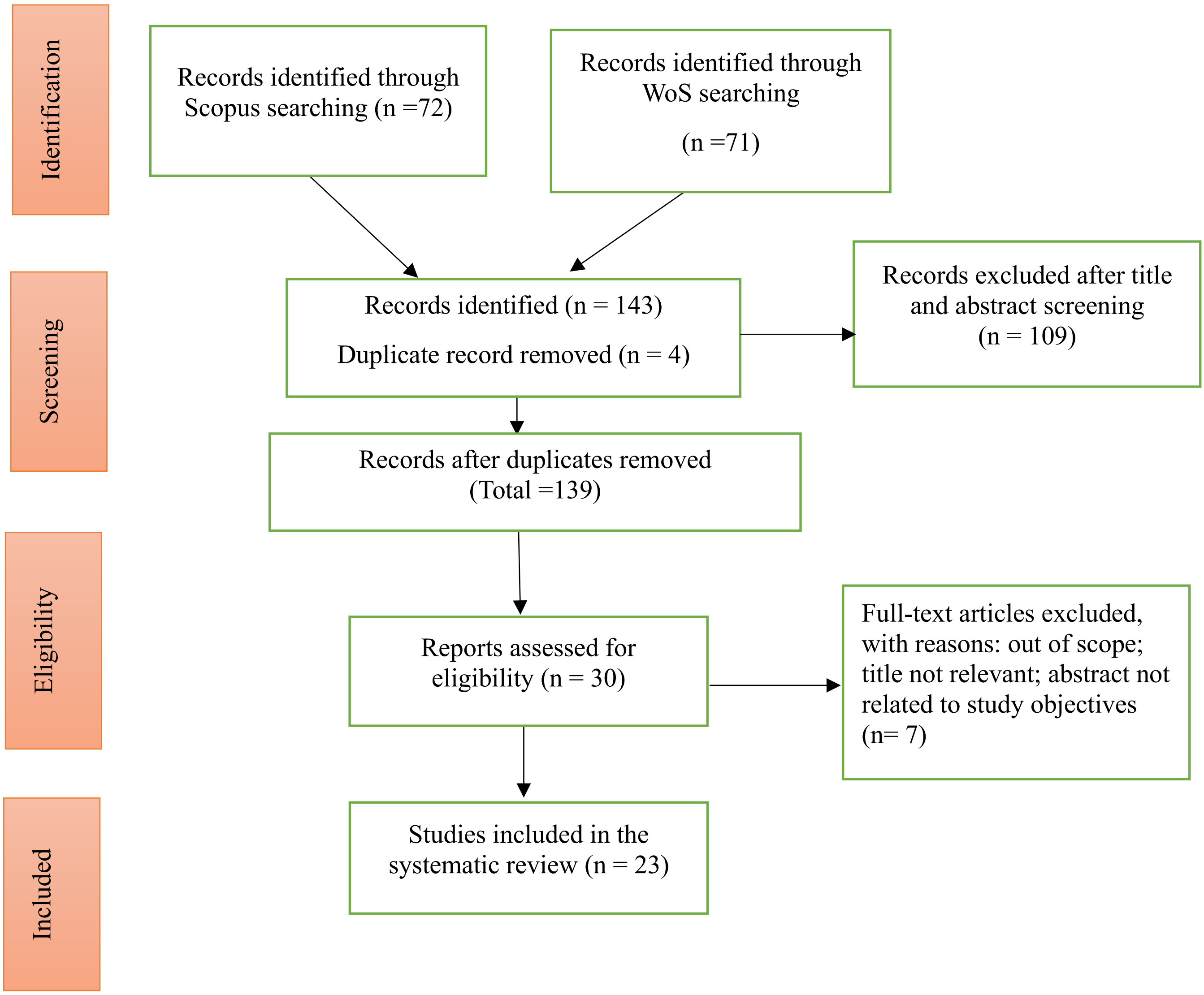

Figure 1: PRISMA 2020 Flow Diagram Illustrating the Study Selection Process
Source: Author's Own Work

Results

The results of this systematic literature review are derived from 23 core empirical studies examining students' voluntary adoption of generative artificial intelligence in higher education and TVET contexts. All findings reported in this section are descriptive and based exclusively on the locked dataset. No interpretation, causal inference, or theoretical evaluation is introduced at this stage. The results are organised using a diagnostic synthesis approach to highlight evidence concentration and imbalance across adoption models and outcome categories.

Study Characteristics of Core Studies

The characteristics of the included core studies are summarised in Table 3. The 23 studies reflect geographically diverse contexts, with most research conducted in higher education settings and predominantly involving undergraduate or mixed undergraduate and postgraduate samples. Sample sizes varied widely across studies, indicating heterogeneity in empirical scope. The generative AI focus was primarily represented by ChatGPT or related GenAI tools used for academic learning and support activities.

Table 3: Study Characteristics of Core Studies (n = 23)

No	Study	Country / Region	Education Level	Sample Size	GenAI Tool	Context
1	Moradi (2025)	China	UG	340	ChatGPT	HE
2	Al-Okaily et al. (2025)	Middle East	UG/PG	485	ChatGPT	HE
3	Polyportis & Pahos (2025)	Europe	HE	355	ChatGPT	HE
4	Zhu et al. (2025)	China	UG	432	GenAI	HE
5	Yang (2025)	China	UG/PG	331	GenAI	HE
6	Arthur et al. (2025)	Ghana	UG	404	ChatGPT	HE
7	Xu & Thien (2025)	China	UG	331	ChatGPT	HE
8	Yakubu et al. (2025)	Nigeria	UG/PG	289	GenAI	HE
9	Amin et al. (2025)	Korea	UG	346	ChatGPT	HE
10	Xu et al. (2025)	China	UG	1190	GenAI	HE
11	Sobaih & Abu Elnasr (2025)	Egypt	PG	410	ChatGPT	HE
12	Chopra et al. (2025)	India / Poland	UG/PG	1074	ChatGPT	HE
13	Caner-Yıldırım (2025)	Turkey	UG	404	ChatGPT	HE
14	Siddiqui et al. (2025)	Malaysia	UG	485	ChatGPT	HE
15	Gupta & Priyanka (2025)	India	UG/PG	309	ChatGPT	HE
16	Pratita et al. (2025)	Indonesia	UG	411	ChatGPT	HE
17	Sergeeva et al. (2025)	Russia	UG	379	GenAI	HE
18	Singh et al. (2025)	India	PG	400	ChatGPT	HE
19	Namatovu & Kyambade (2025)	Uganda	UG	473	ChatGPT	HE
20	Rana & Rai (2025)	India	UG/PG	503	GenAI	HE
21	Bahadur et al. (2024)	Nepal	UG/PG	578	ChatGPT	HE
22	Wang & Wang (2025)	China	UG	432	GenAI	HE
23	Mork et al. (2025)	Nordic / USA	HE	586	ChatGPT	HE

Source: Author's Own Work

Distribution of Adoption Model Families

This subsection reports the distribution of adoption-based theoretical frameworks applied across the core studies. Model classification was conducted at the level of model families to

International Journal of Modern Education IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

ensure consistency in reporting. As shown in Table 4, the evidence base is dominated by the UTAUT family, with UTAUT2 being the most frequently applied model family. TAM appeared less frequently, while hybrid adoption models were rare.

Table 4: Distribution of Adoption Model Families (n = 23)

Model Family	Number of Studies	Percentage
UTAUT2 family	10	43.5%
UTAUT family	8	34.8%
TAM family	4	17.4%
Hybrid (UTAUT2 + additional constructs)	1	4.3%
Total	**23**	**100%**

Source: Author's Own Work

Construct Presence Across Core Studies

This subsection examines how adoption-related outcomes were operationalised across the core studies, with particular attention to the distinction between behavioural intention and use-related outcomes. Table 5 maps each study by model family and outcome category, highlighting outcome boundary concentration. Behavioural intention was the most frequently measured outcome, while use-related outcomes were less consistently operationalised. Continuance-related outcomes were rarely reported.

Table 5: Model × Outcome Matrix (Diagnostic Outcome Mapping)

No	Study	Model family	Behavioural intention	Use-related outcome (use or actual use)	Continuance-related outcome
1	Moradi (2025)	Hybrid	Yes	Yes	Not reported
2	Al-Okaily et al. (2025)	UTAUT	Yes	Yes	Not reported
3	Polyportis & Pahos (2025)	TAM	Yes	Yes	Not reported
4	Zhu et al. (2025)	TAM	Yes	Not reported	Not reported
5	Yang (2025)	UTAUT	Yes	Not reported	Not reported
6	Arthur et al. (2025)	UTAUT2	Yes	Yes	Not reported
7	Xu & Thien (2025)	UTAUT	Yes	Not reported	Not reported
8	Yakubu et al. (2025)	UTAUT	Yes	Not reported	Not reported
9	Amin et al. (2025)	UTAUT2	Yes	Yes	Not reported
10	Xu et al. (2025)	UTAUT	Yes	Yes	Not reported
11	Sobaih & Abu Elnasr (2025)	UTAUT	Yes	Yes	Not reported

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

12	Chopra et al. (2025)	UTAUT	Yes	Yes	Not reported
13	Caner-Yıldırım (2025)	UTAUT2	Yes	Yes	Not reported
14	Siddiqui et al. (2025)	UTAUT	Yes	Not reported	Not reported
15	Gupta & Priyanka (2025)	Hybrid	Yes	Not reported	Not reported
16	Pratita et al. (2025)	TAM	Yes	Not reported	Not reported
17	Sergeeva et al. (2025)	UTAUT2	Yes	Yes	Not reported
18	Singh et al. (2025)	UTAUT2	Yes	Not reported	Not reported
19	Namatovu & Kyambade (2025)	UTAUT2	Yes	Not reported	Not reported
20	Rana & Rai (2025)	UTAUT2	Yes	Yes	Not reported
21	Bahadur et al. (2024)	UTAUT2	Yes	Not reported	Not reported
22	Wang & Wang (2025)	TAM	Yes	Not reported	Not reported
23	Mork et al. (2025)	UTAUT2	Yes	Yes	Not reported

Source: Author's Own Work

Evidence Concentration Along the Intention–Use Continuum

To further examine imbalance within the evidence base, outcomes were mapped along the intention–use continuum, from initial adoption intention to use-related outcomes and continuance-related behaviours. The mapping indicates a pronounced concentration at the behavioural intention stage. Use-related outcomes were measured in a smaller subset of studies, and continuance-related outcomes were rarely operationalised. As a result, the evidence base provides stronger coverage of intention formation than of sustained or repeated use.

Summary of Diagnostic Empirical Patterns

This subsection summarises recurring empirical patterns identified across the core studies using a diagnostic synthesis approach. Across the evidence base, performance expectancy and social influence were frequently examined as predictors of behavioural intention, while effort expectancy and facilitating conditions showed more variable reporting. When habit was included, it was consistently reported as associated with behavioural intention. Studies that extended analysis to use-related outcomes generally reported behavioural intention as linked to use behaviour; however, many studies did not progress beyond intention-focused outcome measurement.

International Journal of Modern Education IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

Discussion

This systematic literature review was conducted as a diagnostic synthesis to examine how empirical research on students' voluntary adoption of generative artificial intelligence has conceptualised and operationalised adoption outcomes. Rather than extending adoption theories or proposing new explanatory models, the discussion focuses on what the accumulated evidence reveals about outcome boundaries, measurement practices, and their implications for student competence development, particularly within TVET-oriented contexts.

The Illusion of Readiness

A central diagnostic insight emerging from this review is the illusion of readiness created by intention-centric adoption research. Across the core studies, behavioural intention dominates as the primary outcome variable, while actual use and continuance-related outcomes receive substantially less empirical attention. This imbalance risks creating a misleading impression that high levels of intention reflect readiness to engage meaningfully with generative AI technologies. In practice, intention signals willingness rather than capability, and willingness does not necessarily translate into effective or sustained use.

The empirical evidence reviewed shows that when behavioural intention is linked to use-related outcomes, the relationship is often statistically significant. However, the limited number of studies that extend beyond intention restricts what can be inferred about students' actual engagement trajectories. High intention scores may therefore overstate students' preparedness to integrate generative AI into their learning practices. From a diagnostic perspective, this suggests that much of the existing literature captures early-stage cognitive acceptance rather than functional readiness or skill acquisition.

This illusion is particularly problematic in voluntary use contexts, where students are not compelled to use generative AI by institutional mandates. In such settings, intention reflects personal inclination rather than demonstrated capability. Treating intention as a proxy for readiness risks conflating attitudinal openness with competence, leading to optimistic conclusions that are not sufficiently grounded in evidence of actual use or mastery.

From Intention to Habit: A TVET Perspective

The limited attention given to continuance and habit-related outcomes highlights a critical gap when viewed through a TVET lens. In vocational and skills-oriented education, competence is developed through repeated practice, routine application, and sustained engagement rather than through initial adoption decisions alone. The absence of continuance-focused outcomes in the reviewed studies indicates that the literature has yet to adequately capture this dimension of learning.

Although habit is occasionally included as a predictor of behavioural intention, it is rarely operationalised as an outcome in its own right. This modelling choice reflects a broader tendency to prioritise intention formation over behavioural stabilisation. From a TVET perspective, this is a significant limitation, as habitual use is a more meaningful indicator of skill internalisation and work readiness than intention alone. Without evidence of sustained use, claims about the educational impact of generative AI remain speculative.

Voluntary use further amplifies this issue. In the absence of external enforcement, sustained engagement depends on perceived relevance, ease of integration into existing practices, and alignment with task demands. The current evidence base provides limited insight into how students move from experimentation to routine use, or how generative AI becomes embedded in learning workflows. As a result, the literature offers a partial view of adoption that stops short of addressing competence formation.

Implications for TVET Research and Practice

The diagnostic patterns identified in this review have important implications for both research and practice in TVET contexts. For researchers, the findings highlight the need to reconsider outcome selection in adoption studies. Continued reliance on behavioural intention as the dominant endpoint constrains the field's ability to assess whether generative AI contributes to meaningful skill development. Future studies would benefit from incorporating use-related and continuance outcomes as primary dependent variables rather than optional extensions.

For practitioners and educators, the findings caution against equating students expressed willingness to use generative AI with readiness to apply these tools effectively in learning or work-related tasks. In TVET settings, where employability and technical competence are central objectives, evaluation frameworks should prioritise observable use patterns, task integration, and sustained engagement. Adoption metrics that stop at intention may provide reassurance without accurately reflecting students' preparedness for real-world application.

Taken together, this review underscores the importance of aligning adoption research with the realities of skills-based education. Generative AI adoption should be understood not merely as a decision to use a tool, but as a process through which competence is gradually developed through repeated and purposeful use. By clarifying outcome boundaries and exposing intention-centric bias, this review contributes a diagnostic perspective that can inform more meaningful evaluation of generative AI in higher education and TVET contexts.

Limitation

Several limitations should be considered when interpreting the findings of this systematic literature review. These limitations are not presented as methodological weaknesses, but as boundary conditions that frame the scope and diagnostic intent of the review.

First, the core synthesis was deliberately restricted to student-only populations in higher education and TVET contexts. This decision was made to preserve population validity and to ensure analytical consistency in examining voluntary adoption behaviour among learners. While this focus strengthens the internal coherence of the findings, it necessarily limits the generalisability of the results to other stakeholder groups such as educators, administrators, or institutional decision-makers. Studies employing mixed samples were therefore excluded from the core synthesis and considered only at the discussion level. As a result, institutional or pedagogical dynamics beyond the student perspective are not systematically represented in the core evidence base.

Second, the available evidence is heavily skewed towards behavioural intention as the primary adoption outcome. Although behavioural intention is a well-established construct in adoption research, the dominance of intention-focused outcomes constrains the ability of this review to

International Journal of Modern Education IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182
draw firm conclusions about actual, sustained, or habitual use of generative AI. Only a subset of studies extended their analysis to use-related outcomes, and none operationalised continuance or habit as a dependent variable. Consequently, the review provides stronger diagnostic insight into intention formation than into post-adoption behaviour or competence development. This imbalance reflects the state of the existing literature rather than a limitation of the review design itself.

Third, the synthesis was constrained by reporting practices in the primary studies. Several articles did not provide complete information regarding the specific generative AI tools examined, the operationalisation of use-related outcomes, or the explicit testing of mediators and moderators. In accordance with the review protocol, such elements were coded conservatively as not reported to avoid inferential assumptions. This approach safeguards the transparency of the synthesis but limits deeper examination of contextual variation and model specification across studies.

Fourth, most of the reviewed studies relied on cross-sectional survey designs and self-reported measures. While such designs are common in adoption research, they restrict the ability to capture temporal dynamics, behavioural change, and learning trajectories over time. In the context of voluntary generative AI use, cross-sectional evidence provides limited insight into how initial adoption intentions evolve into routine practices or sustained competence. Longitudinal and usage-based evidence remains largely absent from the current literature.

Finally, although the included studies span multiple countries and regions, contextual diversity introduces additional caution in interpretation. Differences in institutional policies, access to generative AI tools, disciplinary practices, and cultural norms may shape adoption patterns in ways that are not fully captured within the aggregated evidence. As such, the findings should be interpreted as indicative of dominant empirical tendencies rather than as universally applicable conclusions across all higher education and TVET settings.

Taken together, these limitations delineate the analytical boundaries of the review and reinforce its diagnostic purpose. They also highlight critical gaps in the existing literature, particularly with respect to post-adoption behaviour and competence-oriented outcomes, which are central to understanding the educational implications of generative AI in skills-based learning environments.

Conclusion and Implications

This systematic literature review set out to diagnose how empirical research has examined students' voluntary adoption of generative artificial intelligence in higher education and TVET contexts. Drawing on 23 core student-only studies, the review did not seek to extend adoption theories or propose new explanatory models. Instead, it clarified how adoption outcomes have been measured, where empirical attention has been concentrated, and what can and cannot be claimed based on the existing evidence.

A central conclusion of this review is that the current evidence base is heavily intention centric. Behavioural intention dominates as the primary outcome across studies, while actual use and continuance-related outcomes remain underexamined. Although behavioural intention is frequently found to be a strong predictor when linked to use-related outcomes, the limited scope of post-adoption measurement restricts conclusions about sustained engagement and competence development. As a result, much of the literature captures willingness to use generative AI rather than demonstrated ability to use it effectively.

This imbalance has important implications for how adoption evidence is interpreted, particularly in skills-oriented and TVET contexts. Voluntary adoption should not be equated with readiness, and readiness should not be conflated with competence. Intention reflects attitudinal openness, not mastery. Without evidence of repeated, purposeful use, claims about the educational value of generative AI risk overstating students' preparedness for real-world application. From a diagnostic perspective, adoption does not imply skill readiness, and reported use does not necessarily indicate competence.

The review also highlights the need to reframe research questions guiding generative AI adoption studies. Rather than asking whether students intend to use generative AI, future research should focus on how voluntary use contributes to competence development, task performance, and work readiness. In TVET contexts, where learning outcomes are closely tied to practical capability, adoption research must move beyond intention formation to examine how generative AI becomes embedded in learning routines and skill-building processes.

For educational practice, these findings suggest caution in relying on intention-based indicators as evidence of successful generative AI integration. Institutions and educators should prioritise evaluation approaches that capture observable use patterns, task alignment, and sustained engagement. In voluntary use environments, the emphasis should shift from encouraging adoption to supporting competence-oriented applications of generative AI that align with hands-on learning objectives and occupational demands.

In conclusion, this review contributes by exposing an intention–behaviour gap within the existing adoption literature and by clarifying the boundaries of what current evidence can support. By reframing adoption as a process of competence development rather than a decision to use technology, the review provides a diagnostic foundation for more meaningful research and evaluation of generative AI in higher education and TVET contexts.

Acknowledgements:	Not applicable.
Funding Statement:	This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
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.
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.

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 29 (March 2026) PP. 163-182

Author Contribution Statement:	Mohd Badli Ramli initiated and led the research project, formulated the research questions, constructed the analytical framework, conducted the literature synthesis, and drafted the manuscript. Suhaizal Hashim provided critical supervision, strengthened the interpretative discussion, and contributed to enhancing theoretical integration within the manuscript. Mohd Zulfadli offered methodological insights, reviewed structural coherence, and contributed to improving the clarity of the research narrative. Aida Aisyah assisted in manuscript editing, formatting compliance with journal guidelines, reference cross-checking, and final proofreading prior to submission. All authors have read and approved the final manuscript.

References

Al-Okaily, M., Mater, W., Matar, N., & Shiyyab, F. S. (2025). Understanding of ChatGPT adoption among business school students. *Computers and Education: Artificial Intelligence*, 6, 100441. https://doi.org/10.1016/j.caeai.2025.100441

Amin, M. A., Kim, Y. S., & Noh, M. (2025). Unveiling the drivers of ChatGPT utilization in higher education sectors: The direct role of perceived knowledge and the mediating role of trust in ChatGPT. *Education and Information Technologies*. https://doi.org/10.1007/s10639-024-13095-y

Arthur, F., Salifu, I., & Abam Nortey, S. (2025). Predictors of higher education students' behavioural intention and usage of ChatGPT: The moderating roles of age, gender and experience. *Behaviour & Information Technology.* https://doi.org/10.1080/10494820.2024.2362805

Caner-Yıldırım, S. (2025). Modeling ChatGPT adoption among undergraduates: An integrated UTAUT2 and digital competence framework. *SAGE Open*. https://doi.org/10.1177/21582440251343340

Chopra, G., Bhaskar, P., Purohit, A., & Strzelecki, A. (2025). Unlocking ChatGPT's potential: A comparative study of student adoption intentions in higher education across India and Poland. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13536-2

G. C., S. G. C., Bhandari, P., Gurung, S. K., Srivastava, E., Ojha, D., & Dhungana, B. R. (2024). Examining the role of social influence, learning value and habit on students' intention to use ChatGPT: The moderating effect of information accuracy in the UTAUT2 model. *Cogent Education*, 11(1), 2403287. https://doi.org/10.1080/2331186X.2024.2403287

Gupta, S., & Priyanka, P. (2025). Navigating the path to ChatGPT adoption among Indian students: Unveiling the integration of UTAUT3 and TTF model. *VINE Journal of Information and Knowledge Management Systems*. https://doi.org/10.1108/VJIKMS-02-2024-0052

Moradi, H. (2025). Integrating AI in higher education: Factors influencing ChatGPT acceptance among Chinese university EFL students. *International Journal of Educational Technology in Higher Education*, 22, Article 30. https://doi.org/10.1186/s41239-025-00530-4

Mork, C.-M., Magelssen, M., & Nordheim, L. V. (2025). International perspectives on artificial intelligence in higher education: An explorative study of students' intention to use ChatGPT across the Nordic countries and the USA. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13492-x

Namatovu, A., & Kyambade, M. (2025). Leveraging AI in academia: University students' adoption of ChatGPT for writing coursework assignments through the lens of UTAUT2. *Cogent Education*, 12(1), 2485522. https://doi.org/10.1080/2331186X.2025.2485522

Polyportis, A., & Pahos, N. (2025). Understanding students' adoption of the ChatGPT chatbot in higher education: The role of anthropomorphism, trust, design novelty and institutional policy. *Behaviour & Information Technology*. https://doi.org/10.1080/0144929X.2024.2317364

Pratita, A., Suryanto, T. L. M., Pratama, A., & Wibowo, A. (2025). ChatGPT in education: Investigating students online learning behaviors. *International Journal of Information and Education Technology,* 15(3), 2262. https://doi.org/10.18178/ijiet.2025.15.3.2262

Rana, S., & Rai, P. (2025). Exploring student adoption of ChatGPT: An extended UTAUT2 framework analysis using structural equation modeling. *Journal of Applied Research in Higher Education.* https://doi.org/10.1108/JARHE-09-2024-0519

Sergeeva, O. V., Zheltukhina, M. R., Shoustikova, T., Tukhvatullina, L. R., Dobrokhotov, D. A., & Kondrashev, S. V. (2025). Understanding higher education students' adoption of generative AI technologies: An empirical investigation using UTAUT2. *Contemporary Educational Technology*. https://doi.org/10.30935/cedtech/16039

Siddiqui, T. M., Arifmiboy, Shaadan, N., Mohamed Shuhidan, S. M., & Lokman, A. M. (2025). Factors driving ChatGPT adoption in higher education: A UTAUT-based analysis of student behavioural intentions. *Asian Journal of University Education*, 21(1). https://doi.org/10.24191/ajue.v21i1.42

Singh, S., Singh, P., & Kaur, V. (2025). Understanding ChatGPT adoption among higher education students in Punjab, India: An application of UTAUT2 model. *International Journal of Technology-Enhanced Education*. https://doi.org/10.24310/ijtei.111.2025.20219

Sobaih, A. E. E., & Abu Elnasr, A. E. (2025). Battle of AI chatbots: Graduate students' perceptions of ChatGPT versus Gemini for learning purposes in Egyptian higher education. *Journal of Applied Research in Higher Education*. https://doi.org/10.37074/jalt.2025.8.1.7

Wang, H., & Wang, X. (2025). Enhancing translation accuracy and learning outcomes for low-resource languages: AI fine-tuning and learner adoption factors. *System*, 121, 103807. https://doi.org/10.1016/j.system.2025.103807

Xu, J., Li, Y., Shadiev, R., & Li, C. (2025). College students' use behavior of generative AI and its influencing factors under the unified theory of acceptance and use of technology model. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13508-6

Xu, X., & Thien, L. M. (2025). Unleashing the power of perceived enjoyment: Exploring Chinese undergraduate EFL learners' intention to use ChatGPT for English learning. *Journal of Applied Research in Higher Education*. https://doi.org/10.1108/JARHE-12-2023-0555

Yakubu, M. N., David, N., & Abubakar, N. H. (2025). Students' behavioural intention to use content generative AI for learning and research: A UTAUT theoretical perspective. *Education and Information Technologies.* https://doi.org/10.1007/s10639-025-13441-8

Yang, Y. (2025). Exploring factors influencing L2 learners' use of GAI-assisted writing technology: Based on the UTAUT model. *Computer Assisted Language Learning*. https://doi.org/10.1080/02188791.2025.2505664

Zhu, W., Huang, L., Zhou, X., Li, X., Shi, G., Ying, J., & Wang, C. (2025). Could AI ethical anxiety, perceived ethical risks and ethical awareness about AI influence university students' use of generative AI products? An ethical perspective. *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2024.2323277