Human–Technology Interaction in Generative AI: A Theoretical Review of Technology Acceptance and Cognitive Response

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***Abstract*—The rapid rise of Generative Artificial Intelligence (GenAI) has transformed the way humans interact with technology and has revealed cognitive mechanisms that extend beyond the explanatory scope of traditional technology acceptance models, such as the Technology Acceptance Model (TAM), Technology Acceptance Model 2 (TAM2), and the Unified Theory of Acceptance and Use of Technology (UTAUT). This theoretical review examines the combined role of the Technology Acceptance Model (TAM) and Cognitive Response Theory (CRT) in explaining GenAI-related user behaviors. The increasing involvement of GenAI in knowledge production triggers complex cognitive reactions, including cognitive trust, curiosity, ambivalence, epistemic suspicion, and resistance, which fundamentally shape technology acceptance processes. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, a systematic literature search was conducted in the Web of Science and Scopus databases. From 3,842 records published between 2014 and 2025, duplicates were removed, and the remaining studies underwent title–abstract and full-text screening. In the final stage, 69 publications were included in the review corpus. The findings indicate that, while perceived usefulness and perceived ease of use remain core determinants of GenAI adoption within the TAM framework, integrating CRT highlights the importance of deeper internal mechanisms, such as cognitive reappraisal, epistemic trust, algorithmic scepticism, cognitive load, and curiosity. Post-ChatGPT literature further emphasizes the influence of anthropomorphic cues and cognitive tension on user attitudes, trust calibration, and engagement. Overall, the combined application of TAM and CRT provides a more comprehensive theoretical lens for understanding GenAI interactions by concurrently capturing cognitive, emotional, and behavioural processes. This integrative approach offers a comprehensive lens for understanding cognitive, emotional, and behavioral processes in GenAI interactions.**

Keywords*—*Generative Artificial Intelligence; Technology Acceptance Model; Cognitive Response Theory; Human-AI Interaction; cognitive trust

I. Introduction

A. *The Rise of Generative Artificial Intelligence Systems*

The rapid advancement of artificial intelligence technologies throughout the 2020s has ushered in a new era marked by the emergence of Generative Artificial Intelligence (GenAI). Unlike traditional analytical AI systems, GenAI models are capable of processing existing data and generating novel content, including text, images, audio, and software code. Prominent examples include ChatGPT, Copilot, Gemini, Midjourney, and Stable Diffusion. These systems extend human cognitive and creative capacities and fundamentally reshape the nature of digital production (Goodfellow et al. [28]; Şahin ve Kardaş [80]). As a result, human–technology interaction has shifted from passive information consumption to collaborative co-creation processes (Shneiderman [77]; Vaswani et al. [87]).

This transformation has triggered substantial cognitive restructuring in how individuals access information, learn, create, and make decisions (Brynjolfsson and McAfee [10]). In educational contexts, for instance, GenAI personalizes learning experiences and simultaneously raises concerns related to cognitive trust, ethical awareness, and critical thinking (Kasneci et al. [42]; Gökçe ve Atik [29]). Despite these advantages, GenAI also introduces cognitive and ethical risks. Overreliance on AI-generated outputs may increase susceptibility to authority bias and weaken reflective judgment (Mitchell and Krakauer [60]; Karagöz [41]). Uncertainties regarding the accuracy, transparency, and accountability of AI-generated content further challenge established mechanisms of cognitive trust (Bender et al. [8]). Accordingly, explaining GenAI adoption requires moving beyond purely behavioral approaches and incorporating cognitive responses, trust, and curiosity into analytical frameworks.

Today, individuals increasingly act as cognitive partners who actively think with, question, and interpret AI systems (Şen [81]). The rise of GenAI, therefore, represents not only a technological milestone but also a profound cognitive transformation that necessitates theoretical models capable of integrating technology acceptance with cognitive evaluation processes.

B. *Technology Acceptance Model (TAM), TAM2 and UTAUT*

The Technology Acceptance Model (TAM), originally developed by Davis [18], is one of the most influential frameworks for explaining individuals' intentions to adopt new technologies. Its core constructs—perceived usefulness and perceived ease of use—shape user attitudes and behavioral intentions, positioning TAM as a foundational model in information technology adoption research (Dülek et al. [23]; Özdemir ve Yolcu [65]). TAM has been extensively validated across diverse domains, including education (McIlroy et al. [57]), e-government (Özdemir ve Yolcu [65]), mobile commerce (Erdoğan [27]; Kurtuldu ve Seyhun [46]), and health informatics (Sançar ve Kayserili [73]).

Subsequent extensions led to the development of Technology Acceptance Model 2 (TAM2), which incorporated social influence, voluntariness, experience, and job relevance as additional determinants of perceived usefulness (Venkatesh and Davis [88]). Building on this evolution, the Unified Theory of Acceptance and Use of Technology (UTAUT) integrated performance expectancy, effort expectancy, social influence, and facilitating conditions into a unified explanatory framework (Venkatesh et al. [89]). UTAUT has demonstrated strong explanatory power in contexts such as mobile banking, healthcare, and public services (Erdoğan [26]; Pournik et al. [68]).

However, recent research suggests that traditional acceptance models exhibit important limitations when applied to interaction-based technologies such as GenAI (Ammenwerth [5]; Lee et al. [48]).

- Cognitive reflection and thought processes remain largely external to these models.
- Psychological factors such as trust, curiosity, and emotional responses are treated indirectly rather than as core components.
- Users are primarily conceptualized as behavioral decision-makers rather than cognitive actors.

Consequently, explaining GenAI adoption necessitates enriching TAM and UTAUT with cognitive response-oriented perspectives capable of capturing reflective thinking, trust formation, and evaluative mental processes. Empirical evidence in higher education further suggests that trust should be treated as a foundational (preceding) construct in GenAI adoption. In particular, Strzelecki [79] shows that trust in ChatGPT significantly shapes behavioral intention and precedes traditional acceptance evaluations in the adoption process.

C. Cognitive Response Theory (CRT)

Cognitive Response Theory (CRT), originally introduced by Greenwald [30], posits that individuals generate cognitive reactions—favorable, unfavorable, or neutral—when exposed to persuasive stimuli, and that these internally generated thoughts play a central role in attitude formation and persuasion outcomes. Subsequent work by persuasion researchers further elaborated this perspective by emphasizing that message recipients are active processors who construct internal thoughts, counterarguments, and evaluations rather than passively receiving information (Cacioppo and Petty [13]; Petty et al. [66]; Eagly and Chaiken [24]).

CRT has served as the conceptual foundation for influential persuasion models, including the Elaboration Likelihood Model (ELM) and the Heuristic–Systematic Model (HSM). Owing to its focus on internal thought generation and evaluative processing, CRT has been widely applied across psychology, marketing, political communication, health communication, and educational research.

Within the context of GenAI, cognitive responses are elicited not by static messages but by dynamic, personalized, and context-sensitive interactions. Users continuously evaluate the accuracy, coherence, ethicality, and relevance of AI-generated outputs through ongoing cognitive reflection. These evaluations shape trust, reliance, skepticism, and learning-related outcomes (Riley et al. [70]). Accordingly, CRT offers a powerful theoretical lens for understanding how users interpret, question, and mentally respond to GenAI systems.

D. Need for Theoretical Integration

Taken together, the existing body of research indicates that prior studies on Generative Artificial Intelligence have largely developed along two parallel yet weakly connected streams. One stream primarily applies Technology Acceptance Model–based frameworks to explain GenAI adoption by focusing on perceived usefulness, perceived ease of use, and behavioral intention (Davis [18]; Venkatesh and Davis [88]; Venkatesh et al. [89]). These approaches offer valuable insights into adoption outcomes and usage intentions, yet they tend to conceptualize users mainly as rational decision-makers and provide limited explanations of how users cognitively interpret, evaluate, and respond to GenAI outputs (Ammenwerth [5]; Lee et al. [48]).

A second stream concentrates on cognitive, ethical, and trust-related dimensions such as epistemic trust, cognitive load, curiosity, ambivalence, and skepticism (Petty et al. [66]; Riley et al. [70]; Bender et al. [8]). Although these studies provide rich accounts of internal mental processes, they often examine such mechanisms in isolation and do not systematically integrate technology acceptance structures (Chen et al. [16]; Christodoulou and Zembylas [17]). From a broader cognitive perspective, meaning-making processes are inherently interpretive and context-dependent, suggesting the need for more integrated theoretical frameworks (Tunç ve Görmez [84]). As synthesized through the systematic review process and the classifications presented in Table IV to Table VII, the current literature lacks a comprehensive framework capable of jointly explaining acceptance behaviors and cognitive response mechanisms in the post-ChatGPT context.

The present study addresses this gap by positioning itself as an integrative theoretical review that systematically combines Technology Acceptance Model perspectives with Cognitive Response Theory to capture acceptance evaluation and cognitive–affective processes within a unified analytical lens.

II. Research Questions and Purpose

The primary purpose of this review is to systematically analyze how the Technology Acceptance Model (TAM, TAM2, UTAUT) and Cognitive Response Theory have been used to explain user interaction with generative artificial intelligence systems. By examining the applications, variable structures, and integration potential of these two theoretical perspectives within the GenAI domain, the study seeks to develop a conceptual synthesis that reflects the cognitive, emotional, and behavioral complexity of contemporary AI-mediated interactions.

Traditional Technology Acceptance Models (e.g., TAM, UTAUT) offer strong explanatory power for users' rational attitudes and behavioral intentions toward technology. In contrast, CRT provides insights into individuals' cognitive reactions, trust formation, counter-arguing, and critical evaluation processes. Since GenAI systems shape user interaction not only functionally but also emotionally, ethically, and cognitively, an integrative approach combining TAM and CRT holds significant potential for developing a more comprehensive understanding of user behavior. Thus, the overarching aim of this study is not merely to summarize the existing literature but to conceptually assess the intersection of TAM and CRT, and evaluate their integrability in the GenAI era.

Accordingly, the specific objectives of this study are as follows:

- O1: To identify which variables, contexts, and technological platforms (e.g., ChatGPT, Copilot, Gemini) are associated with the application of TAM, TAM2 and UTAUT in explaining user interaction with generative AI systems.
- O2: To examine how Cognitive Response Theory has been applied in GenAI research, and how users' cognitive, emotional, and ethical responses to AI-generated outputs have been categorized.
- O3: To evaluate how these two theoretical approaches (TAM/UTAUT and CRT) complement each other and under which conditions they can form an integrative explanatory framework.
- O4: To identify theoretical and methodological gaps in the literature and propose future directions regarding model development, scale construction, and experimental designs.

Based on these aims, the following research questions were formulated:

- RQ1: How have TAM Models (TAM1, TAM2, UTAUT) been used in GenAI-Focused Studies?
- RQ2: To what extent have cognitive response theory (CRT) and other cognitive/emotional reactions been addressed in GenAI-Focused Studies?
- RQ3: What conceptual shifts, user responses, and new variables have emerged in GenAI interactions in the post-ChatGPT period (2022–2025)?
- RQ4: Have TAM and the Cognitive Response Approach been used together, and which theoretical frameworks do such studies adopt?
- RQ5: What theoretical and practical benefits can be gained from integrating TAM and the cognitive response approach in explaining GenAI interactions?

III. METHODOLOGY

This study is a systematic review and a meta-analysis–based conceptual analysis that examines the literature on the Technology Acceptance Model (TAM, TAM2, UTAUT) and Cognitive Response Theory within the context of GenAI systems. The primary objective is to determine how these two theories have been applied individually and in an integrated manner, to analyze the new concepts and variables emerging in the post-ChatGPT period, and to develop theoretical orientation proposals for future research.

In this respect, the study not only summarizes the existing literature but also aims to achieve a theoretical synthesis by discussing how technology acceptance and cognitive response processes can be reinterpreted within an integrative model framework.

A. Literature Search Strategy

In this study, a systematic review approach was adopted and structured in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The literature search covered international peer-reviewed academic journals published between 2014 and 2025. The year 2014 was selected as the starting point because the introduction of the Generative Adversarial Networks (GANs) architecture by Goodfellow et al. [28] marked the institutionalization of modern generative artificial intelligence research.

The search process was conducted in the Web of Science (WoS) Core Collection and Scopus databases, using both narrow and expanded keyword strings to reach comprehensive literature on generative artificial intelligence, technology acceptance models, and cognitive response theory. Searches were performed across all text fields (Title, Abstract, Author Keywords, Keywords Plus), and only studies containing terms such as "generative artificial intelligence", "GenAI", "ChatGPT", and "Large Language Models (LLMs)" were included.

These core GenAI terms were combined using the AND operator with technology-acceptance–related concepts ("technology acceptance model", "TAM", "perceived usefulness", "perceived ease of use", "attitude toward use", "behavioral intention") and cognitive-response concepts ("cognitive response theory", "cognitive response", "trust", "curiosity"). The search strings are presented in Table I. The literature search was conducted on WoS and Scopus, and studies of a similar nature but not focused on GenAI were excluded. Access to full texts and construction of the dataset were completed between December 2024 and July 2025.

TABLE I. SEARCH STRINGS USED TO SEARCH DATABASES

Topic	Search string
Generative Artificial Intelligence	"generative artificial intelligence" OR "generative AI" OR "GenAI" OR "ChatGPT" OR "large language model" OR "LLM"
AND	
Technology Acceptance & Cognitive Response Concepts	("technology acceptance model" OR "TAM" OR "perceived usefulness" OR "perceived ease of use" OR "behavioral intention" OR "attitude toward use") AND ("cognitive response theory" OR "cognitive response") AND ("trust" OR "curiosity")

Within the scope of the study, only open-access, peer-reviewed, and primary research articles were included. The search results were systematically transferred into Excel, and the retrieved records were categorized into eight separate Excel files based on the thematic scope of the research. These files were subsequently merged into a single unified dataset, and duplicate studies were removed to obtain a set of unique records.

The remaining studies were independently evaluated by two researchers. The screening process was conducted sequentially at the title, abstract, and full-text levels, and any disagreements were resolved through discussion. As a result of the eligibility assessment, a total of 69 studies were included for detailed analysis.

B. Inclusion and Exclusion Criteria

In this systematic review, the inclusion and exclusion process was defined in accordance with PRISMA guidelines. The selection of studies was conducted based on specific theoretical, methodological, and accessibility criteria. The aim was to evaluate the relationship between generative artificial intelligence, technology acceptance, and cognitive responses solely through findings obtained from primary empirical research.

1) Inclusion Criteria:

TABLE II. INCLUSION CRITERIA BY CATEGORY

Category	Inclusion Criterion
Scope	The study must examine user interactions with GenAI and include terms such as "generative artificial intelligence," "GenAI," "ChatGPT," or "LLM."
Topic Focus	The study must evaluate concepts within the framework of technology acceptance and cognitive responses (CRT, cognitive response, trust, curiosity).
Theoretical Coverage	The study must include at least one core concept related to technology acceptance theories (TAM components: perceived usefulness, perceived ease of use, attitude, behavioral intention) AND at least one concept associated with the cognitive response approach.
Study Type	Only primary research articles (quantitative, qualitative, or mixed-methods) are included; reviews, editorials, opinion pieces, and conference abstracts are excluded.
Access Type	Only peer-reviewed and full-text accessible articles are included.
Language of Publication	The study must be published in English.
Publication Period	Articles published between 2014 and 2025 are included.

2) Exclusion Criteria:

TABLE III. EXCLUSION CRITERIA BY CATEGORY

Category	Exclusion Criterion
Out-of-scope	Studies not related to generative artificial intelligence (GenAI), or focused solely on classical artificial intelligence / machine learning; studies that do not include the terms "generative artificial intelligence," "GenAI," "ChatGPT," or "LLM" were excluded.
Topic Exclusion	Studies that do not address technology acceptance models (TAM components) or cognitive responses (CRT, cognitive response, trust, curiosity) were excluded.
Theoretical Exclusion	Studies that do not provide a theoretical framework related to technology acceptance, user behavior, or cognitive responses; studies focusing only on technical models, algorithms, or system performance were excluded.
Study Type Exclusion	Review articles, meta-analyses, editorials, book chapters, opinion papers, conference abstracts, short papers and studies without full-text access were excluded.
Access Exclusion	Non–peer-reviewed studies, studies without full-text availability, or archival/document-based works were excluded.
Language Exclusion	Studies published in languages other than English were excluded.
Publication Period Exclusion	Articles published before 2014 were excluded from the scope of the review.

C. Data Collection and Coding Process

The inclusion and exclusion procedures applied in this systematic review were conducted in accordance with the PRISMA flow diagram standards, and the process is summarized in Fig. 1. All records retrieved from the literature search were organized within an Excel-based data management system. Eight separate Excel files created for each search theme were later merged to form a single master dataset. In the initial stage, a total of 3,842 records were retrieved from the Web of Science (n = 2,446) and Scopus (n = 1,396) databases; duplicate records were removed, eliminating 806 repeated studies from the dataset. After this step, 3,036 studies proceeded to the title and abstract screening phase.

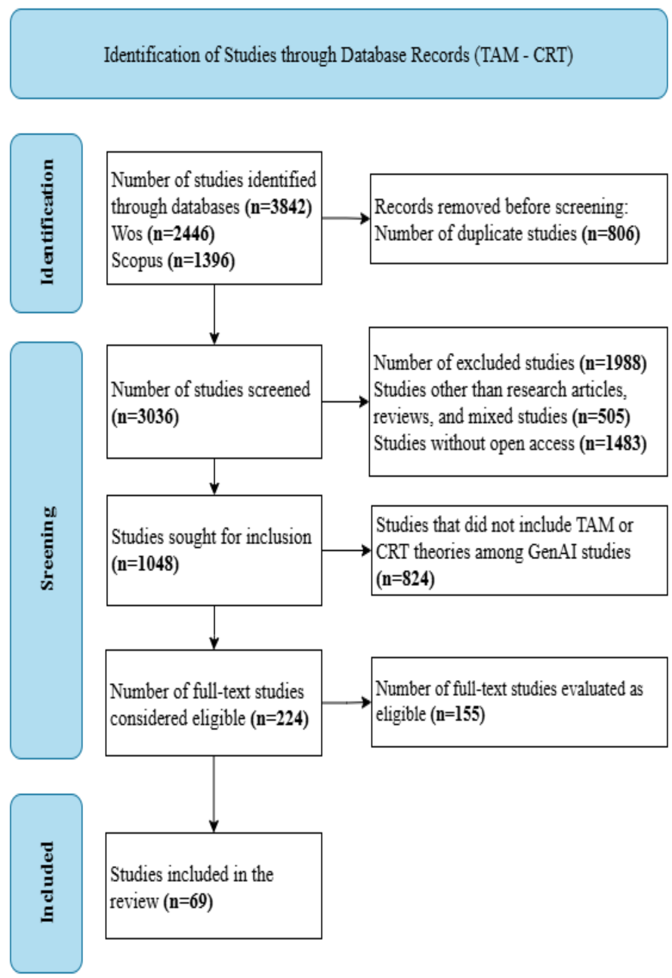

Fig. 1. PRISMA 2020 flow diagram.

In the second stage, studies not meeting the exclusion criteria listed in Table III were removed. Documents that were not research articles, editorials, review papers, records without full-text access and out-of-scope studies were excluded, resulting in the removal of 1,988 studies. Subsequently, the inclusion criteria defined in Table II were applied. Although GenAI-focused, 824 studies were excluded because they did not contain variables related to technology acceptance models (TAM components) or concepts associated with the cognitive response approach (CRT, cognitive response, trust, curiosity). After these steps, the number of studies eligible for full-text review was finalized as 224.

The full-text evaluation process was conducted independently by two researchers; studies were compared based on their alignment with the GenAI–TAM–CRT framework. Discrepancies were resolved through discussion. As a result of this evaluation, 155 studies that did not meet the criteria for theoretical integration were excluded, and a total of 69 studies were included in the final review. The included studies were entered into a coding table containing variables such as "author(s)", "article title", "publication year", "DOI", "short content summary", and "alignment with the GenAI–TAM–CRT framework". This table enhanced the comparability of the studies and ensured consistency throughout the review analysis.

IV. FINDINGS

A. RQ1: How have TAM Models (TAM1, TAM2, UTAUT) been used in GenAI-Focused Studies?

The consolidated Table IV shows that studies conducted within the GenAI domain largely preserve the theoretical core of the Technology Acceptance Model while simultaneously expanding it with psychological, pedagogical, and social components required by different contexts and user groups. Across all 41 reviewed studies, perceived usefulness (PU) and perceived ease of use (PEOU) remain central constructs for explaining GenAI adoption; these variables consistently emerge as the primary predictors of behavioral intention among students, educators, healthcare professionals, pharmacists, software engineers, and consumers. This continued reliance on PU and PEOU—despite GenAI's dynamic, creative, and nontraditional nature—demonstrates that TAM remains a stable reference framework for modeling technology acceptance. However, the table also makes clear that TAM is rarely used in its "pure" form in GenAI-related research. GenAI systems introduce interactive, unpredictable, creative, and sometimes risk-laden experiences, meaning users interpret these technologies not only through cognitive appraisals (usefulness and ease of use) but also through emotional, ethical, social, and pedagogical evaluations. For this reason, most studies expand TAM with additional variables tailored to the specific context. For example, studies involving faculty members enrich TAM with AI literacy, TPACK, trust, self-efficacy, and instructional fit [21], [31], [35], [43], [50], [52], [64], [75], [83], [96]. These works demonstrate that pedagogical competence, ethical awareness, and trust shape GenAI acceptance beyond the classical PU–PEOU mechanism.

Similarly, studies conducted in consumer and service environments—such as GenAI-supported clothing customization—extend TAM with enjoyment, trust, perceived risk, social influence, and experiential quality [17], [36]. These constructs reflect emotional and social dimensions of GenAI use, including concerns about uncertainty, authenticity, human-like interaction, and the balance between craftsmanship and automation. In such contexts, behavioral intention cannot be fully explained through cognitive evaluations alone, making emotional and experiential constructs essential extensions of the model.

A further pattern illustrated in the table is TAM's hybridization with additional theoretical frameworks. In higher education research, TAM is frequently integrated with TTF, UTAUT, TPB, SRL, SDT, and motivational self-system models [2], [25], [36], [39], [45], [47], [49], [52], [59], [76], [78], [86], [95]. These hybrid models highlight the need to understand GenAI not merely as a technological tool but as a pedagogical, psychological, and social actor. For instance, motivational self-system variables are integrated into PU and PEOU in language learning contexts [36], while studies involving preservice teachers demonstrate that self-efficacy and professional identity meaningfully expand TAM [31], [52].

The diversity of empirical contexts represents another critical finding. GenAI acceptance is examined not only in higher education but also across health sciences, pharmacy, consumer markets, software engineering, public communication, and doctoral research writing. This diversity indicates that TAM's use as a "general-purpose framework" in GenAI studies is not merely a preference but a methodological necessity. For example, GenAI is perceived as an "assistant", "collaborator", or "replacement" in software engineering; large-scale public opinion studies categorize attitudes toward GenAI [56]; and doctoral students' ethical dilemmas concerning GenAI use in academic writing are systematically analyzed [69].

Finally, Table IV shows that GenAI adoption occurs within a far more complex and multi-layered environment than traditional information systems. Although PU and PEOU remain foundational, GenAI introduces constructs such as autonomy concerns, creative control, ethical ambiguity, trust requirements, social comparison, instructional alignment, and task–technology fit. These contextual features necessitate expanding TAM with new domain-specific factors. Overall, the consolidated evidence demonstrates that, in the context of generative AI, the technology acceptance model has evolved into a flexible and adaptive analytical framework. While the structural core of TAM—perceived usefulness and perceived ease of use—remains essential, contemporary GenAI research consistently expands the model with context-specific cognitive, emotional, ethical, and social constructs. These extensions, along with frequent integrations of complementary theories, allow TAM to capture the multi-layered, interactive, and sometimes unpredictable nature of GenAI systems. This shift suggests that understanding GenAI acceptance requires models that go beyond classical rational evaluation and incorporate the dynamic cognitive and socio-emotional mechanisms shaping user interaction.

TABLE IV. TECHNOLOGY ACCEPTANCE–ORIENTED STUDIES ON GENERATIVE AI

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T4-01	[59]	Mirriahi et al.	TAM + Self-Regulated Learning	Education	SRL–TAM integration
T4-02	[3]	Almeida et al.	Technology Acceptance Model	Recruitment	Professional GenAI acceptance
T4-03	[33]	Haddad et al.	TAM + User Experience	Urban design	Interface usefulness
T4-04	[4]	Alshamy et al.	TAM (mixed-methods extension)	Clinical education	Clinical GenAI adoption
T4-05	[1]	Al-Abdullatif	TAM + Trust + Intelligent TPACK	Faculty	AI literacy and trust
T4-06	[37]	Huang et al.	TAM + Trust + Enjoyment	Consumers	Trust-driven adoption
T4-07	[64]	Nevárez Montes & Elizondo-Garcia	TAM + Theory of Reasoned Action	Higher education	Acceptance pathways
T4-08	[85]	Ursavaş et al.	TAM + Self-efficacy + Social norms	Students	Peer-driven norms
T4-09	[61]	Mohamed et al.	TAM + Anxiety + Social influence	Education	Anxiety effects
T4-10	[2]	Almassaad et al.	TAM + Task–Technology Fit	Students	Task–technology fit
T4-11	[72]	Sallam et al.	TAM + Risk + Psychosocial factors	ChatGPT users	Risk perception
T4-12	[75]	Shata & Hartley	TAM + Social Cognitive Theory	Academics	Trust-based policy views
T4-13	[14]	Calleja & Camilleri	TAM (qualitative lens)	Teachers	Qualitative perceptions
T4-14	[4]	Alshamy et al.	Technology Acceptance Model	University	Group comparison
T4-15	[94]	Xiao et al.	TAM + Task–Technology Fit	Sustainability education	Sustainability-oriented use
T4-16	[19]	Dekerlegand et al.	Technology Acceptance Model	Health sciences	Ethics-focused training
T4-17	[52]	Liu et al.	TAM + Self-efficacy	Pre-service teachers	Pedagogical readiness
T4-18	[17]	Christodoulou & Zembylas	TAM + Ethical framework	Education	Emotional–ethical dimensions

B. RQ2: To what Extent have Cognitive Response Theory (CRT) and other Cognitive/Emotional Reactions been addressed in GenAI-Focused Studies?

An examination of CRT-related articles shows that the explicit use of cognitive response theory under its formal name is relatively rare in the GenAI literature. However, the core assumptions of CRT—internal evaluation, mental argumentation, cognitive reframing, and cognitive processing—are widely embedded across studies, as summarized in Table V. The first cluster of work demonstrates that cognitive trust, risk assessment, and epistemic filtering mechanisms prominently shape user responses during GenAI interaction. Studies explaining cognition-based trust and risk modeling in innovation contexts [38], systematically analyzing trust, reliance, and resistance among students [67], and demonstrating how cognitive trust emerges from perceptions of fairness, transparency, and accountability [91] all reveal the production of pro–con arguments, mental modeling of risk, and cognition-based trust—processes that lie at the heart of CRT. Similarly, research centering epistemic trust [74] shows that cognitive filters toward information sources determine trust in ChatGPT, while work examining transparency and ethical signals [15] demonstrates that such cues reduce counter-arguments generated by users. Together, these studies affirm GenAI's strong capacity to trigger cognitive responses. A second group of studies focuses on the cognitive mechanisms that GenAI accelerates or burdens within learning environments. CATLM-based research assessing the interaction between cognitive processing depth and emotional response [55], studies using cognitive presence to show how ChatGPT influences cycles of critical thinking and inquiry [63], and work examining cognitive and emotional reappraisal jointly [96] illustrate how GenAI activates CRT-like inner thought processes during learning—revision, inference-making, restructuring, and doubt generation. In contrast, studies modeling cognitive overload and burnout caused by extensive GenAI use [22], research showing that over-reliance on GenAI undermines active learning processes [12], and analyses distinguishing between deep and superficial cognitive effort [44] highlight the negative dimension of cognitive responses. These findings indicate that GenAI use is linked not only to technology acceptance but also to conflicting processes such as cognitive ease versus excessive cognitive load.

A third cluster addresses cognitive reactions in service and consumer contexts, where pre-existing beliefs, mental models, and service-switching intentions guide user evaluations. Studies showing that prior beliefs shape cognitive reactions to GenAI service failures [55], that the risk–trust–intention chain is influenced by the perceived accuracy of AI-generated health information [32], and that multidimensional trust structures are tied to behavioral outcomes [20] demonstrate how expectations, assumptions, and mental frameworks determine the direction of cognitive responses. These patterns reveal that the same GenAI stimulus can produce highly divergent cognitive outcomes across individuals—tolerance, resistance, abandonment, or re-evaluation.

TABLE V. COGNITIVE AND TRUST-ORIENTED FRAMEWORKS IN GENERATIVE AI RESEARCH

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T5-01	[67]	Piller et al.	Socio-technical system + Trust/Risk	Innovation systems	Trust–risk dynamics in innovation
T5-02	[90]	Wang et al.	SOR + Trust Calibration + TRA	Students / GenAI use	Cognitive trust–distrust responses
T5-03	[38]	Huynh & Aichner	FAT framework	Trust formation	Transparency–fairness–trust link
T5-04	[1]	Al-Abdullatif	TAM + Trust + Intelligent TPACK	Teachers	Trust-based GenAI acceptance
T5-05	[32]	Guo et al.	Uncertainty Reduction Theory	Health information (ChatGPT)	Cognitive reframing of trust
T5-06	[20]	Đerić et al.	Multidimensional Trust Model	GenAI systems	Trust dimension differentiation
T5-07	[74]	Schäfer et al.	Epistemic Trust	Science vs. ChatGPT	Source credibility effects
T5-08	[15]	Calzada et al.	Trustworthy AI Framework	Ethics & transparency	Managing cognitive counter-arguments
T5-09	[96]	Zou et al.	CATLM	GenAI feedback	Cognitive–affective processing
T5-10	[63]	Nasr et al.	CoI (Cognitive Presence)	Critical thinking	Deep cognitive engagement
T5-11	[55]	Ma et al.	Cognitive–Affective Model	Adaptation processes	Joint cognitive–affective evaluation
T5-12	[22]	Dong et al.	Cognitive Load Theory	Burnout & overload	Cognitive load–burnout cycle
T5-13	[53]	Lv et al.	Mental Models + Beliefs	User reactions	Belief-driven cognitive switching
T5-14	[44]	Klar	Cognitive Load + Adaptation	ChatGPT use	Shallow vs. deep processing
T5-15	[37]	Huang et al.	TAM + Cognitive–Emotional–Social Model	User intention	Integrated acceptance mechanisms

In sum, the reviewed articles ([10], [15], [20], [22], [32], [38], [44], [53], [55], [63], [67], [74], [91], [96]) demonstrate that although CRT has rarely been employed explicitly in GenAI studies, its core sequence—stimulus → cognitive evaluation → behavioral outcome—is reflected across numerous disciplines in different forms. Cognitive trust, cognitive load, cognitive presence, mental models, preconceived beliefs, and cognitive dependency all represent distinct facets of the internal cognitive responses triggered by GenAI stimuli. Collectively, these findings indicate that CRT provides an implicit yet powerful foundation for understanding cognitive mechanisms in GenAI interactions and that future GenAI research can benefit from more explicit and comprehensive CRT-based modeling.

C. RQ3: What Conceptual Shifts, user Responses, and New Variables have emerged in GenAI Interactions in the Post-ChatGPT Period (2022–2025)?

A review of post-2022 ChatGPT-based studies shows a marked transformation in both the theoretical framing of GenAI interactions and the nature of user responses. The most salient feature of this period is the shift from explaining GenAI use solely through technology acceptance models to conceptualizing it increasingly through multilayered processes, including cognitive evaluation, emotional response, moral positioning, institutional security perceptions, anthropomorphic cues, and algorithmic skepticism, as synthesized in Table VI. First, the structure of trust in GenAI systems has been substantially redefined. Across applications ranging from supply chains to institutional data responsibility communication, trust is conceptualized not merely as an assessment of technical accuracy but as a cognitive evaluation anchored in transparency, accountability, institutional responsibility, and data justice [6], [7], [51], [67].

During this period, trust depends not only on perceptions of output accuracy but also on beliefs about system intention, ethical integrity, institutional governance, and the balance of human–AI authority. For example, studies show that clinicians express stronger trust when GenAI is framed not as an authority that replaces judgment but as a secondary cognitive aid supporting human reasoning [32]. Similarly, institutional data responsibility and stakeholder involvement strengthen trust by shaping users' perceptions of algorithmic intention and organizational fairness [51].

Second, a large portion of recent research focuses on cognitive skepticism, ambivalent emotional states, and trust–resistance cycles emerging from GenAI interactions. Studies in educational and consumer contexts demonstrate that individuals simultaneously generate positive and negative internal arguments when encountering GenAI outputs. Ambivalence in student responses to ChatGPT reflects the co-activation of cognitive assessments regarding both academic usefulness and ethical/security risks [17], [58], [75]. Likewise, consumers evaluating human-produced versus GenAI-produced digital outputs exhibit algorithm aversion, driven by cognitive schemas suggesting that GenAI may err, misinterpret context, or lack aesthetic intention [71]. These findings indicate that users' judgments are shaped not simply by performance but by cognitive evaluations of whether the system possesses human-like qualities, intentionality, and accountability [11], [82], [86].

Third, the 2022–2025 literature highlights the emergence of new cognitive reaction variables triggered by GenAI use. Concepts such as reliance and resistance have been systematically modeled for the first time in GenAI contexts [91], marking a shift toward more nuanced explanatory frameworks. Studies show that high trust can lead to over-reliance that weakens critical filtering, while low trust triggers avoidance and rejection. This trust calibration perspective reveals that users evaluate GenAI outputs not only in terms of accuracy but also in relation to cognitive autonomy and perceived control.

Fourth, the concept of curiosity has been reconceptualized. Before 2022, curiosity was typically viewed as a stable cognitive trait; however, post-ChatGPT studies show that GenAI interactions can either suppress or stimulate curiosity depending on usage patterns. In STEM contexts, excessive dependence on GenAI can weaken curiosity, whereas integration with inquiry-based or problem-based learning enhances deeper cognitive exploration [38]. Similar patterns appear in design and creative fields, where trust in GenAI interacts with creativity and curiosity: some users perceive GenAI as a tool that enhances creative exploration, while others frame it as a ready-made answer engine that threatens originality [93].

Fifth, several studies analyze how anthropomorphic representations—such as "friendly helper" or "digital assistant"—reshape user cognition [86]. Anthropomorphic cues serve as powerful cognitive triggers that influence user expectations and trust. For some users, these cues generate excessive trust and emotional closeness; for others, they provoke concerns about manipulation or system intention. This suggests that linguistic framing in GenAI systems acts as a cognitive anchor comparable in importance to system performance.

Finally, research examining misinformation and verification processes demonstrates that user perceptions of GenAI are increasingly guided not by classical technology acceptance factors but by constructs such as perceived security, source transparency, institutional responsibility, traceability, and moral agency [40], [51]. This shift indicates that post-ChatGPT GenAI interactions are examined through dimensions of cognitive ethics, institutional trust, moral evaluation, and epistemic accuracy rather than only through performance-based acceptance models.

Overall, the 2022–2025 literature reveals that GenAI interaction has evolved from a technological innovation into a multifaceted phenomenon that reorganizes users' cognitive schemas and reshapes foundational psychological processes such as trust and curiosity. Studies indicate that GenAI can enrich critical thinking while simultaneously fostering automated cognitive shortcuts; strengthen trust while also generating institutional skepticism; stimulate curiosity while also risking its suppression. Consequently, post-ChatGPT GenAI research conceptualizes cognitive responses not as linear outcomes but as dynamic, multidimensional processes shaped by context and system design choices.

TABLE VI. CONTEXTUAL AND COGNITIVE PERSPECTIVES ON TRUST IN GENERATIVE AI

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T6-01	[7]	Bai et al.	Supply chain trust; GenAI–blockchain synergy	Agricultural supply chains	Quality trust via GenAI–blockchain
T6-02	[6]	Azeez & Adeate	Trust norms; data justice; AI ethics	Data governance (Africa)	Trust norms and skepticism
T6-03	[62]	Munir et al.	ML-based trust management	6G networks	Perceived reliability
T6-04	[17]	Christodoulou & Zembylas	Emotion theory; ambivalence	University students	Dual cognitive responses
T6-05	[93]	Wu & Liu	Achievement emotions framework	Informal speaking practice	Emotion-driven engagement
T6-06	[92]	Wang et al.	Technology acceptance + personality traits	Gen Z designers	Mixed cognitive reactions
T6-07	[71]	Rix et al.	Algorithm aversion / discounting theory	Digital products	Algorithm aversion
T6-08	[86]	Van Es & Nguyen	Anthropomorphism; social presence	AI framing	Over-/under-trust effects
T6-09	[75]	Shata & Hartley	Technology acceptance + communication framework	Faculty adoption	Cognitive tension in adoption
T6-10	[67	Piller et al.	Innovation management; trust & risk	GenAI-enabled innovation	Context-sensitive trust
T6-11	[91]	Wang et al.	SOR + trust calibration	GenAI use	Reliance–resistance pathway
T6-12	[9]	Borden et al.	Media ethics; moral agency	GenAI–media relations	Moral agency attribution
T6-13	[40]	Jaidka et al.	Misinformation + perceptual cognition	Information ecosystems	Trust–misinformation duality
T6-14	[51]	Lim et al.	Stakeholder theory	Institutional GenAI systems	Participatory trust building
T6-15	[54]	Lyu et al.	Usage practices; trust/distrust	Faculty practices	Coexisting trust–distrust
T6-16	[34]	Hayudini et al.	Inquiry-based learning; curiosity	STEM education	Curiosity-sustaining practices

D. RQ4: Have TAM and the Cognitive Response Approach been used together, and which Theoretical Frameworks do such studies adopt?

The systematic review indicates that although technology acceptance models are widely used in GenAI-focused research, their integration with the cognitive response approach remains highly limited. Most studies employing TAM or extended TAM frameworks continue to emphasize traditional constructs such as perceived usefulness, perceived ease of use and behavioral intention, while cognitive or cognitive–affective evaluation processes are typically examined under separate theoretical lenses. Within the reviewed dataset, only three studies were identified that explicitly combine TAM and the cognitive response approach within a single theoretical model, as summarized in Table VII. This highlights a notable conceptual gap in the GenAI literature.

The first of these studies is conducted by Ma et al. [55], who integrate the Extended TAM with the cognitive–affective model to examine how GenAI-induced cognitive reappraisal and perceived empathy contribute to sociocultural adaptation. Their findings indicate that cognitive responses are not merely supplementary to technology-use intentions but constitute fundamental mechanisms that enhance explanatory power. This demonstrates how cognitive and affective processes can strengthen TAM structures in GenAI contexts. The second study, Zou et al. [96], combines TAM with the cognitive–affective theory of learning (CATLM) to investigate how GenAI-based visualized feedback influences students' writing processes. The results show that GenAI feedback affects not only perceived usefulness but also deeper responses such as cognitive willingness and emotional reactions. This work underscores the potential of integrating cognitive response mechanisms into TAM to yield richer models of GenAI acceptance in learning environments. The third study, Huang et al. [36], focuses on consumer behavior and unites TAM with cognitive–emotional evaluation constructs. In GenAI-supported personalized services, behavioral intention is shown to derive from both cognitive appraisals (e.g., perceived usefulness) and emotional value. This approach illuminates how psychological and affective dimensions intersect with technology acceptance, thereby enhancing TAM's predictive capacity for consumer contexts.

Taken together, these three studies represent the limited but illustrative attempts to jointly apply TAM and the cognitive response approach in GenAI research. Their findings reveal that cognitive response processes—such as reappraisal, cognitive willingness, and integrated cognitive–emotional evaluations—provide substantial explanatory power for understanding technology acceptance. However, this integration is not yet a dominant trend, suggesting that the inherently cognitive and affective nature of GenAI interactions calls for more systematic incorporation of cognitive response theories into technology acceptance models. This need points toward promising avenues for future theoretical development.

TABLE VII. COGNITIVE–AFFECTIVE PERSPECTIVES ON GENERATIVE AI USE

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T7-01	[55]	Ma et al.	Cognitive–Affective Model (CAPS + COR)	International students	Sociocultural adaptation via GenAI
T7-02	[96]	Zou et al.	CATLM (Cognitive–Affective Theory of Learning)	EFL writing / HCI	Emotion-enhanced learning outcomes
T7-03	[36]	Huang et al.	Cognition–Emotion Integrated Model	Consumer services	Cognitive–emotional acceptance

E. RQ5: What theoretical and practical benefits can be gained from Integrating TAM and the Cognitive Response Approach in explaining GenAI Interactions?

The systematic review indicates that, although technology acceptance models are widely used in GenAI-focused research, their integration with the cognitive response approach is still very limited. Most studies employing TAM or extended TAM frameworks continue to emphasize traditional constructs such as perceived usefulness, perceived ease of use and behavioral intention, while cognitive or cognitive–affective evaluation processes are usually examined using different theoretical perspectives. Only three studies were identified within the dataset that explicitly combine TAM and the cognitive response approach within a single theoretical model. This highlights a notable conceptual gap in the GenAI literature. The first of these studies integrates the Extended TAM with the cognitive–affective model to examine how GenAI-induced cognitive reappraisal and perceived empathy contribute to sociocultural adaptation. The findings suggest that cognitive responses are fundamental mechanisms that enhance explanatory power, rather than merely supplementary to technology-use intentions. This shows how cognitive and affective processes can reinforce TAM structures in GenAI contexts.

The second study (96) combines TAM with the cognitive–affective theory of learning (CATLM) to investigate how GenAI-based visualized feedback influences students' writing processes. The results show that GenAI feedback affects not only perceived usefulness, but also deeper mechanisms, such as cognitive willingness and emotional reactions. Together, these studies highlight the potential of integrating cognitive response mechanisms into TAM to create more comprehensive models of GenAI acceptance in learning environments. The third study [36] combines TAM with cognitive–emotional evaluation constructs in order to examine behavioral intention in GenAI-supported personalized services. The findings demonstrate that behavioral intention derives from both cognitive appraisals (e.g., perceived usefulness) and emotional value. This illustrates how psychological and affective dimensions intersect with technology acceptance, thereby enhancing TAM's predictive capacity in consumer contexts. Taken together, these three studies represent limited but illustrative attempts to apply TAM alongside the cognitive response approach in GenAI research. Their findings reveal that cognitive response processes, such as reappraisal, cognitive willingness, and integrated cognitive–emotional evaluations, provide substantial explanatory power for understanding technology acceptance. Nevertheless, this integration is not yet a dominant trend, suggesting that the inherently cognitive and affective nature of GenAI interactions necessitates the systematic incorporation of cognitive response theories into technology acceptance models. This points towards promising avenues for future theoretical development.

V. DISCUSSION

This systematic review demonstrates that interactions with Generative Artificial Intelligence cannot be fully explained through traditional technology acceptance frameworks alone. The findings indicate that users engage in layered evaluative processes that extend beyond the classical Technology Acceptance Model constructs of perceived usefulness and perceived ease of use. Across diverse contexts, including cultural adaptation (Ma et al. [55]), learning processes (Zou et al. [96]), and consumer decision-making (Huang et al. [36]), similar cognitive–affective dynamics emerge. Despite contextual variation, users consistently rely on processes such as reappraisal, emotional regulation, cognitive willingness, and anthropomorphic meaning-making. These patterns suggest that GenAI interactions are grounded not only in functional evaluations but also in complex cognitive and affective mechanisms.

This tendency aligns with broader conceptual shifts in the literature in which GenAI is increasingly framed not merely as a technological tool but as a partner advisor or cognitive support entity. Ma et al. illustrate how users integrate GenAI into personal and cultural adjustment processes through positive reappraisal, while Zou et al. [96] show that GenAI-supported feedback enhances learning performance, emotional responses and cognitive motivation. Together, these findings indicate that GenAI interactions operate within a domain where cognitive and affective processes are inseparable.

The results further reveal the limited explanatory power of standalone technology acceptance models in GenAI contexts. Traditional TAM assumes relatively low cognitive demand and predictable user evaluations. In contrast, GenAI requires users to engage in more complex cognitive processes. As shown by Huang et al. [36], consumer decisions are shaped by both cognitive and emotional factors, which exposes the limitations of TAM's rationalistic assumptions in high-cognitive-demand environments. Unlike conventional technologies, GenAI users must simultaneously decide on adoption and evaluate the accuracy, human-likeness, trustworthiness, and cognitive boundaries of AI-generated outputs. Such multidimensional processes are more effectively captured through cognitive response approaches. A key insight emerging from RQ4 is that only three studies within the reviewed dataset, namely Ma et al. [55], Zou et al. [96], and Huang et al. [36], systematically integrate TAM with cognitive response theory. Each study independently demonstrates that cognitive–affective processes significantly influence GenAI usage intentions. Considered together, these studies suggest that GenAI reshapes the psychological foundations of technology acceptance by shifting decision-making toward cognitive evaluation, emotional reaction and personal meaning construction.

The theoretical implications discussed under RQ5 further clarify why TAM and cognitive response theory complement each other. While TAM explains the structural components of user decisions, such as usefulness, ease of use, and intention cognitive response theory captures the internal mental processes, including deliberation, reappraisal, emotional regulation and cognitive motivation. Integrating these perspectives enables a more comprehensive explanation of both the external predictors of behavior and their internal cognitive logic. For example, the reappraisal mechanisms identified by Ma et al. [55] illuminate adaptation processes beyond the explanatory scope of TAM. Zou et al. [96] show that cognitive willingness shapes learning intentions, while Huang et al. [36] emphasize the role of emotional value in enriching the affective dimension of technology acceptance.

VI. Conclusion

This study concludes that explaining Generative Artificial Intelligence interactions requires moving beyond standalone technology acceptance models. The findings demonstrate that the cognitive and emotional reactions elicited by GenAI are integral components of technology acceptance rather than peripheral influences. Integrating Technology Acceptance Model perspectives with cognitive response theory therefore provides a more robust framework for understanding how users evaluate trust interpret outputs and form usage intentions. By synthesizing prior research through a systematic review, this study contributes a multidimensional perspective on human–GenAI interaction that captures behavioral, cognitive and affective processes simultaneously. From a theoretical standpoint, the integration of TAM and cognitive response theory clarifies why GenAI demands more intensive cognitive evaluation than earlier technologies. From a practical perspective, it supports the design of GenAI systems that are sensitive to user psychology, reduce cognitive load, balance emotional responses, and strengthen trust.

Overall, this research highlights the need for future studies to develop integrative models that explicitly incorporate cognitive–affective mechanisms into technology acceptance research. By making the multidimensional nature of GenAI explicit, this study offers a theoretically grounded contribution that advances current understanding and aligns with the expectations of advanced academic research.

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