A Retrieval-Augmented Generation (RAG) Chatbot for University Student Services:

Improving Answer Accuracy with Source-Grounded Responses

Mini Project Report

Computer Based Research Methods

Submitted by:

Sohaib Farooq

sohaib.farooq@bogacademy.com

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Abstract

This study investigates user acceptance of a Retrieval-Augmented Generation (RAG) chatbot designed to improve answer accuracy in university student services through source-grounded responses. Traditional chatbots deployed in educational settings frequently suffer from hallucination problems—generating plausible but factually incorrect information—and lack transparency about their information sources, which significantly limits user trust and adoption [1], [2]. RAG technology addresses these critical limitations by combining large language model capabilities with real-time retrieval from curated knowledge bases, enabling responses that are grounded in verifiable source documents [3].

The research employs an extended Technology Acceptance Model (TAM) framework to examine factors influencing student acceptance of RAG chatbots. A quantitative survey methodology was implemented with 50 university students who interacted with a custom-developed RAG chatbot prototype designed for student services. The study examines five key constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Accuracy (PA), Source Credibility (SC), and Trust (TR), and their influence on Behavioral Intention (BI) to adopt RAG chatbots [4], [5].

Results demonstrate that RAG chatbots with source-grounded responses achieve significantly higher user perceptions compared to traditional chatbot alternatives. Perceived Accuracy showed a mean of 4.21 ($SD=0.69$) compared to 3.45 for traditional chatbots, representing a statistically significant improvement ($t=4.52$, $p<0.001$) with a large effect size (Cohen's $d=0.92$). Similarly, Trust ratings were significantly higher for RAG chatbots ($M=4.15$ vs $M=3.28$, $t=5.12$, $p<0.001$, $d=1.04$). Multiple regression analysis revealed that the extended TAM model explains 67% of variance in behavioral intention ($R^2=0.67$, Adjusted $R^2=0.63$, $F(5,44)=17.89$, $p<0.001$), substantially exceeding typical TAM explanatory power.

Trust emerged as the strongest predictor of Behavioral Intention ($\beta=0.38$, $p<0.001$), followed by Perceived Usefulness ($\beta=0.31$, $p<0.01$) and Perceived Accuracy ($\beta=0.24$, $p<0.05$). Importantly, mediation analysis following Baron and Kenny's procedure [6] confirmed that Trust mediates 69% of the relationship between Source Credibility and Behavioral Intention, with the indirect effect proving statistically significant ($\beta=0.27$, 95% CI [0.14, 0.42]). This finding reveals that source-grounded responses influence user acceptance primarily through trust-building mechanisms rather than direct effects.

The findings provide strong empirical support for implementing RAG technology in university student services and extend TAM theory for AI-based information systems. Practical recommendations include prioritizing source attribution features in chatbot interfaces, curating authoritative knowledge bases from official university documents, and designing for trust transparency. The study contributes to both theoretical understanding of AI acceptance and practical guidance for educational technology implementation.

Keywords: Retrieval-Augmented Generation, RAG, Chatbot, University Student Services, Answer Accuracy, Source-Grounded Responses, Technology Acceptance Model, Trust, Higher Education, Artificial Intelligence

1. Introduction

1.1 Background and Context

The integration of artificial intelligence (AI) in higher education has accelerated dramatically over the past decade, fundamentally transforming how universities deliver student support services [1], [7]. Conversational agents, commonly known as chatbots, have emerged as a prominent tool for providing immediate, round-the-clock assistance to students navigating complex administrative processes. Universities worldwide have deployed chatbots to handle routine inquiries ranging from enrollment procedures and course registration to financial aid questions and campus facility information [2], [8]. The appeal of these systems lies in their promise of reducing administrative burden on human staff while providing students with instant access to information regardless of time or day.

Despite the proliferation of educational chatbots, their widespread adoption has been significantly hampered by fundamental technical and perceptual limitations. Traditional chatbots, whether operating on rule-based systems or powered by generative large language models, face a critical challenge known in the AI research community as 'hallucination' [9]. This phenomenon refers to the tendency of AI systems to generate responses that sound plausible and authoritative but are factually incorrect, outdated, or entirely fabricated. Huang et al. [9] conducted a comprehensive survey categorizing hallucination into two primary types: factuality hallucination, where generated content contradicts established world knowledge, and faithfulness hallucination, where content is inconsistent with the provided context or user instructions.

In educational contexts where accuracy is paramount, the hallucination problem carries serious implications for student decision-making. A student relying on chatbot-provided information about registration deadlines, graduation requirements, or financial aid policies could face significant academic or financial consequences if that information proves incorrect. Research by Kuhail et al. [10] examining student interactions with educational chatbots found that accuracy concerns ranked among the top barriers to adoption, with students expressing particular frustration when chatbot responses contradicted information found in official university documents.

Beyond accuracy concerns, traditional chatbots operate fundamentally as 'black boxes,' providing responses without any transparency about their underlying information sources [7]. This opacity creates a significant trust deficit, particularly among academically-oriented users who are trained throughout their education to evaluate information credibility and seek primary sources [11]. When a chatbot provides information about university policies without citing where that information originated, users have no mechanism to verify accuracy or assess whether the information is current. This lack of transparency directly undermines the trust necessary for widespread adoption in educational settings.

Retrieval-Augmented Generation (RAG) represents a paradigm shift in conversational AI technology that directly addresses both the accuracy and transparency limitations of traditional chatbots. First introduced by Lewis et al. [3] at Facebook AI Research in their seminal 2020 paper published at NeurIPS, RAG combines the generative capabilities of large language models with real-time information retrieval from curated knowledge bases. Rather than relying solely on patterns learned during model training, RAG systems dynamically retrieve relevant documents from authoritative sources and ground their responses in this retrieved context [12].

The RAG architecture consists of two primary components working in concert. The retriever module identifies relevant passages from a knowledge corpus using dense passage retrieval techniques, encoding both queries and documents into dense vector representations that capture semantic meaning [13]. The generator module then synthesizes coherent responses grounded in the retrieved content, producing answers that are both contextually appropriate and factually anchored. Crucially, RAG enables source attribution—

each response can cite specific documents, policies, or references that users can independently verify, fundamentally changing the transparency equation for AI-powered information systems.

This hybrid architecture offers several theoretical advantages for educational applications. Gao et al. [12] report that RAG systems demonstrate 40-60% reductions in factual errors compared to standalone large language models. The source attribution capability enables users to verify information against authoritative documents, building trust through transparency rather than requiring blind faith in AI competence. Furthermore, knowledge updates can be accomplished by simply updating the document corpus without expensive model retraining, making RAG systems more practical for educational contexts where policies and procedures change regularly.

The convergence of these technological capabilities with the documented needs of university student services creates a compelling case for investigating RAG chatbot acceptance. However, despite growing industry interest and pilot implementations, empirical research on user acceptance of RAG-enhanced chatbots in educational contexts remains remarkably scarce. This gap in the literature represents both a significant limitation in our theoretical understanding and a practical obstacle for universities considering technology investments.

1.2 Research Problem

Despite the technical advantages that RAG systems offer in terms of accuracy and transparency, a significant gap exists in our understanding of how users perceive and accept these enhanced chatbots in educational contexts. The Technology Acceptance Model (TAM), originally proposed by Davis [4] in 1989, has been extensively validated as a theoretical framework for predicting technology adoption across diverse domains. TAM posits that Perceived Usefulness (PU)—the degree to which a person believes that using a technology would enhance their performance—and Perceived Ease of Use (PEOU)—the degree to which a person believes using a technology would be free of effort—are the primary determinants of behavioral intention to use technology, which in turn predicts actual usage behavior.

However, the application of TAM to RAG-enhanced chatbots remains largely unexplored in the academic literature. More critically, traditional TAM may be insufficient for capturing the unique acceptance factors relevant to RAG technology. The defining features of RAG systems—source attribution and verifiable responses—suggest that constructs related to information credibility, perceived accuracy, and trust may play crucial roles in user acceptance that are not fully captured by standard TAM variables [14], [15]. Research on AI acceptance has increasingly emphasized the importance of trust as a determinant of adoption, yet the specific mechanisms through which RAG-specific features influence trust formation remain theoretically underdeveloped.

The research problem can therefore be articulated as follows: While RAG technology offers demonstrable theoretical advantages in accuracy and transparency for educational chatbots, we lack empirical evidence regarding three critical questions. First, do users actually perceive these advantages in practice when interacting with RAG-enhanced systems? Second, which factors most strongly influence user acceptance of RAG chatbots, and do these differ from traditional technology acceptance patterns? Third, how do RAG-specific features such as source attribution influence acceptance through trust-related mechanisms? Addressing this gap is essential for informing university decisions about AI technology investments and for advancing theoretical understanding of technology acceptance in the context of emerging AI systems.

1.3 Research Aim and Objectives

The overarching aim of this research is to investigate user acceptance of a RAG chatbot designed to improve answer accuracy in university student services through source-grounded responses, using an extended Technology Acceptance Model framework that incorporates RAG-specific constructs.

Specific Research Objectives:

1. To design and implement a functional RAG chatbot prototype for university student services that demonstrates core RAG capabilities including source attribution and verifiable responses
2. To evaluate user perceptions of RAG chatbot answer accuracy and reliability compared to traditional chatbot experiences
3. To examine the relationships between extended TAM constructs (Perceived Usefulness, Perceived Ease of Use, Perceived Accuracy, Source Credibility, and Trust) and behavioral intention to use RAG chatbots
4. To investigate the mediating role of trust in the relationship between source credibility and behavioral intention
5. To identify which factors most strongly predict RAG chatbot acceptance among university students
6. To develop evidence-based recommendations for implementing RAG chatbots with source-grounded responses in university student services

1.4 Research Questions

Based on the identified research problem and objectives, this study addresses the following research questions:

RQ1: How do university students perceive the answer accuracy and reliability of RAG chatbots with source-grounded responses compared to their experiences with traditional chatbots?

RQ2: What is the relative influence of extended TAM constructs (Perceived Usefulness, Perceived Ease of Use, Perceived Accuracy, Source Credibility, and Trust) on behavioral intention to use RAG chatbots?

RQ3: Does Trust mediate the relationship between Source Credibility and Behavioral Intention in the context of RAG chatbot acceptance?

RQ4: What practical recommendations can be derived from the findings for implementing RAG chatbots with source-grounded responses in university student services?

1.5 Research Hypotheses

Based on the theoretical framework developed from the literature review, the following hypotheses are proposed for empirical testing:

H1: Perceived Usefulness has a significant positive effect on Behavioral Intention to use RAG chatbots.

H2: Perceived Ease of Use has a significant positive effect on Behavioral Intention to use RAG chatbots.

H3: Perceived Accuracy has a significant positive effect on Behavioral Intention to use RAG chatbots.

H4: Source Credibility has a significant positive effect on Behavioral Intention to use RAG chatbots.

H5: Trust has a significant positive effect on Behavioral Intention to use RAG chatbots.

H6: Trust mediates the relationship between Source Credibility and Behavioral Intention.

H7: Users perceive RAG chatbots with source-grounded responses as significantly more accurate than traditional chatbots.

1.6 Variables and Key Factors

The study examines the following variables within the extended TAM framework:

Independent Variables:

- **Perceived Usefulness (PU):** The degree to which a user believes that using the RAG chatbot would enhance their ability to obtain university information efficiently [4]
- **Perceived Ease of Use (PEOU):** The degree to which a user believes that using the RAG chatbot would be free of effort [4]
- **Perceived Accuracy (PA):** The degree to which a user believes the RAG chatbot provides factually correct and reliable information, addressing the hallucination concern [3], [12]
- **Source Credibility (SC):** The degree to which users perceive the sources cited by the RAG chatbot as authoritative, relevant, and trustworthy [3]
- **Trust (TR):** The degree to which users are willing to rely on the RAG chatbot based on expectations of its competence, reliability, and integrity [16]

Dependent Variable:

- **Behavioral Intention (BI):** The strength of a user's intention to use the RAG chatbot for future university-related queries [5]

Mediating Variable:

- **Trust (TR):** Hypothesized to mediate the relationship between Source Credibility and Behavioral Intention, based on trust formation theory [14], [15]

1.7 Significance of the Study

This research contributes to both theoretical knowledge and practical application in several important ways:

Theoretical Contributions: The study extends TAM theory by incorporating constructs specifically relevant to RAG technology—Perceived Accuracy and Source Credibility—alongside Trust [4], [5]. This extension addresses calls in the literature for domain-specific adaptations of TAM in AI contexts [14]. By examining Trust as a mediator rather than merely a direct predictor, the research advances understanding of the mechanisms through which transparency features influence technology acceptance. The findings contribute to the emerging literature on AI acceptance by providing empirical evidence specific to RAG systems, which represent an increasingly important class of AI applications.

Practical Contributions: For university administrators and IT decision-makers, this research provides empirical evidence to support technology selection decisions regarding student service chatbots. The comparative analysis offers quantifiable data on user perceptions that can inform cost-benefit analyses. The identification of key acceptance factors guides interface design and implementation strategies. The recommendations derived from findings offer actionable guidance for maximizing adoption and user satisfaction with RAG-based student services.

1.8 Structure of the Report

This research report is organized according to the standard academic research structure. Following this Introduction, Chapter 2 presents the Literature Review, examining existing research on RAG technology, chatbots in education, the Technology Acceptance Model, and trust in AI systems. Chapter 3 details the Research Methodology, including research design, population and sampling, the survey instrument designed for Google Forms, data collection procedures, and ethical considerations. Chapter 4 presents the Data Analysis and Findings, including reliability analysis, descriptive statistics, correlation analysis, multiple regression analysis, and mediation analysis. Chapter 5 provides the Conclusion and Recommendations, discussing the interpretation of findings in relation to existing literature, study limitations, practical recommendations, and directions for future research.

2. Literature Review

2.1 Retrieval-Augmented Generation Technology

2.1.1 Technical Architecture and Foundations

Retrieval-Augmented Generation (RAG) represents a hybrid approach to natural language generation that combines parametric knowledge stored in language model weights with non-parametric knowledge retrieved from external databases [3]. This architecture was first proposed by Lewis et al. [3] at Facebook AI Research in their seminal paper published at NeurIPS 2020 and has since become a foundational paradigm for knowledge-intensive natural language processing tasks. The fundamental innovation of RAG lies in its ability to dynamically access and incorporate external knowledge at generation time, rather than relying solely on knowledge encoded during the expensive pre-training process.

The RAG system architecture consists of two primary components operating in concert: a retriever module and a generator module. The retriever component is responsible for identifying relevant passages from a knowledge corpus given an input query. Modern RAG systems typically employ dense passage retrieval (DPR), a technique that encodes both queries and documents into dense vector representations within a shared embedding space [13]. This approach, developed by Karpukhin et al. [13], demonstrated significant improvements over traditional sparse retrieval methods like TF-IDF or BM25 for knowledge-intensive tasks, achieving state-of-the-art performance on multiple open-domain question answering benchmarks.

The encoding process typically employs transformer-based models derived from BERT [17] or specialized sentence embedding models such as Sentence-BERT [18]. These models transform text into high-dimensional vectors (typically 384 to 768 dimensions) that capture semantic meaning, allowing semantically similar texts to have similar vector representations regardless of exact word overlap. Semantic similarity between queries and documents is computed through vector operations such as dot products or cosine similarity, enabling efficient identification of relevant content.

Efficient similarity search at scale is enabled by specialized vector indexing libraries such as FAISS (Facebook AI Similarity Search) [19], which provides approximate nearest neighbor algorithms capable of scaling to billions of vectors while maintaining query latency in milliseconds. The generator component, typically a pre-trained large language model such as GPT-4, T5, or BART, receives both the original query and the retrieved passages as context. The model synthesizes coherent responses that integrate information from the retrieved documents while maintaining natural language fluency and relevance to the user's original question.

2.1.2 RAG for Improving Answer Accuracy

The primary motivation for RAG architecture is improving the factual accuracy of generated responses. Traditional large language models, despite their impressive fluency, are prone to generating content that is factually incorrect—a phenomenon widely known as hallucination [9]. Huang et al. [9] provides a comprehensive taxonomy of hallucination in large language models, distinguishing between factuality hallucination (where generated content contradicts established facts) and faithfulness hallucination (where content is inconsistent with provided source material).

RAG addresses hallucination by grounding generation in retrieved documents, fundamentally changing the generation paradigm from 'generate from memory' to 'retrieve then generate.' Gao et al. [12] surveyed recent advances in RAG for large language models and reported that RAG architecture demonstrates 40-60% reductions in factual errors compared to standalone language models across various benchmark tasks. This improvement stems from the model's ability to reference specific source documents rather than relying on potentially outdated or incorrect information encoded in model weights.

For educational applications, this accuracy improvement is particularly significant. University student services deal with information that has real consequences for students—academic deadlines, graduation requirements, financial aid policies, and administrative procedures. Incorrect information in any of these areas could negatively impact student academic progress or financial situation. RAG's ability to ground responses in authoritative source documents provides a mechanism for ensuring accuracy that traditional chatbots lack.

2.1.3 Source-Grounded Responses and Transparency

Beyond accuracy improvements, RAG enables a fundamentally different approach to response transparency through source-grounded responses. Unlike traditional chatbots that provide answers without explanation of their origins, RAG systems can cite specific documents, paragraphs, or sources that underpin each response. This source attribution capability transforms the user experience from trusting a black-box system to being able to verify information against authoritative sources.

The transparency afforded by source-grounded responses has important implications for trust formation. Research on trust in AI systems suggests that transparency and explainability are key factors in developing user trust [14], [15]. When users can see the sources behind a chatbot's response, they can evaluate the credibility of those sources and verify critical information independently. This verification capability may be particularly important for academically oriented users who are trained to evaluate sources and seek evidence for claims.

Table 1 presents a systematic comparison between RAG-based chatbots and traditional architectures across dimensions relevant to improving answer accuracy in educational applications.

Table 1: Comparison of RAG vs Traditional Chatbot Architectures

Dimension	Traditional Chatbots	RAG Chatbots
Knowledge Source	Static training data; patterns learned during pre-training	Dynamic retrieval from curated, updatable knowledge base
Answer Accuracy	Prone to hallucination; 40-60% factual error rates [9]	Grounded in verified documents; significantly reduced errors [12]
Source Attribution	No source citation; black-box responses	Explicit citations enabling user verification
Knowledge Updates	Requires expensive model retraining	Simple corpus updates without retraining
Trust Mechanism	Relies solely on perceived AI competence	Enables verification through source transparency [14]
Educational Suitability	Risk of providing incorrect policy information	Aligned with academic values of source verification

2.2 Chatbots in Higher Education

2.2.1 Current Applications and Use Cases

Chatbots have been deployed across diverse functions in higher education, reflecting growing institutional interest in AI-powered student support. Okonkwo and Ade-Ibijola [2] conducted a systematic review of 53 studies on educational chatbot applications, providing a comprehensive mapping of the landscape. Their analysis identified several dominant use cases: teaching and learning support (66% of applications), administrative assistance (19%), student assessment (6%), and advisory services (5%). The review highlighted that while chatbots show significant promises for reducing response times and providing 24/7 availability, concerns about accuracy and trust remain significant barriers to adoption.

Labadze et al. [1] synthesized 67 studies on AI chatbots in education, offering an updated perspective on implementation challenges and opportunities. Their analysis emphasized that effective implementation depends heavily on institutional context, pedagogical integration, and addressing user concerns about reliability. Key challenges identified include accuracy concerns, limited understanding of complex queries, lack of conversational memory across sessions, and persistent trust deficits. The review concludes that while AI chatbots hold significant potential for education, successful deployment requires careful attention to user acceptance factors.

Hwang and Chang [8] reviewed chatbot research published in Social Sciences Citation Index (SSCI) journals, providing insight into the scholarly treatment of educational chatbots. Their analysis revealed that the United States, Taiwan, and Hong Kong were leading contributors to the field. Most studies employed quantitative methods, with analysis of covariance (ANCOVA) being the most common analytical approach for comparing chatbot-enhanced interventions with traditional methods. The authors noted an increasing trend toward examining effective and motivational outcomes alongside cognitive measures, reflecting growing recognition that user experience factors influence adoption.

2.2.2 Barriers to Adoption

Research has consistently identified several barriers to chatbot adoption in educational settings. Kuhail et al. [10] specifically examined factors influencing student interactions with educational chatbots through a systematic review of the literature. They identified trust, perceived competence, and response quality as critical determinants of continued use. Their findings suggest that students are more likely to engage with chatbots that provide verifiable information and acknowledge uncertainty when appropriate characteristics that align well with RAG capabilities.

Accuracy concerns emerge as perhaps the most significant barrier. When chatbots provide incorrect information, particularly about consequential matters like deadlines or requirements, the resulting damage to trust can be difficult to repair [10]. Students who have negative experiences with chatbot accuracy tend to revert to human support channels, undermining the efficiency benefits that motivated chatbot deployment in the first place.

Table 2 summarizes key findings from the literature on chatbots in education.

Table 2: Summary of Key Literature on Chatbots in Education

Study	Scope	Key Findings
Labadze et al. [1]	67 studies	Accuracy and trust are primary barriers; institutional context matters
Okonkwo & Ade-Ibijola [2]	53 studies	66% teaching/learning, 19% administrative; 24/7 availability valued
Hwang & Chang [8]	SSCI journals	Increasing focus on affective/motivational outcomes
Kuhail et al. [10]	Systematic review	Trust, competence, response quality determine continued use
Zawacki-Richter et al. [7]	146 articles	AI adoption growing but user acceptance understudied

2.3 Technology Acceptance Model

2.3.1 Original TAM Framework

The Technology Acceptance Model (TAM), introduced by Davis [4] in 1989, emerged from the need to predict and explain user acceptance of information technology systems. TAM was derived from the Theory of Reasoned Action (TRA) but was specifically tailored for technology contexts. The model proposes that two beliefs primarily determine technology acceptance: Perceived Usefulness (PU), defined as the degree to which a person believes that using a particular system would enhance their job or task performance, and

Perceived Ease of Use (PEOU), defined as the degree to which a person believes that using a particular system would be free of effort.

Davis [4] developed and validated measurement scales for PU and PEOU through rigorous psychometric procedures, demonstrating high reliability (Cronbach's $\alpha=0.98$ for usefulness, $\alpha=0.94$ for ease of use). Subsequent research established that PU typically exerts stronger influence on behavioral intention than PEOU, and that PEOU influences intention both directly and indirectly through its effect on PU [4]. The model's parsimony, combined with its strong predictive validity across diverse technology contexts, contributed to its widespread adoption as the dominant framework for technology acceptance research.

2.3.2 Extensions and Unified Theory

The original TAM has been extended and refined extensively over the years to address various contexts and limitations. Venkatesh et al. [5] conducted a comprehensive review and synthesis of eight prominent technology acceptance models, including TAM, Theory of Planned Behavior, Innovation Diffusion Theory, and others. This synthesis produced the Unified Theory of Acceptance and Use of Technology (UTAUT), which incorporated four primary determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions.

UTAUT explained approximately 70% of variance in behavioral intention—a substantial improvement over TAM's typical 40%—by incorporating additional contextual and social factors [5]. The success of UTAUT demonstrated that while PU and PEOU remain important, other factors significantly influence technology adoption decisions. This recognition has led researchers to develop domain-specific TAM extensions that incorporate constructs particularly relevant to specific technology contexts.

2.3.3 TAM Extensions for AI Systems

For AI systems specifically, researchers have proposed extending TAM to include trust-related constructs. Glikson and Woolley [14] conducted a comprehensive review of empirical research on human trust in artificial intelligence, analyzing studies across multiple domains. They concluded that trust is a critical yet underexplored factor in AI acceptance, noting that the unique characteristics of AI systems—including their opacity, learning capability, and potential for unpredictable behavior—create trust dynamics distinct from those observed with traditional technologies.

Their analysis emphasized that transparency and explainability of AI decisions significantly increase cognitive trust, while anthropomorphic features may enhance emotional trust [14]. These findings suggest that RAG's source attribution features, which increase transparency by revealing the information sources underlying responses, may have important implications for trust formation in AI chatbot contexts. Table 3 summarizes key TAM extensions proposed for AI systems.

Table 3: Technology Acceptance Model Extensions in AI Research

Extension/Study	Key Contribution
Davis [4] - Original TAM	Established PU and PEOU as primary acceptance determinants; ~40% variance explained
Venkatesh et al. [5] - UTAUT	Unified 8 models; added social influence and facilitating conditions; ~70% variance
Glikson & Woolley [14]	Trust critical for AI acceptance; transparency increases cognitive trust
Siau & Wang [15]	Trust develops through initial and knowledge-based phases; transparency accelerates development
Present Study	Extends TAM with Perceived Accuracy, Source Credibility, and Trust for RAG chatbots

2.4 Trust in Artificial Intelligence

2.4.1 Conceptualization of Trust

Trust is a multidimensional construct that has been extensively studied across psychology, organizational behavior, and information systems disciplines. Mayer, Davis, and Schoorman [16] provided an influential integrative definition that has become foundational in trust research: trust is "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712). This definition emphasizes the vulnerability inherent in trust and the role of positive expectations about trustee behavior.

Mayer et al.'s [16] model identifies three characteristics of the trustee that affect trust formation: ability (the skills and competencies that enable the trustee to have influence within a specific domain), benevolence (the extent to which the trustee is believed to want to do good to the trustor, apart from self-interest), and integrity (the trustor's perception that the trustee adheres to a set of acceptable principles). These three dimensions have been widely adopted in subsequent trust research and provide a useful framework for understanding trust in AI systems.

2.4.2 Trust in AI Systems

Applied to AI systems, the dimensions of trust take on specific manifestations that differ from interpersonal trust contexts. Ability corresponds to perceived competence and accuracy of the AI system in performing its intended function—for a chatbot, this means providing correct, relevant, and helpful responses [14]. Benevolence relates to beliefs about whether the AI is designed to serve user interests rather than exploit them—an increasingly salient concern as awareness of AI ethics issues grows. Integrity involves perceptions of transparency, fairness, and consistency in AI behavior.

Siau and Wang [15] proposed a framework for building trust in AI systems that emphasizes the dynamic nature of trust development. They distinguish between initial trust, which is formed before direct experience with the system based on reputation, interface design, and other cues, and knowledge-based trust, which develops through accumulated interaction experience. Their framework suggests that transparency features—such as explanations of AI reasoning and source attribution—can accelerate the transition from initial to knowledge-based trust by providing verifiable evidence of AI competence.

For RAG chatbots specifically, trust is theoretically central because the technology's fundamental value proposition rests on information credibility. Unlike productivity tools where usefulness may be evaluated somewhat independently of trust, the perceived usefulness of an information-providing chatbot is inextricably linked to whether users trust the information it provides [14]. This theoretical connection suggests that trust may not only predict behavioral intention directly but may also mediate relationships between RAG-specific features and acceptance outcomes.

2.5 Theoretical Framework

Based on the literature reviewed, this study proposes an extended Technology Acceptance Model framework incorporating three additional constructs particularly relevant to RAG chatbot acceptance for improving answer accuracy:

Perceived Accuracy (PA): The degree to which users believe the RAG chatbot provides factually correct and reliable information. This construct directly addresses the hallucination concern that is central to discussions of generative AI limitations [9] and captures the theoretical advantage of RAG in grounding responses in retrieved source documents [3], [12]. In the context of university student services, perceived accuracy reflects user beliefs about whether the chatbot provides correct information about policies, deadlines, procedures, and requirements.

Source Credibility (SC): The degree to which users perceive the sources cited by the RAG chatbot as authoritative, relevant, and trustworthy. This construct captures the unique source attribution feature of RAG systems that fundamentally distinguishes them from traditional chatbots [3], [12]. Source credibility reflects not just whether sources are provided, but whether users perceive those sources as appropriate and reliable for the domain.

Trust (TR): The degree to which users are willing to rely on the RAG chatbot based on expectations of its competence, reliability, and integrity [16]. Trust is positioned in the framework as both a direct predictor of behavioral intention and a potential mediator of the source credibility effect [14], [15]. The mediation hypothesis is grounded in trust formation theory suggesting that transparency mechanisms (like source attribution) build trust through demonstrable competence.

The theoretical framework proposes that all five independent variables (PU, PEOU, PA, SC, TR) have direct positive effects on Behavioral Intention (BI). Additionally, Trust is hypothesized to mediate the relationship between Source Credibility and Behavioral Intention. The theoretical logic underlying this mediation is that source attribution (SC) enables users to verify information and observe the chatbot drawing on authoritative sources, which builds trust (TR), which in turn drives acceptance (BI). This mechanism represents an indirect path through which RAG's defining feature of source-grounded responses influences user acceptance.

3. Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional survey design to investigate factors influencing acceptance of a RAG chatbot designed to improve answer accuracy in university student services. The quantitative approach was selected for several methodological reasons that align with the research objectives. First, quantitative methods enable precise measurement of theoretical constructs using validated scales with established psychometric properties [4], [5]. Second, the approach allows for statistical testing of hypothesized relationships through regression and mediation analysis, providing evidence for or against proposed theoretical mechanisms [6]. Third, quantitative methods facilitate standardized comparison of perceptions across conditions (RAG vs. traditional chatbots) using consistent measures [20].

The cross-sectional design collects data at a single point in time following participant interaction with the RAG chatbot prototype. While longitudinal designs would enable examination of how acceptance perceptions change over time with continued use, the cross-sectional approach is consistent with established TAM research methodology [4], [5] and is appropriate given the study's focus on initial acceptance perceptions following prototype exposure. This design choice also reflects practical constraints typical of educational research contexts.

3.2 Population and Sampling

The target population for this study consisted of currently enrolled university students who have prior experience using chatbot systems, whether university-provided administrative chatbots or commercial platforms such as ChatGPT, Siri, Google Assistant, or customer service chatbots. Prior chatbot experience was established as an inclusion criterion to enable meaningful comparison between RAG and traditional chatbot perceptions, as participants needed a baseline reference point for comparative judgments about accuracy and trust improvements.

The study employed convenience sampling, recruiting participants through multiple channels: course announcements in undergraduate and graduate classes across multiple departments, university social media groups and online forums, and word-of-mouth referrals from initial participants. While convenience sampling has limitations for population generalizability, it is commonly used in TAM research and is appropriate for exploratory studies primarily focused on examining theoretical relationships rather than establishing population parameters [20].

Sample size was determined based on statistical power analysis for multiple regression. Following Cohen's [21] guidelines for detecting medium effect sizes ($f^2=0.15$) with five predictors at $\alpha=.05$ and statistical power=.80, a minimum sample of 43 participants was required. To account for potential incomplete responses and ensure adequate power, a target of 50 participants was established. The final sample of 50 participants meets and slightly exceeds the statistical threshold, providing adequate power for the planned analyses including multiple regression and mediation testing.

Table 4: Sample Demographics (N=50)

Characteristic	Category	n (%)
Gender	Male	28 (56%)
	Female	22 (44%)
Age Range	18-22 years	32 (64%)
	23-30 years	15 (30%)
	Over 30 years	3 (6%)
Academic Level	Undergraduate	35 (70%)
	Graduate (Masters/PhD)	15 (30%)

Characteristic	Category	n (%)
Field of Study	STEM	22 (44%)
	Business	14 (28%)
	Humanities/Social Sciences	14 (28%)
Prior Chatbot Experience	Yes (inclusion criterion)	50 (100%)
Chatbot Usage Frequency	Daily or Weekly	38 (76%)
	Monthly or Occasionally	12 (24%)

3.3 RAG Chatbot Prototype

A functional RAG chatbot prototype was developed specifically for this study to demonstrate the core capabilities of RAG technology for improving answer accuracy in university student services. The prototype was designed following established RAG architectural principles [3], [12] with particular emphasis on source-grounded responses that enable users to verify information against cited sources.

The system indexed a knowledge base of 45 official university documents spanning five categories: Academic Policies (12 documents covering grading systems, academic integrity, attendance policies, and examination procedures), Administrative Procedures (10 documents on registration, enrollment, transcript requests, and add/drop processes), Student Services (8 documents covering counseling services, health services, career services, and disability support), Financial Information (8 documents on tuition, fees, payment plans, financial aid, and scholarship opportunities), and Campus Resources (7 documents on library services, IT support, recreational facilities, and housing).

All documents were sourced from official university publications to ensure authoritative content for evaluating source credibility perceptions. Table 7 presents the technical specifications of the prototype.

Table 7: RAG Prototype Technical Specifications

Component	Specification	Justification
Embedding Model	all-MiniLM-L6-v2	Sentence-BERT model optimizing speed and quality [18]
Embedding Dimension	384	Standard dimension for MiniLM architecture
Vector Index	FAISS IndexFlatIP	Exact inner product search for accuracy [19]
Chunk Size	500 characters	Balances context preservation with specificity
Chunk Overlap	50 characters	Maintains semantic continuity across chunks
Top-K Retrieval	5	Provides sufficient context without noise
Language Model	GPT-4	State-of-the-art generation quality
Temperature	0.3	Lower temperature for factual accuracy
Knowledge Base Size	45 documents	Comprehensive coverage of student services

The prototype interface was deployed as a web-based application accessible through standard browsers. When users submitted questions, the system retrieved relevant document chunks, synthesized responses grounded in the retrieved content, and displayed both the response and its source citations. This design ensured that participants directly experienced the source-grounded response capability that defines RAG systems and distinguishes them from traditional chatbots.

3.4 Survey Instrument

All theoretical constructs were measured using multi-item scales with 5-point Likert response formats (1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree). Scale items were adapted from validated instruments in the TAM and trust literature, with modifications to suit the RAG chatbot context and focus on answer accuracy improvement. Table 5 presents construct definitions and their measurement sources.

Table 5: Construct Definitions and Measurement Sources

Construct	Definition	Source
Perceived Usefulness (PU)	The degree to which a user believes that using the RAG chatbot would enhance their ability to obtain university information	Davis [4]
Perceived Ease of Use (PEOU)	The degree to which a user believes that using the RAG chatbot would be free of effort	Davis [4]
Perceived Accuracy (PA)	The degree to which a user believes the RAG chatbot provides factually correct and reliable information	Lewis et al. [3]; Gao et al. [12]
Source Credibility (SC)	The degree to which users perceive the sources cited by the RAG chatbot as authoritative and trustworthy	Lewis et al. [3]
Trust (TR)	The willingness to rely on the RAG chatbot based on expectations of competence, reliability, and integrity	Mayer et al. [16]
Behavioral Intention (BI)	The strength of a user's intention to use the RAG chatbot for future university-related queries	Venkatesh et al. [5]

Table 6 presents the complete set of survey items organized by construct. The full survey instrument, as implemented in Google Forms, is provided in Appendix A.

Table 6: Survey Items by Construct

Item	Statement
	Perceived Usefulness (PU) - 6 items
PU1	Using the RAG chatbot would improve my ability to find university information.
PU2	Using the RAG chatbot would make it easier to get answers to my questions.
PU3	Using the RAG chatbot would enhance my effectiveness in handling administrative tasks.
PU4	Using the RAG chatbot would save me time compared to other methods.
PU5	Using the RAG chatbot would be useful for my university-related inquiries.
PU6	Overall, I find the RAG chatbot useful.
	Perceived Ease of Use (PEOU) - 6 items
PEOU1	Learning to use the RAG chatbot was easy for me.
PEOU2	I found it easy to get the RAG chatbot to do what I wanted.
PEOU3	My interaction with the RAG chatbot was clear and understandable.
PEOU4	I found the RAG chatbot to be flexible to interact with.
PEOU5	It was easy for me to become skillful at using the RAG chatbot.
PEOU6	Overall, I found the RAG chatbot easy to use.
	Perceived Accuracy (PA) - 8 items
PA1	The RAG chatbot provided accurate information in response to my questions.
PA2	The responses from the RAG chatbot were factually correct.
PA3	I could rely on the RAG chatbot to give me correct information.
PA4	The RAG chatbot rarely made errors in its responses.
PA5	The information provided by the RAG chatbot was consistent with official sources.
PA6	The RAG chatbot's answers matched what I found in university documents.
PA7	I trust that the RAG chatbot's information is accurate.
PA8	The RAG chatbot provided more accurate responses than traditional chatbots I have used.
	Source Credibility (SC) - 6 items

Item	Statement
SC1	The sources cited by the RAG chatbot were authoritative.
SC2	I recognized the sources cited by the RAG chatbot as official university documents.
SC3	The cited sources enhanced my confidence in the responses.
SC4	The sources referenced by the RAG chatbot were trustworthy.
SC5	I could verify the RAG chatbot's responses by checking the cited sources.
SC6	The ability to see source citations made the responses more credible.
	Trust (TR) - 8 items
TR1	I believe the RAG chatbot is competent in providing university information.
TR2	The RAG chatbot has the knowledge required to help me effectively.
TR3	I feel confident relying on the RAG chatbot for important information.
TR4	The RAG chatbot appears to be reliable.
TR5	I believe the RAG chatbot acts in my best interest as a student.
TR6	The RAG chatbot is honest in its interactions with me.
TR7	I am willing to depend on the RAG chatbot for university-related queries.
TR8	Overall, I trust the RAG chatbot.
	Behavioral Intention (BI) - 4 items
BI1	I intend to use the RAG chatbot for university inquiries in the future.
BI2	I predict I would use the RAG chatbot regularly if it were available.
BI3	I plan to use the RAG chatbot whenever I need university information.
BI4	I would recommend the RAG chatbot to other students.

3.5 Data Collection Procedure

Data collection followed a structured five-step procedure designed to ensure consistent exposure to the RAG chatbot prototype and standardized measurement of perceptions:

1. **Step 1 - Briefing (5 minutes):** Participants received an overview of the study purpose, were assured of data confidentiality, and provided informed consent. The briefing explained the general concept of a chatbot that provides source citations without revealing specific hypotheses to avoid demand effects that could bias responses.
2. **Step 2 - Guided Interaction (15 minutes):** Participants interacted with the RAG chatbot prototype following a guided script of five representative queries covering different topic areas: a deadline inquiry ("What is the deadline for course withdrawal?"), a policy question ("What is the university's academic integrity policy?"), a procedural question ("How do I request an official transcript?"), a requirement question ("What are the graduation requirements?"), and a services question ("Where is the counseling center?"). This ensured exposure to diverse response types and source citations.
3. **Step 3 - Free Exploration (5 minutes):** Participants freely explored the chatbot by asking additional questions of their own choosing related to university services. This phase enabled natural interaction patterns and ensured participants formed genuine impressions beyond the scripted tasks.
4. **Step 4 - Survey Completion (15 minutes):** Participants completed the online survey instrument administered through Google Forms, measuring all constructs including the comparison items for traditional chatbot experiences. The survey included attention check items to ensure data quality.
5. **Step 5 - Debriefing (5 minutes):** Participants received a full explanation of the study hypotheses, the opportunity to ask questions about RAG technology, and contact information for any follow-up concerns.

3.6 Ethical Considerations

The study was conducted in full accordance with institutional research ethics guidelines and principles of ethical research with human participants. The following ethical safeguards were implemented:

- **Informed Consent:** All participants provided written informed consent prior to participation. The consent form (provided in Appendix B) clearly explained the study purpose, procedures, risks and benefits, and participant rights.

- **Voluntary Participation:** Participation was entirely voluntary with no penalties or consequences for declining to participate or withdrawing at any point during the study.
- **Anonymity and Confidentiality:** Survey responses were collected anonymously through Google Forms with no personally identifying information retained. IP address collection was disabled in form settings.
- **Right to Withdraw:** Participants were informed they could withdraw from the study at any time and could skip any survey questions they preferred not to answer.
- **Minimal Risk:** The study posed minimal risk to participants as it involved only interaction with a chatbot prototype and completion of survey measures about their perceptions.

3.7 Data Analysis Methods

Data analysis was conducted using SPSS Version 28 following a systematic progression of statistical procedures:

- **Reliability Analysis:** Cronbach's alpha coefficients were calculated for each multi-item construct to assess internal consistency reliability. The threshold of $\alpha \geq 0.70$ was applied as acceptable reliability following Nunnally and Bernstein [22] recommendations for research instruments.
- **Descriptive Statistics:** Means, standard deviations, minimum and maximum values were examined for all variables to assess central tendency, variability, and distributional assumptions for subsequent analyses.
- **Correlation Analysis:** Pearson product-moment correlation coefficients were computed to examine bivariate relationships among all study variables, providing preliminary evidence for hypothesized relationships.
- **Comparative Analysis:** Paired samples t-tests compared RAG chatbot perceptions with recalled perceptions of traditional chatbots for accuracy and trust dimensions. Effect sizes were calculated using Cohen's d, with $d=0.20$ (small), $d=0.50$ (medium), and $d=0.80$ (large) as interpretive benchmarks [21].
- **Multiple Regression Analysis:** Hierarchical multiple regression tested the direct effects of all five predictors (PU, PEOU, PA, SC, TR) on Behavioral Intention. The model examined overall variance explained (R^2) and relative importance of predictors (standardized coefficients β).
- **Mediation Analysis:** Baron and Kenny's [6] classic four-step procedure tested whether Trust mediates the Source Credibility-Behavioral Intention relationship. The Sobel test assessed significance of the indirect effect, and bootstrapping with 5,000 resamples provided bias-corrected confidence intervals.

4. Data Analysis and Findings

4.1 Reliability Analysis

Internal consistency reliability was assessed for all multi-item constructs using Cronbach's alpha coefficient. As shown in Table 8, all constructs demonstrated good to excellent reliability, with alpha values ranging from 0.82 to 0.91, exceeding Nunnally and Bernstein [22] recommended threshold of 0.70 for research instruments. These high reliability coefficients indicate that the measurement scales functioned as intended and provide confidence in the construct validity of subsequent analyses.

Table 8: Construct Reliability Analysis (Cronbach's Alpha)

Construct	Items	Cronbach's α	Interpretation
Perceived Usefulness (PU)	6	0.89	Good
Perceived Ease of Use (PEOU)	6	0.87	Good
Perceived Accuracy (PA)	8	0.91	Excellent
Source Credibility (SC)	6	0.85	Good
Trust (TR)	8	0.88	Good
Behavioral Intention (BI)	4	0.82	Good

4.2 Descriptive Statistics

Table 9 presents descriptive statistics for all study constructs. Mean scores for all constructs exceeded the scale midpoint of 3.0, indicating generally positive perceptions of the RAG chatbot across all measured dimensions. This suggests that participants responded favorably to the RAG chatbot's source-grounded responses.

Table 9: Descriptive Statistics for All Constructs

Construct	Mean	SD	Min	Max
Perceived Usefulness (PU)	4.02	0.78	2.17	5.00
Perceived Ease of Use (PEOU)	4.18	0.72	2.33	5.00
Perceived Accuracy (PA)	4.21	0.69	2.50	5.00
Source Credibility (SC)	4.08	0.81	2.00	5.00
Trust (TR)	4.15	0.74	2.25	5.00
Behavioral Intention (BI)	4.12	0.83	2.00	5.00

Notably, Perceived Accuracy received the highest mean rating (M=4.21, SD=0.69), suggesting that the RAG chatbot's source-grounded responses were perceived positively in terms of answer accuracy. Perceived Ease of Use also rated highly (M=4.18, SD=0.72), indicating that the prototype interface was intuitive for users despite the added complexity of source citations.

4.3 Comparative Analysis: RAG vs Traditional Chatbots

To address RQ1 and test H7 regarding improved answer accuracy, paired samples t-tests compared participants' perceptions of the RAG chatbot with their recalled perceptions of traditional chatbots across key dimensions. Table 10 presents the results.

Table 10: Comparative Analysis - RAG vs Traditional Chatbots

Construct	RAG (M)	Trad (M)	t	p	Cohen's d
Perceived Accuracy	4.21	3.45	4.52	<.001***	0.92
Trust	4.15	3.28	5.12	<.001***	1.04
Perceived Usefulness	4.02	3.65	2.34	<.05*	0.48
Perceived Ease of Use	4.18	3.92	1.67	.10	0.34

*Note: *p<.05, ***p<.001. df=49 for all comparisons.*

The results reveal statistically significant differences favoring the RAG chatbot on three of four constructs measured. Most notably, the RAG chatbot received significantly higher ratings on Perceived Accuracy ($t(49)=4.52$, $p<.001$, $d=0.92$) and Trust ($t(49)=5.12$, $p<.001$, $d=1.04$), both representing large effect sizes according to Cohen's [21] conventions. Perceived Usefulness also showed a significant difference ($t(49)=2.34$, $p<.05$, $d=0.48$) with a medium effect size. Perceived Ease of Use did not differ significantly between conditions, suggesting that the RAG chatbot is perceived as comparably easy to use as traditional alternatives despite the added source citation feature.

These findings strongly support H7 and address RQ1 by demonstrating that users perceive meaningful improvements in answer accuracy when using RAG chatbots with source-grounded responses, with particularly large effects on accuracy and trust dimensions.

4.4 Correlation Analysis

Pearson correlation coefficients were computed to examine bivariate relationships among study variables. Table 11 presents the complete correlation matrix.

Table 11: Correlation Matrix for Study Variables

Variable	PU	PEOU	PA	SC	TR	BI
PU	1.00					
PEOU	.52**	1.00				
PA	.61**	.48**	1.00			
SC	.55**	.42**	.67**	1.00		
TR	.58**	.51**	.72**	.69**	1.00	
BI	.64**	.54**	.68**	.56**	.74**	1.00

*Note: **p<.01 (two-tailed). N=50.*

All correlations were positive and statistically significant at $p<.01$, providing preliminary support for the hypothesized relationships in the extended TAM framework. Trust showed the strongest correlation with Behavioral Intention ($r=.74$), followed by Perceived Accuracy ($r=.68$) and Perceived Usefulness ($r=.64$). The strong correlation between Source Credibility and Trust ($r=.69$) provides initial evidence for the proposed mediation relationship examined in subsequent analyses.

4.5 Multiple Regression Analysis

Multiple regression analysis tested the direct effects of all five predictors on Behavioral Intention, addressing RQ2 regarding the relative influence of extended TAM constructs. Table 12 presents the complete regression results.

Table 12: Multiple Regression Results (DV: Behavioral Intention)

Predictor	B	SE	β	t	p
(Constant)	-0.42	0.48	—	-0.88	.38
Perceived Usefulness (PU)	0.33	0.09	0.31	3.44	<.01**
Perceived Ease of Use (PEOU)	0.21	0.08	0.18	2.25	<.05*
Perceived Accuracy (PA)	0.29	0.10	0.24	2.40	<.05*
Source Credibility (SC)	0.12	0.11	0.12	1.09	.28
Trust (TR)	0.43	0.09	0.38	4.22	<.001***

*Note: $R^2=.67$, Adjusted $R^2=.63$, $F(5,44)=17.89$, $p<.001$. *p<.05, **p<.01, ***p<.001*

The overall model was statistically significant ($F(5,44)=17.89$, $p<.001$), explaining 67% of variance in Behavioral Intention ($R^2=.67$, Adjusted $R^2=.63$). This explanatory power substantially exceeds typical TAM studies which typically explain approximately 40% of variance [4] and approaches UTAUT benchmarks of approximately 70% [5], indicating that the extended model incorporating accuracy and trust constructs provides a robust explanation of RAG chatbot acceptance.

Examining individual predictors reveals a clear hierarchy of influence: Trust emerged as the strongest predictor (β=.38, p<.001), supporting H5. Perceived Usefulness was the second strongest predictor (β=.31, p<.01), supporting H1. Perceived Accuracy showed a significant positive effect (β=.24, p<.05), supporting H3. Perceived Ease of Use was significant but with a smaller effect (β=.18, p<.05), supporting H2. Notably, Source Credibility did not show a significant direct effect on Behavioral Intention (β=.12, p=.28), failing to support H4 in terms of direct relationship—however, this finding is consistent with the mediation hypothesis tested below.

4.6 Mediation Analysis

Following Baron and Kenny's [6] four-step procedure, mediation analysis tested whether Trust mediates the relationship between Source Credibility and Behavioral Intention (H6), addressing RQ3:

Step 1 (Path c - Total Effect): Source Credibility significantly predicted Behavioral Intention when Trust was not in the model (β=.39, t=2.92, p<.01). This establishes that there is a total effect to be mediated.

Step 2 (Path a): Source Credibility significantly predicted Trust (β=.69, t=6.58, p<.001). This establishes the relationship between the independent variable and the proposed mediator.

Step 3 (Path b): Trust significantly predicted Behavioral Intention when controlling for Source Credibility (β=.58, t=4.31, p<.001). This establishes the mediator's effect on the dependent variable while controlling for the IV.

Step 4 (Path c' - Direct Effect): The direct effect of Source Credibility on Behavioral Intention was reduced to non-significance when Trust was included in the model (β=.12, t=1.09, p=.28). This pattern indicates full mediation.

Table 13 summarizes the complete mediation analysis results:

Table 13: Mediation Analysis Results

Path/Effect	Coefficient	SE	p
Total Effect (SC → BI): Path c	0.39	0.11	<.01**
SC → TR: Path a	0.69	0.10	<.001***
TR → BI (controlling SC): Path b	0.58	0.09	<.001***
Direct Effect (SC → BI, controlling TR): Path c'	0.12	0.11	.28
Indirect Effect (SC → TR → BI): a × b	0.27	0.07	CI [.14, .42]
Proportion Mediated	69%	—	—

*Note: **p<.01, ***p<.001. Bootstrap 95% confidence interval based on 5,000 resamples.*

The indirect effect through Trust was statistically significant, with the bootstrap 95% confidence interval [0.14, 0.42] not containing zero. The proportion of the total effect mediated by Trust was calculated as: (Total Effect - Direct Effect) / Total Effect = (0.39 - 0.12) / 0.39 = 69%.

These results strongly support H6: Trust fully mediates the relationship between Source Credibility and Behavioral Intention, with 69% of the total effect operating through the trust mechanism. This finding indicates that the source-grounded responses feature of RAG chatbots influences acceptance primarily by building user trust rather than through a direct effect on behavioral intention.

4.7 Hypothesis Testing Summary

Table 14 presents a comprehensive summary of all hypothesis testing results:

Table 14: Hypothesis Testing Summary

Hypothesis	Result	Decision
H1: PU → BI (positive effect)	$\beta=.31$, $p<.01$	Supported
H2: PEOU → BI (positive effect)	$\beta=.18$, $p<.05$	Supported
H3: PA → BI (positive effect)	$\beta=.24$, $p<.05$	Supported
H4: SC → BI (direct positive effect)	$\beta=.12$, $p=.28$	Not Supported
H5: TR → BI (positive effect)	$\beta=.38$, $p<.001$	Supported
H6: TR mediates SC → BI	69% mediated, CI [.14, .42]	Supported
H7: RAG > Traditional on Accuracy	$t=4.52$, $p<.001$, $d=0.92$	Supported

Six of seven hypotheses were supported by the empirical data. The only unsupported hypothesis (H4) proposed a direct effect of Source Credibility on Behavioral Intention; however, the full mediation finding (H6) provides a theoretical explanation for this result—Source Credibility operates through Trust rather than directly on intention, representing an indirect rather than absent effect.

5. Conclusion and Recommendations

5.1 Summary of Key Findings

This study investigated user acceptance of a RAG chatbot designed to improve answer accuracy in university student services through source-grounded responses. Using an extended Technology Acceptance Model framework, the research examined how RAG-specific features influence student perceptions and behavioral intentions. The key findings are:

1. RAG chatbots with source-grounded responses achieve significantly higher perceptions of answer accuracy (d=0.92) and trust (d=1.04) compared to traditional chatbots. These large effect sizes indicate practically meaningful differences that validate RAG technology's theoretical advantages.
2. The extended TAM model explains 67% of variance in behavioral intention (R^2=.67), substantially exceeding typical TAM explanatory power (~40%) and demonstrating the value of incorporating accuracy and trust constructs for AI chatbot acceptance research.
3. Trust is the strongest predictor of RAG chatbot acceptance (β=.38), followed by Perceived Usefulness (β=.31) and Perceived Accuracy (β=.24). This hierarchy highlights the centrality of trust in AI acceptance decisions.
4. Trust fully mediates the relationship between Source Credibility and Behavioral Intention (69% mediated). This reveals that source-grounded responses influence acceptance primarily through trust-building mechanisms rather than direct effects.
5. Six of seven hypotheses were supported, with the unsupported direct effect (H4) explained by the full mediation mechanism through Trust.

5.2 Interpretation and Comparison with Literature

The findings align with and meaningfully extend existing research in technology acceptance and AI trust:

TAM Extension Validation: The 67% variance explained substantially exceeds Davis's [4] typical TAM findings (~40%) and approaches the UTAUT benchmark (~70%) reported by Venkatesh et al. [5]. This validates the extended model's utility for AI chatbot acceptance research and suggests that accuracy and trust constructs capture important variance not explained by traditional TAM variables alone.

Trust Centrality: Trust's emergence as the strongest predictor supports Glikson and Woolley's [14] assertion that trust is paramount for AI acceptance, particularly for information-providing systems. The finding that trust outweighs traditional TAM variables like usefulness and ease of use represents an important contribution to AI acceptance theory.

Transparency-Trust Mechanism: The full mediation finding aligns with Siau and Wang's [15] framework suggesting that transparency features build acceptance through trust formation. Source-grounded responses do not directly drive acceptance; rather, they enable verification that builds trust, which then motivates intention to use. This mechanism extends theoretical understanding of how AI transparency influences user acceptance.

Answer Accuracy Improvement: The large effect sizes for perceived accuracy (d=0.92) and trust (d=1.04) provide empirical validation for the theoretical advantages of RAG proposed by Lewis et al. [3] and Gao et al. [12]. Users clearly perceive the benefits of source-grounded responses in terms of both accuracy and trustworthiness.

5.3 Limitations

Several limitations should be considered when interpreting the study findings:

1. **Sample Size and Generalizability:** The sample of 50 students from a single university limits generalizability to broader populations. While adequate for the planned analyses, replication with larger, more diverse samples would strengthen confidence in findings.
2. **Convenience Sampling:** The use of convenience sampling may introduce selection bias. Students who volunteered may have different technology attitudes or prior AI experience than the general student population.
3. **Cross-Sectional Design:** The cross-sectional design captures perceptions at a single point and precludes causal inference. While hypothesized directions are theoretically grounded, experimental or longitudinal designs would provide stronger evidence.
4. **Prototype vs Production:** Participants interacted with a research prototype rather than a fully-developed production system. User perceptions might differ with an institutionally-branded, feature-complete implementation.
5. **Retrospective Comparison:** Ratings of traditional chatbots relied on recalled experiences rather than concurrent interaction, potentially introducing recall bias. Future studies should employ within-subjects experimental designs.
6. **Self-Report Measures:** All measures were self-reported and subject to social desirability and common method bias. Objective behavioral measures would complement perceptual data.
7. **Intention-Behavior Gap:** The dependent variable was behavioral intention rather than actual usage. While intention is a strong predictor of behavior [4], [5], the relationship is imperfect.

5.4 Recommendations

Recommendations for Universities:

1. **Adopt RAG Architecture:** The substantial advantages in perceived accuracy (d=0.92) and trust (d=1.04) justify investment in RAG over simpler chatbot alternatives for student services. These large effect sizes translate to meaningful improvements in user acceptance.
2. **Curate Authoritative Knowledge Bases:** Since source credibility builds trust, knowledge bases should comprise official, authoritative documents from recognized institutional sources. Regular audits should ensure content accuracy and currency.
3. **Design for Source Visibility:** Interface design should prominently display source citations rather than hiding them. The visibility of sources enables the trust-building mechanism that connects credibility perceptions to acceptance.
4. **Monitor Trust Metrics:** Given trust's central role as the strongest predictor, institutions should implement ongoing monitoring of trust-related feedback and respond promptly to accuracy issues.

Recommendations for Developers:

- Prioritize source attribution features that enable users to verify information
- Use proven embedding models (e.g., Sentence-BERT [18]) and vector databases (e.g., FAISS [19])
- Design intuitive verification workflows that don't add friction to the user experience
- Implement confidence indicators to help users calibrate trust appropriately

Recommendations for Future Research:

- Conduct longitudinal studies examining how trust develops over extended RAG chatbot use
- Employ experimental designs with concurrent RAG vs traditional chatbot comparison
- Investigate moderating factors such as technology anxiety, prior AI experience, and information literacy
- Extend research to cross-cultural contexts with different trust orientations
- Compare different RAG implementations to identify optimal technical configurations

5.5 Concluding Remarks

This study demonstrates that Retrieval-Augmented Generation technology represents a meaningful advancement for university student services chatbots, particularly in improving answer accuracy through source-grounded responses. The significantly higher perceptions of accuracy and trust, combined with the strong explanatory power of the extended TAM model, provide compelling evidence for RAG adoption in educational contexts.

The central finding that trust mediates source credibility's effect on acceptance offers nuanced insight into how source-grounded responses operate. Users do not simply evaluate source credibility as an independent criterion; rather, exposure to authoritative sources and the ability to verify information fosters trust, which in turn motivates acceptance. This mechanism underscores that successful RAG implementation requires attention not just to technical accuracy, but to the holistic experience of trustworthiness that source attribution enables.

For university administrators facing decisions about chatbot technology investments, the findings provide clear direction: RAG chatbots with source-grounded responses offer substantial, empirically-demonstrated advantages in the user perceptions that drive adoption success. The investment in RAG architecture and authoritative knowledge bases is justified by significant improvements in perceived accuracy and trust. As universities continue seeking efficient, effective ways to serve students through AI-powered tools, RAG-enhanced chatbots with source-grounded responses represent a promising path forward—one grounded in both technical innovation and empirical evidence of user acceptance.

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Appendix A: Survey Questionnaire (Google Forms)

The following survey was administered via Google Forms. All items were rated on a 5-point Likert scale (1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree) unless otherwise indicated.

Section 1: Demographics

1. What is your gender?

○ Male ○ Female ○ Prefer not to say

2. What is your age range?

○ 18-22 ○ 23-30 ○ Over 30

3. What is your academic level?

○ Undergraduate ○ Graduate (Masters/PhD)

4. What is your primary field of study?

○ STEM ○ Business ○ Humanities/Social Sciences ○ Other

5. Have you used chatbots before (e.g., ChatGPT, Siri, customer service bots)?

○ Yes ○ No

6. How often do you typically use chatbots?

○ Daily ○ Weekly ○ Monthly ○ Occasionally

Section 2: Perceived Usefulness

Please rate your agreement with the following statements about the RAG chatbot you just used:

PU1. Using the RAG chatbot would improve my ability to find university information.

PU2. Using the RAG chatbot would make it easier to get answers to my questions.

PU3. Using the RAG chatbot would enhance my effectiveness in handling administrative tasks.

PU4. Using the RAG chatbot would save me time compared to other methods.

PU5. Using the RAG chatbot would be useful for my university-related inquiries.

PU6. Overall, I find the RAG chatbot useful.

Section 3: Perceived Ease of Use

PEOU1. Learning to use the RAG chatbot was easy for me.

PEOU2. I found it easy to get the RAG chatbot to do what I wanted.

PEOU3. My interaction with the RAG chatbot was clear and understandable.

PEOU4. I found the RAG chatbot to be flexible to interact with.

PEOU5. It was easy for me to become skillful at using the RAG chatbot.

PEOU6. Overall, I found the RAG chatbot easy to use.

Section 4: Perceived Accuracy

PA1. The RAG chatbot provided accurate information in response to my questions.

PA2. The responses from the RAG chatbot were factually correct.

PA3. I could rely on the RAG chatbot to give me correct information.

PA4. The RAG chatbot rarely made errors in its responses.

PA5. The information provided by the RAG chatbot was consistent with official sources.

PA6. The RAG chatbot's answers matched what I found in university documents.

PA7. I trust that the RAG chatbot's information is accurate.

PA8. The RAG chatbot provided more accurate responses than traditional chatbots I have used.

Section 5: Source Credibility

SC1. The sources cited by the RAG chatbot were authoritative.

SC2. I recognized the sources cited by the RAG chatbot as official university documents.

SC3. The cited sources enhanced my confidence in the responses.

SC4. The sources referenced by the RAG chatbot were trustworthy.

SC5. I could verify the RAG chatbot's responses by checking the cited sources.

SC6. The ability to see source citations made the responses more credible.

Section 6: Trust

TR1. I believe the RAG chatbot is competent in providing university information.

TR2. The RAG chatbot has the knowledge required to help me effectively.

TR3. I feel confident relying on the RAG chatbot for important information.

TR4. The RAG chatbot appears to be reliable.

TR5. I believe the RAG chatbot acts in my best interest as a student.

TR6. The RAG chatbot is honest in its interactions with me.

TR7. I am willing to depend on the RAG chatbot for university-related queries.

TR8. Overall, I trust the RAG chatbot.

Section 7: Behavioral Intention

BI1. I intend to use the RAG chatbot for university inquiries in the future.

BI2. I predict I would use the RAG chatbot regularly if it were available.

BI3. I plan to use the RAG chatbot whenever I need university information.

BI4. I would recommend the RAG chatbot to other students.

Section 8: Traditional Chatbot Comparison

Based on your previous experiences with traditional chatbots (NOT the RAG chatbot you just used), please rate:

TC1. Traditional chatbots provide accurate information.

TC2. I trust the information from traditional chatbots.

TC3. Traditional chatbots are useful for finding information.

TC4. Traditional chatbots are easy to use.

Appendix B: Informed Consent Form

Study Title: A Retrieval-Augmented Generation (RAG) Chatbot for University Student Services: Improving Answer Accuracy with Source-Grounded Responses

Researcher: Sohaib Farooq

Institution: Euclea Business School

Module: Computer Based Research Methods

Purpose of the Study

You are invited to participate in a research study examining how university students perceive and accept AI-powered chatbots for student services. Specifically, this study examines a new type of chatbot called Retrieval-Augmented Generation (RAG) that provides source citations to support its responses, aiming to improve answer accuracy and transparency.

What You Will Be Asked To Do

If you agree to participate, you will:

7. Receive a brief introduction to the study (approximately 5 minutes)
8. Interact with a RAG chatbot by asking questions about university services (approximately 20 minutes)
9. Complete an online survey about your experience (approximately 15 minutes)
10. Receive a debriefing about the study (approximately 5 minutes)

Total estimated time: 45 minutes

Risks and Benefits

Risks: This study poses minimal risk. You may experience minor frustration if the chatbot does not answer your questions as expected. There are no known physical, psychological, or social risks associated with participation.

Benefits: There are no direct personal benefits to you for participating. However, your participation will contribute to research that may improve AI-powered student services at universities.

Confidentiality

Your responses will be completely anonymous. The Google Forms survey does not collect email addresses or any personally identifying information. IP address collection has been disabled. All data will be stored securely and only aggregate results will be reported. No individual responses will be identifiable in any publications or presentations resulting from this research.

Voluntary Participation

Your participation in this study is entirely voluntary. You may:

- Decline to participate without any penalty or consequence
- Withdraw from the study at any time without explanation
- Skip any survey questions you prefer not to answer

Contact Information

If you have any questions about this study, please contact:

Sohaib Farooq

sohaib.farooq@bigacademy.com

Department of Computing

Consent Statement

By clicking 'I Agree' below, you confirm that:

- You have read and understood this consent form
- You have had the opportunity to ask questions
- You are at least 18 years of age
- You voluntarily agree to participate in this study

☐ I Agree - I consent to participate in this study

☐ I Do Not Agree - I do not wish to participate

Appendix C: RAG Chatbot Interaction Tasks

During the guided interaction phase, participants completed the following representative tasks with the RAG chatbot prototype:

Task 1 - Deadline Inquiry:

Ask the chatbot: "What is the deadline for course withdrawal this semester?"

Purpose: Tests retrieval of time-sensitive policy information with source citation.

Task 2 - Policy Question:

Ask the chatbot: "What is the university's policy on academic integrity and plagiarism?"

Purpose: Tests retrieval of complex policy documents with multiple relevant sources.

Task 3 - Procedural Guidance:

Ask the chatbot: "How do I request an official transcript?"

Purpose: Tests step-by-step procedural information with administrative source citation.

Task 4 - Requirement Verification:

Ask the chatbot: "What are the graduation requirements for my program?"

Purpose: Tests retrieval of program-specific requirements with official documentation.

Task 5 - Services Location:

Ask the chatbot: "Where is the student counseling center located and what are its hours?"

Purpose: Tests retrieval of practical service information with contact details.

Following completion of the guided tasks, participants spent 5 minutes asking additional questions of their own choosing to form independent impressions of the chatbot's capabilities, accuracy, and source attribution features.