AN AI-DRIVEN CAREER GUIDANCE MODEL FOR COMPUTING STUDENTS IN UGANDAN UNIVERSITIES

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DECLARATION

I declare that this dissertation titled "**An AI-Driven Career Guidance Model for Computing Students in Ugandan Universities"** is my original work, and to the best of my knowledge, it has never been submitted to any university or institution for any academic award whatsoever.

ABSTRACT

This study proposes the design, development, and evaluation of a novel AI-driven career guidance model tailored specifically for computing students in Ugandan universities. Addressing the limitations of traditional counseling, skill-job market mismatches, and specific socio-economic challenges within the Ugandan context, this study leverages advanced machine learning techniques, including explainable AI (XAI), to provide personalized, data-informed, and transparent career pathways. The model integrates diverse data sources such as academic performance, psychometric profiles, and real-time local job market trends to recommend suitable career paths, relevant upskilling courses, and local institutional programs. Through a mixed-methods approach, including system development, quantitative performance evaluation, and qualitative user studies with Ugandan students and career counselors, this research aims to validate the model's effectiveness, usability, and ethical implications. The anticipated outcome is a robust, scalable, and culturally sensitive prototype that not only bridges the gap between educational output and industry demand in Uganda but also contributes a novel theoretical framework for AI-driven career guidance in emerging economies. This study proposes the design, development, and evaluation of a novel AI-driven career guidance model tailored specifically for computing students in Ugandan universities. Addressing the limitations of traditional counseling, skill-job market mismatches, and specific socio-economic challenges within the Ugandan context, this study leverages advanced machine learning techniques, including explainable AI (XAI), to provide personalized, data-informed, and transparent career pathways. The model integrates diverse data sources such as academic performance, psychometric profiles, and real-time local job market trends to recommend suitable career paths, relevant upskilling courses, and local institutional programs. Through a mixed-methods approach, including system development, quantitative performance evaluation, and qualitative user studies with Ugandan students and career counselors, this research aims to validate the model's effectiveness, usability, and ethical implications. The anticipated outcome is a robust, scalable, and culturally sensitive prototype that not only bridges the gap between educational output and industry demand in Uganda but also contributes a novel theoretical framework for AI-driven career guidance in emerging economies.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
NLP	Natural Language Processing
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
ML	Machine learning
DL	Deep learning
EDM	Educational Data Mining
LA	Learning analytics
ICT	Information and Communication Technology
LSTM	Long short-term memory network
CF	Collaborative Filtering
CBF	Content-Based Filtering
MF	Matrix Factorization
TF/IDF	Term frequency–inverse document frequency
SLR	Systematic Literature Review
DSR	Design Science Research
XAI	Explainable Research
GDPR	General Data Protection Regulations
KBF	Knowledge-Based Filtering
MDPI	Multidisciplinary Digital Publishing Institute
NCBI	National Center for Biotechnology Information
IEEE	Institute of Electrical and Electronics Engineers
UX/UI	User Experience/User Interface

CHAPTER 1: INTRODUCTION

1.1 Background and Context

The global employment landscape is undergoing rapid transformation as technological innovation, automation, and new industry sectors continue to reshape the world of work (Lazarova et al., 2023). These developments are altering skill requirements and influencing how individuals prepare for their professional trajectories(Attwell & Hughes, 2019). In response, higher education institutions are increasingly expected to equip graduates with the flexibility, digital competence, and problem-solving capacity needed to navigate uncertain and evolving career pathways (Ndibalema, 2025; Tabar & Saberi, 2023). Yet many established career counseling frameworks have not kept pace with these demands(Tabar & Saberi, 2023; Tedeschi et al., 2025). Traditional models often remain generalized and static, offering limited scope for data-informed, personalized support that reflects present-day labor market dynamics (Assiri et al., 2020). At the same time, the proliferation of emerging occupations has made career decision-making more complex for students and recent graduates. The challenge of aligning personal interests, academic backgrounds, and skill sets with a fast-shifting employment landscape frequently results in uncertainty and, for some, career choices that do not reflect existing opportunities (Heimo et al., 2020; Yahya et al., 2024). According to (EESC, 2018) such misalignment can contribute to underemployment, job insecurity, and reduced satisfaction. Although human career counselors play an important role, their work is constrained by time, workload, and the inherently subjective nature of advisory interactions (Santosh Mhatre et al., 2024). In many regions, including developing countries, access to high-quality counseling services is further limited by financial, infrastructural, and geographical barriers. Consequently, students often depend on informal networks for guidance, even when such information may be outdated or only loosely connected to actual labor market conditions.

Recognizing these challenges, universities and policymakers worldwide have sought to strengthen digital literacy, experiential learning, and lifelong learning components within higher education (Namuwonge, 2024). Parallel to these efforts, artificial intelligence (AI) has gained visibility as a tool with significant potential to enhance career support services. AI-enabled systems can synthesize large datasets spanning academic records, skills profiles, and real-time labor market indicators to generate personalized, objective guidance at scale (Trujillo et al., 2025). These tools offer the possibility of widening access to timely and evidence-based recommendations, thereby supporting more informed decision-making among learners.

In Sub-Saharan Africa, however, global technological shifts intersect with longstanding structural constraints (Ndibalema, 2025). The region's growing youth population, persistent graduate unemployment, and limited higher education resources intensify the need for effective, context-specific career guidance. East Africa illustrates this tension clearly (Otwine et al., 2022). Although technological innovation across the region has increased demand for digital skills, employers continue to report gaps between university training and workplace expectations. Uganda reflects these trends (Guàrdia et al., 2021). Guided by Vision 2040 and the National ICT Policy, the country's ICT sector contributes more than 9% to GDP and continues to expand in areas such as software engineering, cloud computing, cybersecurity, and AI (Jennifer, 2024). Despite this growth, institutional career services such as those at Makerere University and Mbarara University of Science and Technology remain centralized, unevenly resourced, and not fully aligned with labor market needs (Ndibuuza et al., 2021). As a result, many computing students rely heavily on peer networks and informal sources of advice (Mugisha & Nambatya, 2019), reinforcing patterns of skills mismatch and weakening the country's broader innovation potential. Several digital initiatives have attempted to modernize career support in Uganda, yet many fall short of addressing rapidly changing occupational demands. Emerging AI-based guidance tools offer new opportunities, but their use in African higher education remains limited. Moreover, systems developed in high-resource settings are often opaque, functioning as “black boxes” that do not clearly explain how recommendations are produced (Adadi & Berrada, 2018; Zhang, 2025). Limited transparency can undermine users’ trust and hinder adoption. It obscures potential biases that may affect the fairness of recommendations, an important consideration in educational contexts where ethical sensitivity is essential. Considering these gaps, this study proposes an AI-driven career guidance model tailored to the needs of computing students in Uganda, incorporating emotional intelligence (Khare et al., 2024), context awareness, and explainability to enhance transparency and interpretability (Gunning et al., 2019). Integrating explanations is intended to support user trust, provide clearer justification for recommendations, and promote fairness in decision-making processes. The model aims to deliver individualized, context-aware guidance that reflects both academic preparation and local labor market trends. In doing so, it contributes to national priorities related to youth employability, the development of a knowledge-based economy, and Uganda’s broader digital transformation agenda.

1.2 The Imperative for Ai-Driven Career Guidance For Students

Students today navigate a labour market that is changing more quickly than traditional career guidance systems can support (Lazarova et al., 2023). Many struggle to identify suitable career paths because they lack clear information about emerging professions, required skills, and the relevance of their academic choices (Assiri et al., 2020; Sarkar et al., 2020). School and university guidance services provide valuable support, but high student-to-counsellor ratios, limited resources, and outdated tools often prevent students from receiving personalised and timely advice. Artificial intelligence offers a practical solution to these challenges. Modern AI systems can analyse large volumes of labour-market data, understand students' skills and interests, and deliver tailored recommendations through interactive digital platforms (E & R, 2025; Shah et al., 2024). These systems make career guidance more accessible by providing continuous support, helping students explore career options, highlight skill gaps, and connect with relevant courses, internships, and training opportunities. This study focuses on the development of an AI-powered career guidance model designed specifically for students. It outlines the technical, pedagogical, and ethical considerations required to create a system that is accurate, inclusive, and trustworthy (Atif et al., 2021; Sworna et al., 2024). Although interest in AI-based guidance is increasing, the essential design requirements for effective and responsible implementation remain fragmented across existing research. By addressing this gap, the study aims to contribute a clear foundation for using AI to support students in making informed and confident career decisions. Overall, this study positions AI as a socio-technical tool that can expand equitable access to career guidance in low-resource higher education environments. By combining human-centered design (Bobeth Janand Schreitter, 2013) with data-driven analysis, the proposed mdel seeks to offer a practical framework for helping students navigate increasingly complex career landscapes.

1.3 Definition of Key Terms

To ensure clarity and a shared understanding throughout this dissertation, key concepts central to the research are defined as follows.

1.3.1 Artificial Intelligence (AI)

Artificial Intelligence refers to the branch of computer science dedicated to creating systems capable of performing tasks that would normally require human intelligence(Korteling et al., 2021). These tasks include, but are not limited to, learning from experience, reasoning to draw conclusions, understanding complex data, adapting to new situations, and making decisions autonomously (Pu et al., 2025). AI systems aim to simulate cognitive functions such as problem-solving, pattern recognition, and language understanding, enabling machines to perform activities ranging from simple automation to complex interactions.

1.3.2 Machine Learning (ML)

Machine Learning is a specialized subset of AI that focuses on developing algorithms that enable computers to learn from and make predictions or decisions based on data (Bringsjord et al., 2018). Unlike traditional programming, where explicit instructions are coded, ML algorithms identify patterns and relationships within large datasets to improve performance over time without direct human intervention . This capability allows ML models to adapt dynamically as new data becomes available, making them essential for applications such as predictive analytics, recommendation systems, and autonomous decision-making (Khanal et al., 2020; Sabitha et al., 2022).

1.3.3 Natural Language Processing (NLP)

Natural Language Processing is an interdisciplinary field within AI that focuses on the interaction between computers and human language (Collobert et al., 2011). NLP techniques enable machines to process, analyze, and generate natural language text or speech in a way that is both meaningful and contextually relevant. Applications of NLP include language translation, sentiment analysis, speech recognition, and conversational agents. (Rahman et al., 2021) by understanding linguistic nuances, syntax, semantics, and context, NLP systems facilitate more natural and effective communication between humans and machines.

1.3.4 Career Guidance (CG)

According to (Piazza Robertaand Magnano, 2017) abroad term that encompasses a range of interventions, including career education and counseling, designed to assist individuals in developing and utilizing the knowledge, skills, and attitudes necessary for making informed decisions regarding their study, work options, and overall life roles.

1.3.5 Career Education

The planned development of knowledge, skills, and attitudes through formal and non-formal learning experiences within educational and training settings, designed to assist individuals in making informed decisions about their educational and professional paths and ensuring effective participation in working life (Nwakanma, 2024).

1.3.6 Career Counseling

An intensive and individualized service that focuses on the interaction between a counselor and an individual (or a small group), aimed at facilitating the exploration of personal challenges and complexities related to career and life planning (Tabar & Saberi, 2023). This specific type of counselling prioritizes culturally attuned advice, respecting everyone's background.

1.3.7 AI-Driven Career Guidance Model

An AI-driven career guidance model refers to an intelligent system that uses artificial intelligence and machine learning techniques to generate individualized career recommendations (Thakkar et al., 2024). These systems analyze student data such as academic performance, skills profiles, and preferences alongside current labor market trends to offer guidance that supports informed career planning. In this study, the model is designed for university students and incorporates elements of emotional intelligence to enhance responsiveness to students' motivations, concerns, and decision-making needs.

1.3.8 Personalized Career Guidance

Personalized career guidance involves tailoring career recommendations to the specific characteristics of an individual student. This includes consideration of their skills, interests, academic background, personal goals, and preferred career trajectories. By integrating emotional intelligence principles, the proposed model also acknowledges the emotional and motivational factors influencing students' choices, ensuring that recommendations remain supportive, relevant, and student-centered.

1.3.9 Labor Market Integration

Labor market integration refers to the process through which individuals enter, participate in, and build sustainable careers within the labor market (Desiderio, 2016). For students, this includes securing employment aligned with their training, developing workplace readiness, and adapting to the expectations and norms of their chosen profession. Successful integration goes beyond initial job acquisition and encompasses continued professional growth, confidence building, and the ability to contribute effectively within a given economic environment (Fahimirad et al., 2019).

1.3.10 Skills Gap

The skills gap describes the mismatch between the competencies required by employers and those possessed by job seekers (Thijs Van Rens & Chan, 2023). In higher education, particularly within fast-changing fields such as computing, the skills gap often emerges from technological advancements that outpace curriculum updates (Ayofe & Ajetola, 2009). Addressing the skills gap requires targeted upskilling initiatives and guidance systems that help students understand the skills they need to remain competitive in the labor market.

1.3.11 Prior Learning Assessment (PLA)

Prior Learning Assessment is a structured process used to evaluate skills and knowledge gained through informal or non-traditional learning experiences. For students, PLA can recognize competencies developed through work, community engagement, freelance activities, or self-directed learning. This recognition supports clearer career planning, enhances confidence, and contributes to more accurate skills matching by acknowledging learning that may not appear in formal academic records.

1.3.12 Skills Matching

Skills matching is the process of aligning an individual's abilities, qualifications, and experiences with the requirements of specific jobs or training programs. In the proposed model, skills matching enables the translation of a student's profile into realistic and meaningful career options based on current labor market demands and the student's aspirations.

1.3.13 Skill Job Mismatch

Skill job mismatch occurs when the competencies of a job seeker do not correspond to the requirements of available positions. Such mismatches can lead to underemployment or dissatisfaction, highlighting the need for guidance tools that offer timely insights and help students bridge gaps through targeted learning opportunities (Comyn & Strietska-Ilina, 2019).

1.3.14 Career Path Recommendation

Career path recommendation involves identifying suitable professional trajectories and relevant training opportunities for an individual (Ghosh et al., 2020). These recommendations are informed by a combination of labor market analysis, student characteristics, and emotional factors that shape decision-making. By integrating these elements, the proposed model aims to support students in identifying pathways that are both feasible and aligned with their personal and professional goals.

1.3.15 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence refers to a set of methods designed to make the processes and outputs of AI models understandable to human users (Dağlarli, 2020). XAI aims to improve transparency, interpretability, and trustworthiness by offering clear explanations for how an AI system arrives at its recommendations or decisions. Although the broader study emphasizes emotional intelligence, XAI remains relevant as a complementary concept for ensuring that AI-supported guidance systems are perceived as credible and reliable within educational environments.

1.3.16 Computing Students

Computing students include undergraduate and postgraduate learners enrolled in programs such as computer science, software engineering, information technology, data science, artificial intelligence, and other related disciplines (Vo, Vu, Vu, Vu, & Mach, 2022). These students typically engage with technical coursework, practical training, and project-based learning that prepare them for careers in digital and technology-driven sectors.

1.3.17 Ugandan Universities

Ugandan universities refer to public and private higher education institutions within Uganda that offer computing or ICT-related degree programs. These institutions play a central role in developing the country's digital workforce and include established national universities as well as emerging private institutions that contribute to training future professionals in the ICT sector.

1.4 Problem Statement

Computing students in Ugandan universities face a persistent and systemic career guidance deficit that undermines their transition from academic training to meaningful participation in the local and global technology workforce (McKinnon & McCrae, 2012; UNCDF, 2021). This deficit contributes to widespread skill mismatches, underemployment, and inefficient utilization of educational investment (Ministry of ICT, 2025). Despite the rapid growth of Uganda's ICT sector and its significant contribution to national GDP, university career support systems have not evolved to meet the complexity and dynamism of the digital economy (UNICEF, 2024). Existing career counseling services are under-resourced, overly generic, and inadequately equipped to provide individualized, data-informed, and contextually relevant guidance to computing students (Jennifer, 2024; Ndibuuza et al., 2021). High student-to-counselor ratios, reliance on static information, and weak institutional prioritization further limit their effectiveness within Uganda's rapidly changing technology ecosystem (KASULE et al., 2023; Otwine et al., 2022). The Ugandan technology job market is highly dynamic, characterized by continuous innovation, emerging job roles, and evolving skill requirements (World Economic Forum, 2023). Many students remain unaware of the full range of career paths available in technology beyond traditional programming or network administration roles (Attwell & Hughes, 2019). This knowledge gap extends to limited understanding of industry expectations, the practical application of technical skills, and the strategies required to secure internships or employment. Consequently, students often graduate with academic qualifications that are poorly aligned with employer needs, while industries struggle to find candidates with the precise combination of technical and soft skills required for competitive roles (ACET, 2025). In addition to institutional constraints, many students and job seekers across Uganda struggle with self-assessment and informed decision-making. A lack of accessible, professional counseling services particularly outside major urban centers restricts the ability of individuals to evaluate their strengths, interests, and values against labor market opportunities. Existing career tests and online tools are often too generic, outdated, or culturally irrelevant to provide actionable insights. Limited awareness of alternative career pathways, combined with the absence of localized, data-driven self-assessment systems, contributes to confusion, dissatisfaction, and unfulfilled potential among university graduates.

While automated career recommendation systems and AI-driven platforms have emerged globally(Majidi & John's Newfoundland, 2018; Vidhya et al., 2024a), their practical utility in the Ugandan and broader Sub-Saharan African contexts remains limited. Most existing AI models are developed and trained using large-scale datasets from Western economies (Ilkou et al., n.d.), which reduces their relevance in regions with distinct socio-economic, cultural, and institutional realities. As a result, these systems often produce generic or inappropriate recommendations that fail to reflect local industry dynamics or integrate effectively with university learning management systems. Furthermore, the "black box" nature of many AI models, which provide recommendations without clear explanations (Collaris & Van Wijk, n.d.), diminishes user trust and understanding (Zylowski et al., 2025). Without transparency and contextual adaptation, such systems risk perpetuating existing biases in gender, socio-economic background, or educational access (L. Xu et al., 2022). These interconnected challenges underscore a critical gap in Uganda's higher education and employment ecosystem (Kakuru, 2022; KASULE et al., 2023). There is an urgent need for an innovative, transparent, and ethically designed AI-driven career guidance system that can provide localized, data-informed, and personalized recommendations for computing students. Such a system should be capable of analyzing individual academic backgrounds, skills, and preferences while aligning them with real-time labor market data and emerging industry trends (Jadhav et al., 2024).

This study, therefore, proposes the design and implementation of an AI-powered conversational career guidance model specifically tailored for computing students in Ugandan universities. The model employs a Retrieval-Augmented Generation (RAG) architecture (Morić et al., 2024) to integrate dynamic data from local job portals, industry reports, and university programs. It aims to deliver personalized, explainable, and contextually relevant guidance that bridges the gap between education and employment. Beyond addressing immediate student needs, the research contributes to Uganda's broader national goals of economic transformation, technological innovation, and inclusive growth under Vision 2040 (Ministry of ICT, 2022). It also advances academic understanding of AI-driven career guidance in low-resource contexts and provides a scalable framework that can be adapted across Sub-Saharan Africa to foster equitable and informed career development (World Economic Forum, 2023).

1.5 Main Aim

To contribute to the development of an AI-driven system model to enhance the accessibility and efficacy of career guidance services for university students and, ultimately, to contribute to their successful integration into the labor market after graduation.

1.6 Specific Objectives

I. To establish and synthesize the requirements for designing and developing AI-driven conversational models for students' career guidance

(Note: This objective was addressed through the scoping review published as: Bisaso, S., Wasswa, W., & Muhumuza, G. (2025). Towards the Application of an NLP-driven Conversational Model for Efficient and Affective Career Guidance for Students: A Scoping Review. *European Journal of Applied Science, Engineering and Technology*, *3*(3), 240-253. https://doi.org/10.59324/ejaset.2025.3(3).16)

II. To design, develop, and test an efficient AI-driven career guidance platform to coordinate migrants' career guidance based on the identified requirements

III. To evaluate the feasibility, acceptability, and of the proposed model.

The completion of Objective 1, achieved through the scoping review, provided the essential foundation for this research. By systematically mapping and synthesizing the existing evidence on requirements, it has directly informed the design, development, and evaluation steps outlined in the subsequent objectives, ensuring that the research is grounded in the actual needs and considerations identified in the literature.

1.7 Research Questions

I. What are the requirements for designing and developing an AI-driven conversational model to coordinate effective career guidance for computing students?

II. What are the specific needs, perceptions, and expectations of students in Ugandan universities regarding digital tools and AI-powered models for career guidance and support?

III. How could we design, develop, and test an efficient AI-driven conversational model to coordinate students' career guidance and their integration into the labour market?

IV. How could we evaluate the feasibility and acceptability of the proposed model?

1.8 Significance of the Study

This study makes important theoretical contributions to the field of AI for social good, particularly in low-resource settings. It introduces a novel framework for AI-driven career guidance designed to address challenges such as data scarcity, dynamic labor market conditions, and cultural diversity in emerging economies. By embedding Explainable AI (XAI) within the sensitive domain of career counseling, the study advances the literature on trustworthy and interpretable AI, demonstrating how transparency can be empirically evaluated. In addition, by engaging directly with computing students, it provides a rare empirical baseline of skills, career aspirations, and labor market realities in Uganda's under-researched computing sector.

Methodologically, the study contributes a hybrid approach for integrating multiple data sources academic records, psychometric assessments, and labor market information into a unified career guidance system. This multimodal integration is essential in low-resource environments where data are fragmented and often incomplete. The research also develops a culturally sensitive mixed-methods evaluation framework, enabling rigorous assessment of AI systems in socio-cultural contexts marked by rapid technological adoption but limited institutional capacity. These methodological innovations establish a foundation for future research on AI in education across Africa and other resource-constrained regions.

Practically, the study provides a pathway to enhance the employability of Ugandan computing students through personalized, data-driven career advice aligned with industry demand. It offers universities insights for curriculum review and development, helping academic programs remain responsive to labor market needs, while also equipping career counselors with an advanced decision-support tool that augments their professional practice. More broadly, the research produces critical evidence to inform policymakers and guide national strategies for workforce development. By presenting a tangible framework and prototype, this dissertation establishes a replicable blueprint for developing equitable and context-aware AI solutions for student career guidance in Uganda and similar contexts.

1.9 Scope and Delimitations of the Study

This study is limited in scope to the design, development, and evaluation of an AI-driven career guidance model tailored for computing students at selected universities in Uganda. The model applies machine learning and Natural Language Processing (NLP) techniques to analyze diverse data inputs, including academic records, self-reported skills and interests, psychometric assessments, and anonymized labor market information. Its outputs include personalized career pathway recommendations, suggestions for relevant upskilling opportunities, and transparent explanations of recommendations. The evaluation will be conducted through user studies with computing students and career counselors, focusing on usability, accuracy, and immediate impact on career decision-making.

The study is, however, bounded by certain delimitations. Empirical data collection and evaluation are geographically restricted to Ugandan universities and industry stakeholders. While the architectural framework may hold broader relevance, direct applicability to other regions without adaptation is not assumed. The target population is limited to computing students, excluding learners from other academic disciplines. Furthermore, the project will produce a validated prototype rather than a fully commercialized product. Large-scale deployment, long-term system maintenance, and national-level integration are beyond the scope of this study. Other delimitations concern the nature of the system and its evaluation. The AI model provides recommendations and explanations but does not incorporate real-time human counseling or mentorship, though it may direct students toward such resources. Psychometric profiling is included, but its depth may be constrained by the availability and cultural appropriateness of standardized instruments in Uganda. Finally, while the evaluation focuses on immediate usability, perceived usefulness, and satisfaction, a longitudinal assessment of graduates' actual career outcomes over several years lies outside the timeframe of this study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a critical review of literature that informs the design, development, and evaluation of an AI-driven career guidance model. It establishes the theoretical, empirical, and technical foundations for the study by examining how Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) are reshaping career guidance practices. The review begins by situating career guidance within global and Sub-Saharan African contexts, highlighting challenges such as limited accessibility, high costs, and the shortage of qualified counselors in low-resource higher education environments. It then discusses major theories of career development that underpin personalized and adaptive guidance. Subsequent sections explore AI-based approaches, including recommendation systems, NLP-driven tools, and the role of Explainable AI (XAI) in enhancing transparency and trust. Ethical considerations related to fairness, bias, and privacy are also addressed. Career guidance bridges education and employment by helping individuals align their skills, interests, and aspirations with labor market opportunities. However, traditional counseling methods, though valuable in personalized settings, struggle to meet the growing demand for scalable and data-informed solutions. The integration of AI and ML technologies offers new possibilities for adaptive, cost-effective, and context-sensitive career support. This review critically analyzes current research on AI-driven guidance systems, their methodologies, and existing gaps, thereby establishing the rationale and significance of this doctoral study (Watts & Fretwell, 2004; Vuorinen & Sampson, 2019).

2.2 The Evolving Landscape of Career Guidance

2.2.1 Global Context: From Traditional to Digital Models

Career guidance has evolved from being a peripheral support service into a central element of educational and labor market systems worldwide (OECD, 2020). This transformation reflects the increasing complexity of global labor markets, the acceleration of technological change, and the diversification of employment pathways, including the rise of the gig economy (Tabar & Saberi, 2023). Traditionally, career services were grounded in face-to-face counseling, standardized psychometric testing, and occupational handbooks (Assiri et al., 2020). While effective in their time, these approaches were limited in scalability and personalization, restricting their ability to respond to the evolving aspirations and diverse needs of students. In developed economies, significant strides have been made toward structured frameworks, professionalized career services, and integration with digital platforms that leverage labor market analytics (EESC, 2018; Sultana, 2010). Nonetheless, these systems continue to face challenges of timeliness, adaptability, and depth of personalization in the face of rapidly changing work environments. According to (Liễu et al., 2018) the onset of the Fourth Industrial Revolution has further complicated these dynamics, with automation, digitization, and emerging sectors demanding career services capable of providing real-time, individualized guidance. Digital platforms powered by AI are increasingly viewed as a solution, though technology and generally AI adoption remain uneven and depend on equitable access and contextual relevance (Rana et al., 2024) In contrast, many developing nations face systemic barriers, including underfunded institutions, inadequate professional training, and weak policy frameworks (ILO, 2022). These gaps further lead to persistent mismatches between graduate skills and labor market needs, deepen youth unemployment, and hinder equitable participation in modern labor markets.

2.2.2 Career Guidance in Sub-Saharan Africa

Sub-Saharan Africa presents a particularly complex landscape for career guidance (World Bank, 2020). Higher education is increasingly recognized as central to economic growth and social development, emphasizing lifelong learning, human capital formation, and improved school-to-work transitions (Pandya et al., 2023). Yet universities across the region often lack sufficient staffing, infrastructure, and funding, leaving career offices overstretched and underdeveloped (Zickafoose et al., 2024). These challenges are especially pronounced in fast-changing sectors such as technology, where industry requirements evolve rapidly (Aasheim et al., 2009; Mardis et al., 2018). Although digitalization is promoted to scale services (Warning et al., 2022), practical implementation faces infrastructural barriers such as limited internet access, high connectivity costs, and inconsistent electricity supply (Talib et al., 2023). Additionally, most AI-powered platforms are developed on Western datasets, producing outputs often irrelevant to African labor markets characterized by informal structures and unique socio-cultural dynamics. This underscores the need for localized, adaptive, and scalable career guidance models (Han et al., 2020).

2.2.3 The Ugandan Context: Challenges and Opportunities

Uganda offers a microcosm of the opportunities and challenges in modernizing career guidance systems (Anne et al., 2018). With a rapidly growing youth population and an expanding ICT sector contributing over 9% to GDP (Ministry of ICT, 2025), there is increasing demand for specialized expertise in software engineering, data science, cloud computing, cybersecurity, and AI by 2025 (KASULE et al., 2023). Despite universities expanding computing programs (such as Makerere University, Mbarara University of Science and Technology), career guidance infrastructure has lagged (Anne et al., 2018; KASULE et al., 2023). Services are typically underfunded, centralized, and insufficiently specialized to meet the evolving needs of computing students. As a result, many students rely on anecdotal advice, peer influence, or outdated information, contributing to persistent skill mismatches and underemployment (Comyn & Strietska-Ilina, 2019). Therefore, AI-driven systems offer a promising solution if designed to be localized, explainable, and sensitive to local realities in Uganda.

2.3 Theoretical Foundations of Career Development

2.3.1 Trait and Factor Approaches

The earliest theories of career development, known as trait and factor approaches, focus on aligning individual characteristics with occupational requirements. (Frank Parsons, 1909) proposed that career success and satisfaction depend on understanding one's abilities, interests, and value, and matching these traits with the demands of specific professions. This approach assumes that both personal traits and job characteristics are relatively stable, allowing for predictable alignment between person and occupation. Building on this foundation, Holland introduced the RIASEC model (McDaniel & Snell, 1999), which classifies individuals and work environments into six categories: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. According to this model (Adlya & Zola, 2022), congruence between a person's type and the work environment leads to higher satisfaction, productivity, and stability. Trait and factor theories have strongly influenced the design of traditional career assessments and continue to shape modern AI-based career matching systems (Yurt, 2025). In such systems, psychometric and personality data are often used to classify users and generate suitable career recommendations (Suryawanshi et al., 2025). However, these models are limited by their assumption of stable traits and occupational structures. In fast-evolving fields such as computing and information technology, skills, job roles, and industry requirements change frequently, making static matching less effective for supporting long-term career development.

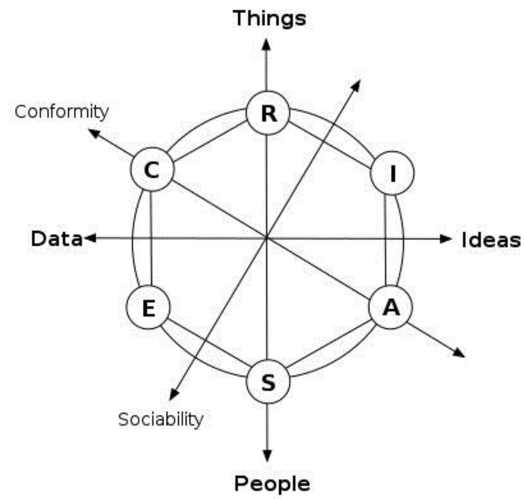


Figure 1: Holland introduced the RIASEC model

2.3.2 Social Cognitive Career Theory (SCCT)

The Social Cognitive Career Theory (SCCT), developed by (Lent et al., 1994), provides a more dynamic and interactional perspective on career development. Drawing from Bandura's (1986) Social Cognitive Theory, SCCT emphasizes the interplay between personal attributes, learning experiences, and environmental conditions (Taurisano et al., 2022). It focuses on three core constructs: self-efficacy, outcome expectations, and personal goals. Self-efficacy refers to one's belief in their capability to perform specific tasks successfully. Outcome expectations are the anticipated results of particular actions or choices. Personal goals represent the intentions that guide effort and persistence toward career outcomes. SCCT also highlights the importance of contextual factors, distinguishing between proximal factors such as access to mentors, learning resources, or technology and distal factors such as family background or institutional support . These factors either facilitate or constrain career progress. For AI-driven career guidance, SCCT offers a strong theoretical basis for building adaptive and personalized systems. Intelligent platforms can assess self-efficacy through academic or skill-based data, model outcome expectations using labor market analytics, and support goal-setting through customized learning pathways. This approach is particularly relevant for Ugandan computing students, who may face unique socio-economic and institutional challenges that influence their career opportunities (Lent et al., 1994). By incorporating SCCT principles, AI-guided systems can become more responsive to users' individual differences and contextual realities, ensuring that recommendations are both realistic and empowering (E & R, 2025).

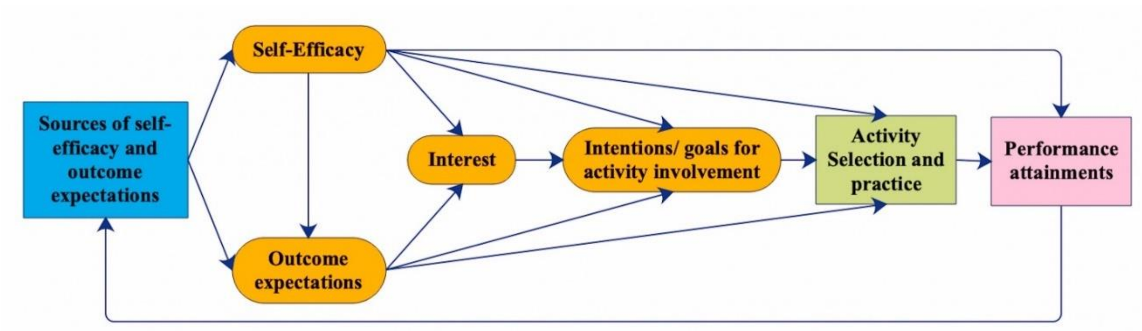


Figure 2:The Social Cognitive Career Theory (SCCT) (Lent et al., 1994)

2.3.3 Constructivist and Narrative Approaches

Constructivist and narrative perspectives view career development as a lifelong process of meaning-making rather than a single decision-making event (Del Corso & Rehfuss, 2011; Zubair & Moazzam, 2024). (Savickas, 2005) Career Construction Theory posits that individuals build their careers by constructing life stories that give personal meaning to their experiences, values, and aspirations. This approach emphasizes adaptability, self-reflection, and identity formation as central to career development. AI technologies can enhance these processes by supporting reflective and narrative engagement. Through data analysis, AI systems can identify patterns in educational records, extracurricular involvement, and personal achievements, helping users recognize emerging themes in their life stories (Jawhar et al., 2024; Pimple & Dhamal, 2025). Visualization tools and interactive feedback can guide students to articulate goals that align with their evolving identities and values (José-García et al., 2022). Such systems not only assist in decision-making but also promote agency, adaptability, and self-awareness qualities essential for navigating today's rapidly changing career landscapes.

2.4 Integrative Relevance for AI-Driven Career Guidance

Each theoretical tradition contributes distinct strengths to the design of AI-driven career guidance systems. Trait and factor theories provide structured profiling and matching frameworks (Suryawanshi et al., 2025). Social Cognitive Career Theory introduces adaptability through self-efficacy, outcome expectations, and contextual influences. Constructivist and narrative theories bring in self-reflection, personal meaning, and continuous learning(Zubair & Moazzam, 2024). Integrating these perspectives supports the development of more holistic and context-sensitive AI models. For Ugandan computing students, such integration ensures that guidance systems respect both personal diversity and the realities of local educational and labor market contexts. Moreover, applying principles of explainable artificial intelligence (XAI) ensures that the resulting recommendations are transparent, interpretable, and ethically aligned (Dağlarli, 2020; Marconi et al., 2021). The combined insights of these theories position AI not merely as a tool for automation but as a catalyst for equitable, reflective, and meaningful career development.

2.4.1 Artificial Intelligence and Machine Learning in Career Guidance

Artificial Intelligence (AI) and Machine Learning (ML) have profoundly transformed the domain of career guidance by enabling highly dynamic and data-driven modeling of the intricate relationships between students' academic performance, acquired skills, practical experiences, and evolving labor market trends (Attwell & Hughes, 2019; Liu et al., 2024). Unlike traditional career counseling, which relies heavily on static occupational information and generalized advice, AI and ML systems can continuously adapt to new data, providing personalized guidance that evolves alongside students' learning trajectories and the changing labor market landscape (Smaldone et al., 2022). A central component of AI-driven career guidance is predictive modeling**,** which utilizes supervised learning algorithms to anticipate the suitability of specific career paths for individual students. By analyzing historical data linking student profiles such as grades, skill assessments, project experience, and psychometric evaluations with subsequent employment outcomes, predictive models can identify patterns that suggest likely success in particular occupations (Choithramani, 2024; Ezaldeen et al., 2022). Techniques such as Support Vector Machines (SVMs), Random Forests (RF), Gradient Boosting Machines (GBM), and neural networks (Dou et al., 2024; Lyu & Liu, 2021) are commonly employed to capture complex, nonlinear relationships between variables. For instance, a model may recognize that a student who demonstrates strong programming proficiency, high analytical reasoning scores, and prior experience in data-oriented projects is likely to excel in roles such as data analyst or software engineer (Okonkwo & Ade-Ibijola, 2020; Verleger & Pembridge, 2018). Beyond prediction, pattern discovery through unsupervised learning plays a critical role in uncovering hidden structures within educational and occupational data (Ilkou et al., n.d.). Methods such as K-Means clustering, hierarchical clustering, and Principal Component Analysis (PCA) allow AI systems to identify latent groupings and trends that may not be immediately apparent to human advisors (Ding chqding, 2004). These latent patterns can reveal clusters of students with similar skill sets, interests, or learning behaviors, facilitating recommendations for interdisciplinary career pathways, skill development opportunities, or specialized training that align with both individual potential and labor market needs. Another cornerstone of AI-powered guidance is the development of recommendation systems (Vidhya et al., 2024b)**,** which personalize career suggestions based on the unique characteristics of each student. Content-based recommendation approaches focus on matching a student's attributes skills, interests, and academic performance to specific career profiles or educational pathways, while collaborative filtering leverages insights from peers with similar profiles to suggest potential career directions (Lops et al., 2011). Hybrid systems, which integrate content-based and collaborative approaches, are particularly effective in mitigating challenges such as the cold-start problem, ensuring that recommendations are both diverse and contextually relevant (Gulzar et al., 2018). A critical enhancement to AI-driven guidance is the integration of labor market intelligence through Natural Language Processing (NLP). By processing unstructured data from online job postings, company websites, and industry reports, NLP algorithms can extract emerging skill requirements, industry trends, and sector-specific opportunities in real time (Vo, Vu, Vu, Vu, Mach, et al., 2022). This capability ensures that career guidance remains aligned with the current demands of the labor market rather than relying on static or outdated occupational information (OECD, 2023). Modern career guidance increasingly utilizes machine learning algorithms to identify complex patterns in multidimensional datasets. Techniques such as Support Vector Machines (SVM), Random Forests, and Naïve Bayes classifiers have been applied to match individuals to careers based on historical education and employment data . For instance, IBM's AI Career Advisor employs cognitive computing to align user skills with industry needs, demonstrating improved adaptability over static rule-based approaches (Calvo et al., 2017). Despite their effectiveness, ML models often face the "black box" issue, where the reasoning behind recommendations is opaque, potentially undermining user trust (Rudin, 2019).

Despite these advancements, significant challenges persist. Many AI systems are trained on Western-biased datasets that may not accurately represent the socio-economic, cultural, and labor market realities of developing countries such as Uganda (Ofosu-Asare, 2025). Furthermore, the use of complex deep learning models often results in opaque "black-box" behavior, where the rationale behind a recommendation is not immediately interpretable (Rudin, 2019). This lack of transparency can reduce trust and limit the usability of AI-guided advice. Explainable AI (XAI) techniques have emerged to address these issues, providing interpretable and actionable explanations that allow students and career advisors to critically understand the basis of recommendations and make informed decisions (Holzinger, 2018; Kieron o'Hara, 2020).

2.4.2 AI's Transformative Impact on Key Technological Domains

The transformative power of AI extends far beyond career guidance, as evidenced by its impact across multiple critical domains. In healthcare, deep learning algorithms have achieved human-level accuracy in medical diagnostics, detecting conditions such as diabetic retinopathy and skin cancer with remarkable precision (Eita & Rizk, 2025; Siddique & Chow, 2021; Williams et al., 2021). AI has also accelerated drug discovery, reducing both time and cost through predictive modeling of molecular interactions and the use of platforms like AlphaFold for protein structure prediction (Bhat & Ahmed, 2025). In finance, AI facilitates real-time fraud detection, algorithmic trading, and risk assessment, leveraging massive datasets to identify patterns beyond human analytical capacity (Aldasoro et al., 2025). Similarly, AI has revolutionized transportation through autonomous vehicles (Iapaolo, 2023), intelligent traffic management, and logistics optimization, where companies such as Tesla and Waymo employ deep learning and computer vision to enhance safety and efficiency(Saki & Soori, 2026). These successes illustrate AI's versatility, adaptability, and ability to process complex, high-dimensional data to generate actionable insights. They provide a strong rationale for the application of AI in career guidance, demonstrating that sophisticated computational models can be harnessed to interpret complex educational and labor market data, generate individualized recommendations, and support decision-making in high-stakes contexts.

2.4.3 Other Advanced AI Techniques

In addition to deep learning, several advanced AI techniques complement and enhance career guidance systems, enabling the construction of hybrid architectures that are both robust and flexible. Case-based reasoning (CBR)**,** for example, draws on previous instances of similar career trajectories to guide decision-making, allowing AI systems to recommend solutions for novel or unconventional career paths based on historical analogues (Marquis et al., 2020). Multi-agent systems (MAS) involve collaborative networks of intelligent agents that can divide complex tasks into modular components. In NLP applications (Tran et al., 2025), MAS can manage different aspects of a conversation, including intent recognition, dialogue management, and explanation delivery, thus enhancing scalability and user experience. Genetic algorithms (GAs) simulate evolutionary processes to iteratively optimize model parameters, improving performance in multi-objective scenarios such as personalized career recommendations or feature selection in complex datasets (Younas, 2014). The strategic combination of these techniques with deep learning facilitates highly adaptive, context-aware, and explainable career guidance systems capable of addressing both common and highly individualized student needs. The most advanced systems combine machine learning with NLP to process both structured and unstructured data (Supriyono et al., 2024). These hybrid models can analyze user-generated content, such as essays or job postings, and apply sentiment analysis, keyword extraction, and semantic matching to provide tailored guidance. LinkedIn's Career Explorer, for example, recommends occupational transitions based on skills derived from user profiles and job descriptions (Pena et al., 2022). Pymetrics uses gamified behavioral assessments for career matching. Although these systems offer enhanced personalization and contextual relevance, they require substantial computational resources and raise privacy concerns due to sensitive personal data.

2.5 Natural Language Processing and Related Technical Foundations

2.6 The Origins of Conversational Agents: ELIZA and Its Legacy

Natural Language Processing (NLP), a core subfield of AI, enables machines to understand, interpret, and generate human language, providing the foundation for conversational agents in career guidance. The first notable conversational agent, ELIZA**,** developed by (Weizenbaum, 1966), used simple pattern-matching techniques to simulate a Rogerian psychotherapist, reflecting user input as questions to create the illusion of understanding. ELIZA's success demonstrated that computers could mimic conversational behavior, laying the groundwork for future interactive systems (Shrager, 2024). Subsequent agents, such as ALICE (Artificial Linguistic Internet Computer Entity) developed (Wallace, 2009), utilized AIML (Artificial Intelligence Markup Language) to provide more dynamic, context-sensitive responses. Modern conversational agents leverage advanced NLP and deep learning models to interpret context, maintain dialogue coherence, and provide personalized guidance, moving beyond pattern-based responses to adaptive, intelligent interactions capable of supporting complex career decisions.

2.6.1 Foundational Language Representation Techniques

A critical component of NLP is the transformation of textual data into computationally tractable formats. Sparse representations**,** such as Bag-of-Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and Latent Semantic Indexing (LSI), encode documents into high-dimensional vectors that capture term frequency and semantic relationships within the text (Juluru et al., 2021; Kamyab et al., 2021). While effective for basic semantic analysis, sparse methods are limited in their ability to capture contextual meaning or polysemy, where a single word may have multiple interpretations. To overcome these limitations, word embeddings were developed. Techniques such as Word2Vec, GloVe, and FastText generate dense, continuous vector representations that encode semantic and syntactic relationships between words (Julien Tissier, 2020; Mikolov et al., 2013). Advanced models like BERT (Bidirectional Encoder Representations from Transformers) address polysemy by generating context-aware representations, ensuring that the meaning of a word is interpreted based on its surrounding textual environment (Devlin et al., 2018; Sammet & Krestel, 2023). For larger textual units, such as sentences, paragraphs, or entire documents, document-level embeddings are used to generate fixed-size, semantically meaningful representations. Models such as Doc2Vec extend Word2Vec principles to represent entire documents (Jang et al., 2020), while Transformer-based approaches, including SBERT (Reimers & Gurevych, 2019), provide efficient and accurate sentence-level embeddings for semantic similarity assessment, classification, and information retrieval. These embeddings are crucial for AI-driven career guidance systems, enabling automated analysis of job descriptions, industry reports, and student portfolios to generate relevant, context-aware career recommendations.

2.7 Ethical and Practical Considerations in AI-Driven Career Guidance

The integration of Artificial Intelligence (AI) into career guidance presents not only opportunities for enhanced personalization and scalability but also significant ethical and practical challenges. In the context of Ugandan universities, where computing students are navigating complex and evolving labor markets, careful consideration of these challenges is essential to ensure that AI-driven systems are responsible, equitable, and effective. Ethical principles and infrastructural constraints must be explicitly incorporated into the design, development, and deployment of such systems to safeguard student interests, promote trust, and maximize the relevance of recommendations (Acharya et al., 2024).

2.8 Fairness and Bias

A central ethical concern in AI-driven career guidance is algorithmic fairness (Li et al., 2021). AI models inherently inherit biases present in their training data, often reflecting structural inequities, historical employment patterns, and prevailing demographic trends in the labor market. This issue is particularly pronounced in systems trained on Western-centric datasets, which may encode assumptions about skill demand, gender representation, and occupational hierarchies that are not applicable in the Ugandan context (Saleh Afroogh, 2023). For example, an AI model trained predominantly on U.S. or European labor data may underestimate the demand for locally relevant ICT skills or misrepresent the entrepreneurial pathways prevalent among Ugandan computing graduates. Mitigating these biases requires deliberate strategies, including the use of localized datasets that reflect the socio-economic realities, educational structures, and labor market dynamics of Uganda. Additionally, fairness-aware machine learning approaches, such as algorithmic auditing, bias correction methods (Ferrara et al., 2023), and regular evaluation against equity metrics, are critical to prevent discriminatory outcomes. Ensuring fairness also involves recognizing the diverse career trajectories of computing students, including both formal employment and entrepreneurial pathways, and providing guidance that is sensitive to these different aspirations.

2.8.1 Transparency and Explainability

The opacity of advanced AI models, often described as the "black-box" problem (Rudin, 2019), poses a significant barrier to trust and adoption in career guidance. Students and academic advisors must be able to understand why a particular recommendation has been generated, especially when decisions directly influence career trajectories and employability (Jackson, 2016; Mgaiwa, 2021). Explainable AI (XAI) provides techniques to illuminate model reasoning, enabling users to evaluate, interpret, and act on recommendations with confidence (Ai et al., 2018; Marconi et al., 2021). In practical terms, XAI in career guidance might involve generating explanations that connect a recommendation to observable student attributes, such as linking a suggested software engineering pathway to demonstrated proficiency in programming languages, problem-solving skills, and exposure to relevant projects. Such transparency not only fosters trust but also facilitates reflective learning, as students gain insight into the rationale underlying their career advice. In the Ugandan context, where skepticism toward emerging technologies can be high, XAI becomes a critical mechanism for bridging cultural and informational gaps between AI systems and end-users.

2.8.2 Privacy and Data Protection

AI-driven career guidance systems necessarily process sensitive personal data**,** including academic records, psychometric assessments, socio-economic background, and skill inventories (Suryawanshi et al., 2025). Protecting this information is paramount to prevent misuse, breaches, or unauthorized profiling. Ethical and legal compliance requires implementing robust data protection measures aligned with international standards, such as the General Data Protection Regulation (GDPR) (EU, 2016), and emerging local regulations, such as Uganda's Data Protection and Privacy Act (Parliament of Uganda, 2019). Technical safeguards include data anonymization to obscure individual identifiers while preserving analytic utility, federated learning to allow model training on local devices without centralizing sensitive data, and secure storage architectures that employ strong encryption and access control (Dougherty, 2021). Equally important are transparent policies for user consent, data governance, and accountability, ensuring that students understand what data is collected, how it is used, and the mechanisms available for recourse in case of misuse. In a resource-constrained environment like Uganda, balancing robust privacy with usability and accessibility remains a critical design challenge.

2.9 Scalability and Infrastructure

The deployment of AI-driven systems in low-resource contexts necessitates careful consideration of scalability and infrastructural constraints (Okolo, 2020). Many existing AI models are computationally intensive and assume continuous high-bandwidth connectivity, assumptions that may not hold in Uganda's university settings. To ensure functionality, AI systems must be designed with lightweight, modular, and hybrid architectures (Sanni, 2024). Microservices architectures allow the system to scale specific components independently, while containerization (e.g., Docker) ensures consistency across heterogeneous computing environments (Hossain et al., 2023). Hybrid cloud approaches, combining local servers with cloud resources, enable computationally demanding processes to be offloaded without compromising data privacy or accessibility (Hasan et al., 2025). Systems must also optimize for intermittent connectivity and limited bandwidth, possibly by incorporating offline capabilities or edge computing strategies that allow local data processing. Such design considerations ensure that AI systems remain usable, reliable, and responsive, even under resource constraints (Durga Prasad Jasti et al., 2024; Wu et al., 2016).

2.10 Related Work

Several global AI-driven career guidance platforms such as LinkedIn Career Insights (Pena et al., 2022) and Job Explorer demonstrate the potential of AI to analyze labor market trends and provide personalized career recommendations. However, these platforms predominantly reflect Western labor market structures, educational systems, and skill valuation frameworks, limiting their applicability in African contexts (Okolo, 2020). In Sub-Saharan Africa, pilot projects have shown feasibility in vocational skill matching or basic job recommendation services, yet these initiatives remain fragmented and lack integration (World Bank, 2019). In Uganda specifically, there is a notable absence of AI systems tailored to students**,** capable of integrating academic performance, psychometric profiling, real-time labor market intelligence.

2.11 Identified Gaps and Research Opportunities

From the preceding review, several critical gaps emerge. First, there is a lack of localization**,** with most AI systems relying on global or Western datasets that fail to capture Ugandan specific labor market realities. Second, opaque recommendation mechanisms undermine trust and usability, emphasizing the need for explainable AI techniques to clarify the rationale behind career guidance (Zylowski et al., 2025). Third, there is insufficient focus on domain-specific needs**,** particularly for computing students, where rapidly evolving technological skill sets necessitate precise, actionable, and timely guidance (Elbadrawy & Karypis, 2016; Sammet & Krestel, 2023). This research addresses these gaps by proposing the development of an AI-driven, explainable, and context-sensitive career guidance model**,** tailored to computing students in Ugandan universities. The model aims to bridge the educational-industrial divide by providing personalized, transparent, and actionable career recommendations, integrating academic performance, local labor market intelligence, and students' unique socio-economic contexts.

2.12 Future Directions in AI Innovation

Looking forward, AI research increasingly emphasizes the creation of adaptive, generalizable, and efficient models**,** offering profound implications for the evolution of career guidance systems (Ezaldeen et al., 2022). Emerging trends include quantum computing (Golec et al., 2024), which has the potential to accelerate complex optimization and recommendation algorithms, and edge AI, enabling real-time, decentralized processing that enhances privacy and accessibility in low-resource environments. Hybrid architectures that combine symbolic reasoning with deep learning offer the promise of greater explainability and adherence to policy constraints (Nawaz et al., 2025), while reinforcement learning with human feedback (RLHF) facilitates continuous alignment of AI recommendations with human values and real-world outcomes. These innovations underscore the trajectory toward AI-driven systems models that are not only computationally powerful but also socially aware, ethically grounded, and user-centric (Acharya et al., 2024; Bobeth Janand Schreitter, 2013). For career guidance in Uganda, such advances hold the potential to create systems that are both contextually relevant and dynamically adaptive, capable of supporting computing students in navigating complex and evolving labor markets with transparency, trust, and actionable insights (Saleh Afroogh, 2023).

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter outlines the methodological approach adopted in this research to design, develop, and evaluate an AI-powered career guidance platform specifically for students. It explains the research paradigm, phases of the research design, data sources, analytical techniques, ethical considerations, and methodological limitations. The study is grounded in a Pragmatic research philosophy, which integrates multiple methodological approaches to produce a practical solution to a real-world challenge: improving access to effective career guidance for students. The overall research framework follows Design Science Research (DSR) principles, emphasizing the creation, refinement, and evaluation of a technological artifact that addresses a significant problem in student career support. The study unfolds across four sequential and interrelated phases. First, a scoping review was conducted to identify and synthesize pedagogical, technological, and functional requirements for a conversational AI model suitable for career guidance. Second, the prototype of the AI-driven conversational system was designed and developed using the CRISP-DM methodology, translating identified requirements into system architecture, dialogue flow, and model configuration. Third, a user-based quantitative evaluation was conducted to assess the system's usability and acceptance based on the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al, 2003), enabling examination of performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intentions. Finally, a fourth phase focused on the design and development of an adoption model intended to guide the integration of the conversational AI system into Ugandan universities, addressing institutional readiness, digital infrastructure, governance structures, stakeholder engagement, and long-term sustainability considerations.

3.2 Aspects of Research

Research is a structured process that seeks to find solutions to complex problems and uncover previously hidden truths (Garg, 2016). A research methodology is a framework used to systematically address research questions, providing a scientific basis for investigations (Bhattacharyya, 2006). It includes the techniques and procedures used to address research problems in a reliable and reproducible way. Researchers must not only be skilled in designing tools like indexes or tests but also be familiar with the theoretical foundations of various methodologies. This means understanding the assumptions behind each approach and assessing their suitability for the specific research context (Pilcher & Cortazzi, 2024). By doing so, researchers can select the most effective methods for addressing their research questions. Research questions generally focus on either exploring the nature of a phenomenon or understanding the relationships between different variables. The first step in the research process is to clearly identify the problem or area of interest. Once the problem is defined, any uncertainties must be addressed to ensure a clear focus (Almusaed et al., 2025a; Lipowski, 2008). Before proposing solutions, researchers must assess the strengths and weaknesses of various methods. The initial phase of scientific research involves forming a precise research question, which requires a deep understanding of the topic (Almusaed et al., 2025b). This understanding is followed by refining the problem through critical rephrasing. Engaging with colleagues or mentors can provide valuable feedback that helps clarify the research question. Researchers often turn to experienced mentors in academia for insights into a range of research challenges (Mazerolle et al., 2015). In organizational research, problems are often identified by administrative bodies, which then assign researchers to investigate the underlying causes and potential solutions (Nottingham & Mazerolle, 2018). In this study, the researcher seeks to conduct a comprehensive analysis of how AI can be leveraged in career guidance systems in

Ugandan universities for student support. The subsequent sections detail the overarching DSR framework, and the specific methods employed for each objective.

3.3 Design Science Research (DSR)

Design Science Research (DSR) is a research paradigm that seeks to extend human and organizational capabilities by creating new and innovative artifacts (Carstensen & Bernhard, 2019; Hevner, 2007). Unlike traditional behavioral science research, which primarily aims to understand and explain phenomena, DSR is fundamentally concerned with the construction and evaluation of artifacts designed to solve identified problems in a specific domain (Carstensen & Bernhard, 2019). These artifacts can take various forms, including models, methods, instantiations such as software systems or prototypes, and social innovations. DSR is inherently iterative, often moving back and forth between the problem space and the solution space, refining the artifact based on evaluation and reflection.

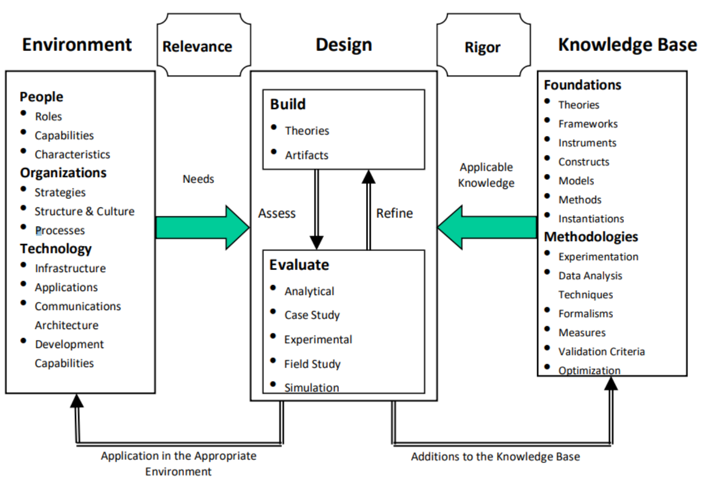


Figure 3: Design Science Research (Hevner, 2007)

Problem Identification and Motivation: Chapter 1 established the challenges that university students face in accessing effective career guidance in low-resource settings and highlighted the potential role of A I in addressing these gaps. Objective 1, which involved conducting a scoping review, strengthened the understanding of this problem by identifying the specific requirements that an AI driven conversational career guidance model must meet for students. Objectives for the Solution: The requirements generated from the scoping review form the concrete design objectives for the artifact and define what the solution must achieve to be effective for student career guidance. Design and Development: Objective 2 encompassed the design and construction of the AI powered conversational model prototype, using the identified requirements as its foundation. The CRISP DM methodology provided a structured approach for handling and integrating the data driven components of the model. Demonstration: The functional prototype created in this phase demonstrates the feasibility of the solution and illustrates how the artifact is intended to address the identified student career guidance challenges. Evaluation: Objective 3 focused on evaluating the prototype using a quantitative approach based on the UTAUT model to determine its usability and user acceptance among students, thereby assessing how well the artifact meets the stated objectives and addresses the original problem.

3.4 Research Philosophy

A research philosophy provides the foundational framework for how researchers understand and approach their studies (Brey & Søraker, 2009; Mccarthy, 1996). It influences the entire research process by shaping assumptions about reality (ontology) (Mohammed Essmat Ibrahim, 2019), the nature and acquisition of knowledge (epistemology) (Bringsjord et al., 2018; Lowrie, 2017), and the role of values (axiology). These philosophical components help guide the selection of research methods and the interpretation of results. Ontology concerns what exists, and the nature of reality being studied. Epistemology examines how knowledge is acquired and validated, while axiology considers how the researcher’s values influence the research. Together, these guide researchers in choosing an appropriate methodology to address their research questions (Lipowski, 2008). Three major philosophical approaches realism, interpretivism, and pragmatism offer different perspectives on reality and knowledge (Overton, 1994). Realism emphasizes an objective reality that exists independent of human perception. Interpretivism, in contrast, focuses on understanding social phenomena through subjective interpretation. Pragmatism adopts a flexible, problem-solving approach, combining elements from various philosophies based on what works best in a given context (Cherryholmes, 1992). The choice of research philosophy is shaped by the nature of the research problem, the type of data, and the context in which the study is conducted. Researchers may collect data through interviews, surveys, observations, or statistical analysis, depending on their philosophical stance. Importantly, while philosophical alignment provides coherence, rigid adherence to a single viewpoint can limit the applicability of findings. A more balanced and flexible approach allows researchers to integrate methodological rigor with philosophical depth.

The study is grounded in pragmatism, a philosophical stance that facilitates the integration of both positivist and interpretivist perspectives (Alharahsheh & Pius, 2020). Pragmatism is particularly suitable for this research as it prioritizes practical outcomes and the usefulness of findings in addressing real-world problems, such as enhancing career guidance for the target migrant population (Cherryholmes, 1992). This philosophy acknowledges the multifaceted nature of reality and advocates for the use of research methods that best answer the study's questions, regardless of their underlying ontological or epistemological assumptions (Lowrie, 2017). Within this pragmatic framework, the study employs quantitative methods, such as UTAUT-based surveys , to measure user acceptance and identify generalizable patterns across the study population. In summary, research philosophy plays a crucial role in ensuring that the study is grounded in clear assumptions and coherent methods.

3.5 Research Design

This research followed a mixed-methods design that integrated both qualitative and quantitative approaches to ensure a comprehensive understanding of user needs and a robust evaluation of the developed platform (Knapik, 2006; Pilcher & Cortazzi, 2024). Research can generally be categorized into two main approaches: deductive and inductive reasoning (Goswami, 2010). These approaches are often structured within frameworks such as Saunders' research onion (Saunders & Tosey, 2012). Deductive reasoning starts with a general theory or hypothesis, which is then tested using empirical data to either confirm or refine the theory (Goswami, 2010). In contrast, inductive reasoning builds theories or generalizations based on specific observations or data points, without starting with a pre-existing hypothesis. The choice between these two methods is pivotal in shaping the research design. Deductive research typically follows a structured process beginning with a literature review to establish a theoretical framework (Almusaed et al., 2025b), followed by hypothesis testing. In contrast, inductive research begins with observations or data collection, which inform the development of a theory. Given that this study focuses on exploring how artificial intelligence (AI) can be applied to career guidance platforms for migrants, the inductive approach is better suited to this context. Since no predefined hypothesis exists and the goal is to uncover patterns and insights, inductive reasoning is more appropriate, as it relies on empirical observations and aims to build understanding from these findings (Klauer & Phye, 2008). Inductive research emphasizes the relationship between observed data and theoretical development. This approach is particularly useful when the researcher aims to draw broader conclusions from specific instances or experiences. By focusing on how AI can enhance career guidance for migrants, the study aims to generate new knowledge based on real-world data and participant experiences, thus advancing understanding in this area.

3.6 Research Strategy

A research strategy outlines the objectives to be achieved and the methodologies to be employed to achieve the desired results using various techniques (Tajvidi & Karami, 2015). The primary objective of this study is to contribute to the development of a digital career support system model that aligns with industry expectations. This model leverages NLP technologies and large language models to support CS/IT students at Ugandan universities. Given the nature of the research problem, the overall strategy a mixed methods was employed. Therefore, the research involved collecting both qualitative and quantitative data using a survey design, as recommended by the onion model for the research process (Saunders & Tosey, 2012).

3.7 Scoping Review Methodology

This review follows the scoping review methodology developed by (Arksey & O'Malley, 2005a), which consists of six key steps: (1) identifying the research question, (2) identifying relevant studies, (3) selecting studies for inclusion, (4) charting the data, (5) collating, summarizing, and reporting the results, and (6) conducting consultations (Arksey & O'Malley, 2005b). This methodological approach was chosen because it provides a comprehensive and flexible way to map the existing literature on a topic, offering a broad overview rather than a narrow, in-depth analysis (Mak & Thomas, 2022). Unlike systematic reviews, scoping reviews allow for the inclusion of a wide range of study designs, making them particularly suitable for exploring emerging or complex research areas (Arksey & O'Malley, 2005b).

3.7.1 Rationale for Method Selection

A scoping review was chosen as the appropriate method for Objective 1 because it allows for the systematic mapping of broad literature in an emerging field, identifying key concepts, evidence, and gaps (Pollock et al., 2024). Given the interdisciplinary nature of the research area, encompassing AI, career guidance, and higher education, a scoping review was ideal for synthesizing diverse study designs and perspectives to comprehensively identify reported essential requirements for the design and development of AI-driven conversational models.

3.7.2 Search Strategy

A comprehensive search of electronic databases was conducted to identify peer-reviewed publications relevant to AI-driven conversational models for career guidance. The search strategy employed a combination of keywords and controlled vocabulary related to key concepts such as "migration," "career guidance," "artificial intelligence," "chatbots," "natural language processing," and "e-learning." Databases included Google Scholar, semantic scholar, ACM Digital Library, springer, and IEEE Xplore. Boolean operators (AND, OR) were used to combine terms, and the search was restricted to English-language publications from 2014 to 2024. For example, an example search string is: (migration OR immigrant OR refugee) AND ('career guidance' OR 'career counseling' OR 'vocational guidance') AND ('artificial intelligence' OR 'chatbots' OR 'conversational AI') AND ('natural language processing' OR 'dialogue system'). A manual search of reference lists from selected studies was also performed to ensure comprehensiveness.

Table 1:Showing Sources of Literature

Database Name	Web Address
ACM Digital Library	dl.acm.org
IEEExplore Digital library	Ieeexplore.ieee.org
Science Direct	Sciencedirect.com
springer	Links.springer.com
MDPI	www.mdpi.com
Frontier	www.frontiersin.org
Nature	www.nature.com
Wiley	www.wiley.com

3.7.3 Study Identification and Selection

The study followed the PRISMA-ScR guidelines (Rethlefsen et al., 2021) to systematically identify and select studies. Our initial search returned 453 unique records after removing duplicates. Firstly, titles and abstracts using broad criteria were screened systematically, and afterwards, a full-text review of 130 potentially relevant articles proceeded to full-text assessment. Then, a stricter inclusion criterion focusing on papers addressing AI-driven conversational models within university career guidance (CG) for effective student support, requiring adequate methodological detail. Leading to only 11 included studies, with the majority of these included studies predominantly between 2019 and 2025, highlights the recent period of significant advancements in this research field, even though our search spanned 2015-2025. To enhance the completeness of the search and identify any missed relevant studies, snowballing techniques were applied, including reference lists manual review and using Google Scholar for forward citation tracking for highly cited articles. All screening and selection steps were performed independently by two reviewers, with disagreements resolved through discussion or consultation with a third, ensuring unbiased selection.

3.7.4 PRISMA Guidelines

Utilizing the PRISMA-ScR checklist guided each step of this review process, facilitating meticulous documentation while contributing to a reproducible and transparent account of the methodology (Haddaway et al., 2022). Commitment to reporting standards enhances the reliability and credibility of the review's findings. As depicted in a Prisma flow diagram(Haddaway et al., 2022), as seen in Figure bellow:

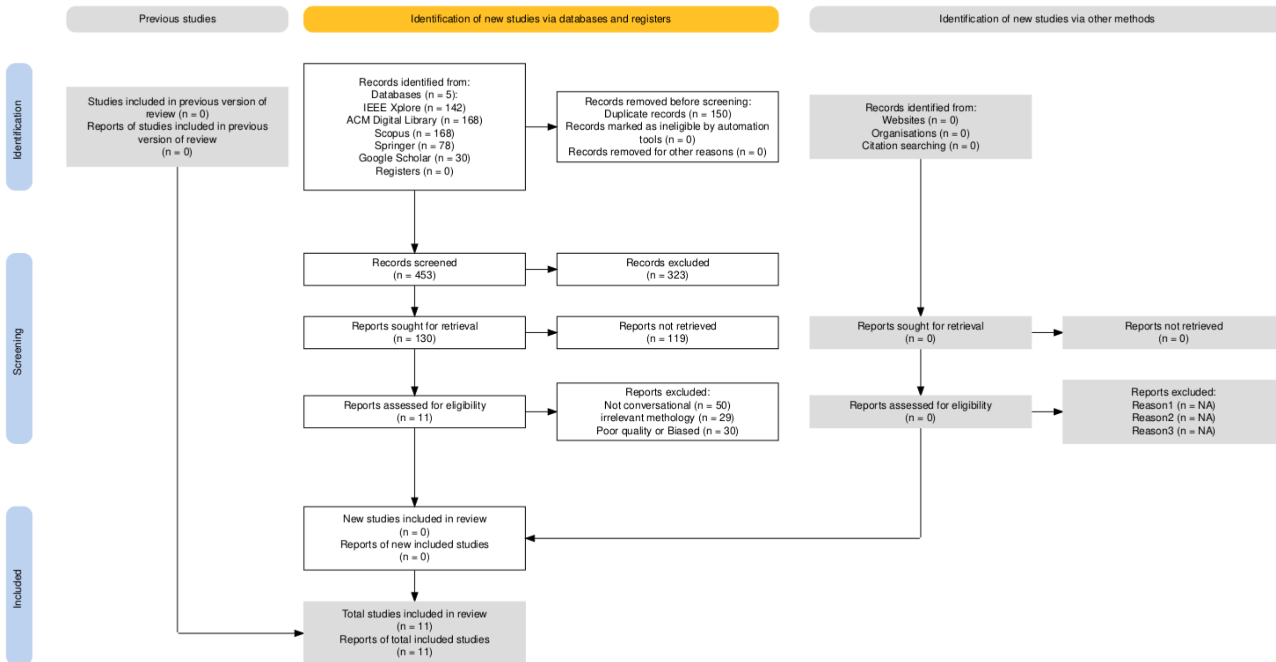


Figure 4: Prisma flow diagram (Haddaway et al., 2022)

3.8 Inclusion Criteria and Exclusion Criteria

To ensure a focused and relevant review, only studies that fulfilled all the inclusion criteria outlined in the table were considered. These criteria were designed to capture empirical research on AI-driven conversational models specifically applied to university career guidance, with emphasis on key dimensions such as language support and cultural sensitivity. Any study not meeting one or more of these criteria was excluded. This rigorous approach ensured that the selected literature remained credible, relevant, and aligned with the scope of the review, see Table below.

Table 2: Showing the Inclusion and Exclusion Criterion

Inclusion Criteria	Exclusion Criteria
I. Empirical research on AI-driven conversational models (chatbots/virtual assistants) for career guidance, counseling, or employability support	I. Focus on non-conversational AI applications (such as general recommendation systems, data mining)
II. Target population: university students or higher education career services	II. Studies not related to the higher education setting
III. Peer-reviewed journal articles or conference proceedings	III. Not peer reviewed, including grey literature (theses, white papers, news articles)
IV. Paper published between 2015 and 2025	IV. Published before 2015
V. Full text available in English	V. Publications not available in English

3.9 Quality Assessment

The study employed an adapted version of the Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2019)to assess the methodological characteristics and trustworthiness of the included studies. Crucially, and in line with scoping review methodology, this quality assessment aimed to provide context on the evidence base's robustness, rather than being a criterion for study inclusion or exclusion. Recognizing that the MMAT evaluates multiple dimensions of a study's design and execution, the focus targeted several aspects relevant to the transparency of the research presented within each included study.

3.10 Data Extraction and Synthesis

A data collection template specifically developed for this analysis was used to extract the critical data for the review, and the results were thus organized along five core themes: Design and Usability, Technical Aspects, Educational Impact, Emotional Awareness, and Moral and Emotional Implications. Study details such as objectives, participants' characteristics, type of AI tool utilized, setting, its characteristics, results, and highlighted limitations or ethical considerations were extracted methodologically. The analytical strategy used was thematic synthesis, chosen on account of it being effective in identifying emerging similarities across multiple different studies in broad-scope reviews. This included coding the data and developing themes that could be mapped altogether to address our key question: What are the needs of design, development, and validation of a conversational AI model to provide effective and efficient career guidance for university students? The second stage of coding involved matching these interpretations to the five thematic lenses. Using a careful, iterative technique, results from different sources of observational designs were integrated to produce the holistic understanding presented in Table 2.

Table 3: Showing details of the selected studies for this review

Author (Year)	Title	Study Details	Weakness / Gap	Proposed Improvement
(Talib et al., 2023)	*Utilizing M-Technologies for AI-Driven Career Guidance in Morocco: An Innovative Mobile Approach*	Explores the application of a conversational AI model using large language models (LLAMA2, GPT, PaLM) with a mobile interface integration. The study evaluates user engagement, satisfaction, and career outcomes.	Internet reliability (rural areas), data privacy, legislative barriers, large language model compatibility, lack of comparable LLMs, and the need for knowledge base development.	Add the offline first functionality, enforce data privacy policies, train LLMs in different dialects (Arabic dialects), enhance Arabic OCR, and develop localized knowledge bases.
(Zylowski et al., 2025)	*User Study on the Trustworthiness, Usability, and Explainability of Intent-based and LLM-based Career Planning Agents*	User study (n=114, comparing form-based, intent-based, and LLM-based agents. Measures trust, usability, explainability, and psychological needs (SDT).	Black-box problem, hallucinations, inflexibility in intent-based models, usability variability, and generic output mismatch.	Improve interaction design, enhance explainability, personalize recommendations, and optimize LLM prompting and context.
(Choithramani, 2024)	*A Personalized Chat Application for Career Profiling: A Case Study*	Case study: developing a chat app using React, Express.js, and OpenAI API. Agile process with iterative testing.	Lack of personalization, ethical/data privacy concerns, high cost, no cultural adaptation, and limited real-time labor market data.	Prioritize ethical AI, integrate user feedback, enhance personalization, use real-time data, and extend to voice features.
(Meyer et al., 2023)	*ChatGPT and Large Language Models in Academia: Opportunities and Challenges*	Editorial on ChatGPT's use in writing, teaching, coding, and grant writing. Discusses benefits, ethics, and user behavior.	Hallucinations, plagiarism risks, unclear pedagogical norms, paywall access, and difficulty quantifying bias.	Use LLMs cautiously, validate content, quantify bias, check outputs with tools, and promote ethical standards.
(T. Lee et al., 2019)	*Intelligent Career Advisers in Your Pocket? A Need Assessment Study of Chatbots for Student Career Advising*	Needs assessment (n=350 US undergraduates). Designed a chatbot, "Sammy," for career advising to students.	Student-to-advisor imbalance, limited personalization, access barriers, and few studies on chatbot advising.	Develop intelligent career chatbots with service tiers. Conduct further effectiveness evaluations.
(Pereira et al., 2023)	*Here's to the Future: Conversational Agents in Higher*	Scoping review of 66 studies (1994–2023) on chatbots in higher education	Few career bots use LLMs. Trust issues, poor training data, limited	Apply user-centric design, test usability, support multilingual NLP,

	Education – A Scoping Review	(support/learning domains).	adaptability, and no evaluation standards.	assess IT infrastructure, and standardize evaluation.
(Thottoli et al., 2024)	*Robo Academic Advisor: Can Chatbots and AI Replace Human Interaction?*	Literature review plus a bibliometric analysis of 67 papers (1984–2023) on chatbots/AI in academic and career advising.	Poor advisor training, rigid models, weak policy awareness, limited student info support, and a lack of chatbot evaluation.	Automate advising with AI, improve NLP interactions, and reduce advisor workload with AI support.
(Chang et al., 2023)	*Educational Design Principles of Using AI Chatbots That Support Self-Regulated Learning in Education*	Proposes chatbot design principles (goal setting, reverse prompting, personalization) for self-regulated learning (SRL) in classrooms.	Unidirectional chatbots, weak personalization, no self-assessment, ethical/data issues.	Teach prompting skills, use learning analytics, develop bi-directional functions, and embed SRL-focused features.
(Nguyen et al., 2022)	*ITCareerBot: A Personalized Career Counselling Chatbot*	Proposes personalised chatbot for IT career counseling. Evaluated via user survey and NLU accuracy (F1-score >85%).	Lack of personalization in career services, limited validation scale, no focus on learner info for adaptation.	Expand personalization using learner data, validate on broader scale, integrate AI (deep learning, RL).
(Bassner et al., 2024)	*Iris: An AI-Driven Virtual Tutor for Computer Science Education*	Introduces Iris (GPT-3.5-Turbo-based tutor) for programming exercises. Evaluated via survey (perceived effectiveness, reliance).	Lack of context awareness in general AI tools, ethical concerns (data privacy), reliance decreases for exams, limited evaluation (self-reported bias).	Optimize prompts, enhance context provision, explore LLM trade-offs (e.g., GPT-4), address ethical concerns.
(Assiri et al., 2020)	*From Traditional to Intelligent Academic Advising: A Systematic Review*	SLR of e-advising systems (2009–2019), classifies by automation level (Simple/Intelligent) and tech (AI, NLP, etc.).	Traditional advising is time-consuming, inconsistent; simple systems lack customization; intelligent systems need large data, lack interactivity/evaluation.	Use AI/expert systems for multi-tasking advising, integrate with university systems, focus on course selection. Future work and student life/career goals
(Janssen et al., 2020)	*Virtual Assistance in Any Context: A Taxonomy of Design Elements for Chatbots*	Develops taxonomy of chatbot design elements (17 dimensions, 49 characteristics). Analyzes 103 chatbots across 23 domains.	Limited empirical validation of taxonomy, fast-changing tech, selective data sources (self-reporting bias).	Use taxonomy to bridge research-practice gap, guide design decisions, identify archetypes. Future: regular empirical updates, key performance measures.

3.11 Documentary Review

An extensive documentary review initiated the model development process (Pfister, 2018). This involved analyzing academic literature on technology adoption theories, existing models for AI implementation in education, Conversational AI applications, and studies pertinent to the socio-technical context of Ugandan higher education. Relevant policy documents and institutional reports concerning career guidance services in Uganda were also examined. This review served to identify foundational constructs, contextual factors, and potential challenges, thereby informing the initial conceptualization of the CAM-CAI-RCHE model and the development of the interview protocol.

3.12 Empirical Study

This empirical study was designed to investigate two distinct aspects of developing an AI-based career guidance model. The study conducted through a quantitative approach, focused on evaluating the model's usability by examining user preferences, learning styles, and interaction patterns. And also guided by a qualitative approach, the study further explored factors influencing the adoption of the designed model within university settings. Together, these studies provide valuable insights for refining the model's design and understanding its potential for effective implementation in higher education contexts.

3.12.1 Usability Study

The first phase of the empirical investigation employed a quantitative research methodology guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Batucan et al., 2022; Rana et al., 2024)to systematically assess user acceptance, preferences, and perceptions regarding an AI-based career guidance system. This phase aimed to evaluate the usability, perceived usefulness, and behavioral intention to use the proposed model among potential users in Uganda's higher education context. Data were collected from 957 participants across 13 universities in Uganda through a self-administered online questionnaire. The survey instrument was structured around the core constructs of the UTAUT model performance expectancy, effort expectancy, social influence, and facilitating conditions to measure factors influencing the adoption and effective utilization of the system. The analysis focused on identifying statistically significant relationships among these constructs and their impact on user acceptance and usability perceptions. Findings from this phase provided empirical evidence on users' readiness and willingness to adopt an AI-based career guidance platform. The results further informed the refinement of the model's design and functionality, ensuring it remains user-centered, accessible, and aligned with institutional and individual career development objectives.

3.13 Study Environment

The study was conducted online to ensure broad participation and accessibility. Participants were drawn from 13 universities representing all five regions of Uganda, with both public and private institutions included. The online format enabled participants to respond at their convenience, enhancing response reliability and data accuracy. Although this phase employed a quantitative approach, it formed part of a broader research framework in which a subsequent qualitative phase explored institutional and contextual factors affecting model adoption. This structured, phased approach allowed the study to combine measurable user data with deeper interpretive insights in later stages.

3.14 Study Population

The target population comprised students, lecturers, and employers associated with computer science and information technology programs across Uganda. Specifically, it included undergraduate students pursuing degrees in computing-related fields, academic staff (lecturers and professors) actively engaged in teaching and student mentorship, and IT managers or employers who routinely interact with graduates and provide industry perspectives on career readiness. Participants were selected from 13 universities, ensuring regional and institutional diversity. Students contributed to evaluating system usability and perceived usefulness for career guidance, while lecturers and employers provided expert insights into its relevance, applicability, and potential for integration into institutional systems.

3.14.1 Sampling Method and Size

Following (Sekaran & Bougie, 2016), sampling is the process of selecting a representative subset from the target population. A probability sampling approach was adopted, combining stratified random sampling and purposive sampling to achieve representativeness and relevance (Teddlie & Yu, 2007). A total of 957 participants were selected using stratified random sampling, ensuring proportional representation of students, lecturers, and industry professionals across the 13 universities. The sample size was determined using the following formula by Krejcie and Morgan (C. Lee & Penyelidikan, 2006)

Equation 1: Sample size formula by Krejcie and Morgan

$$s = \frac{X^2 NP(1-P}{d^2(N-1) + X^2 P(1-P)}$$

where:

Table 4: Showing sample size as determined using the formula

	Meaning	*Value*
s	Required sample size	Result of the formula
(X^2)	Chi-square value for 1 degree of freedom at the desired confidence level	3.841
N	Population size	-

P	Population proportion	0.50 (gives maximum sample size)
d	Degree of accuracy (margin of error)	0.05

Table 5: Showing a summary of The Total Respondents Per Selected Universities

University	Computing/IT departments	Sample size	Region
Mbarara University	Students (CS/IT = 120) Staff (12)	92 12	Southwestern
Bishop Stuart University	Students (CS/IT = 60) Staff (10)	53 10	Southwestern
Ibanda University	Students (CS/IT =45) Staff (5)	37 5	Western
Mountains of the Moon University	Students (CS/IT = 40) Staff (6)	45 6	Western
Makerere University	Students (CS/IT = 180) Staff (15)	123 15	Central
Nexus International University	Students (CS/IT = 60) Staff (10)	53 10	Central/online
Uganda Technology and Management University	Students (CS/IT = 75) Staff (9)	63 9	Central
Busitema University	Students (CS/IT = 80) Staff (15)	67 15	Eastern
Islamic University in Uganda	Students (CS/IT = 75) Staff (10)	63 10	Eastern
Kumi University	Students (CS/IT = 45) Staff (9)	37 9	Northern
Gulu University	Students (CS/IT = 90) Staff (11)	74 11	Northern
ISBAT University	Students (CS/IT = 100) Staff (10)	80 10	Central
Cavendish University	Students (CS/IT = 60) Staff (8)	53 8	Central
TOTALS		**957**	

3.15 Technology (AI) Adoption Model

The second phase utilized a qualitative research approach to investigate the factors influencing the adoption, diffusion, and institutional integration of the proposed AI-based career guidance model within higher education contexts. Drawing on semi-structured interviews and thematic analysis, this phase explored stakeholders' perceptions, organizational readiness, and potential barriers to technological implementation. The qualitative insights generated from this inquiry informed the development of an adoption framework that aligns the model's design with institutional objectives, thereby facilitating strategic AI assimilation and sustainable utilization within university career support infrastructures.

3.15.1 In-depth Qualitative Interviews

The primary empirical component for developing, refining, and conducting an initial validation of the CAM-CAI-RCHE model involved semi-structured interviews with experts. This qualitative approach was chosen to leverage the specialized knowledge and practical experience of individuals deeply familiar with career guidance, higher education administration, technology implementation, and the Ugandan employment landscape (Gill et al., 2008). The aim was to assess the model's perceived relevance, comprehensiveness, applicability, and potential utility from diverse professional perspectives.

3.15.2 Participant Selection and Recruitment

A purposive sampling strategy was utilized to identify and recruit 25 experts. Participants were selected from two primary domains: selected Ugandan universities (a mix of public and private institutions from various regions) and relevant industry organizations operating within Uganda.

3.15.3 Inclusion Criteria

I. Senior academic staff such as Career Services Directors/Managers, Deans of Students, Academic Registrars, and senior IT administrators involved in educational technology.

II. Human Resource (HR) Managers, Talent Acquisition specialists from local Ugandan organizations, multinational corporations operating in Uganda, government institutions/parastatals, and technology experts within AI for development.

3.15.4 Exclusion Criteria

I. University staff whose roles did not encompass educational technology, academic administration, or direct career guidance.

II. Professionals operating entirely outside Uganda or lacking current, relevant organizational affiliations within the Ugandan context.

III. Industry professionals whose responsibilities did not align with recruitment, human resources

IV. management, or the application of AI for development.

V. A general lack of demonstrable experience in higher education administration, talent acquisition, or AI system integration.

3.15.5 Interview Procedure and Data Collection

Semi-structured interviews allowed for a deep exploration of participants' experiences with existing career guidance mechanisms, their views on the potential and challenges of AI-driven solutions, and detailed feedback on the CAM-CAI-RCHE model. The interview guide, informed by the documentary review, featured open-ended questions framed in accessible language. Interactions focused on probing the "why" behind assessments and fostering a rich dialogue about the model's constructs, potential implementation challenges, and practical utility. All sessions were audio-recorded with informed consent.

3.16 Data Analysis

Upon completion, interview recordings were transcribed verbatim. A systematic thematic analysis was undertaken:

I. Transcripts were read and re-read to gain a thorough understanding of the data.

II. Relevant excerpts and arguments pertinent to Conversational AI adoption for career guidance and the CAM-CAI-RCHE model were extracted.

III. Data segments exhibiting similarities in respondent views, notions, and experiences were thematically categorized, with rephrasing for conceptual clarity where necessary. Redundant statements were eliminated.

IV. A final thematic analysis led to the derivation of a set of propositions regarding the CAM-CAI-RCHE model's components and their perceived relevance, contributing to its refinement and initial validation.

3.17 Machine Learning Development (ML)

A CRISP-ML methodology (Wirth & Hipp, 2000; Kolyshkina & Simoff, 2021) will be used to guide the development of the career guidance system model that integrates industry trends, university curricula, and students' personal interests. The process begins with Research and Data Understanding, where the project's feasibility is assessed, evaluation metrics are defined, and data quality is verified in consultation with key stakeholders. In the Data Preparation phase, the required data will be selected, cleaned, and transformed, including the creation of reusable preprocessing pipelines. The Modeling and Model Tuning phase focuses on building and refining machine learning models with appropriate hyperparameter optimization and version control. Model Evaluation then assesses performance against predefined metrics using test data and experiment tracking tools. Finally, in the Deployment and Monitoring phase, the model is integrated into the system and continuously monitored to detect performance drift, ensuring long-term reliability and relevance.

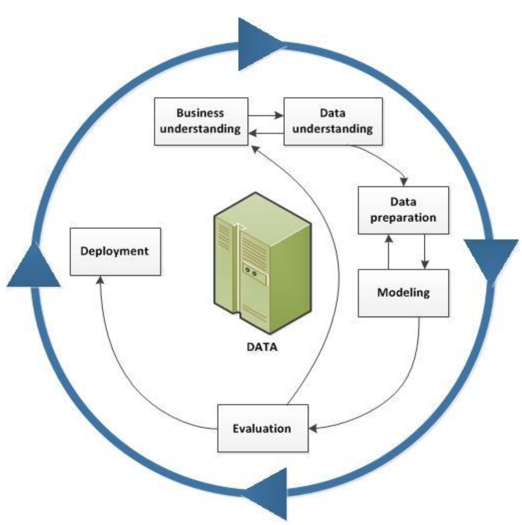


Figure 5:Diagram of the CRISP-ML Methodology

3.18 Retrieval-Augmented Generation (RAG) Integration

To enhance the accuracy and contextual grounding of the conversational guidance system, a Retrieval-Augmented Generation (RAG) architecture was integrated into the AI component of the platform (Gao et al., 2023; Siriwardhana et al., 2023). The RAG approach combines neural retrieval methods with generative language modelling, enabling the system to draw on verified and domain-specific information during interactions. In practice, the RAG pipeline retrieves relevant documents from curated sources, including university programme guides, occupational standards, labour market reports, and institutional career-support materials. These retrieved texts then serve as contextual input for the generation module, allowing the system to produce responses that are both contextually informed and verifiable (Salemi & Zamani, 2024). The use of RAG addresses a key limitation of standalone generative models namely, their reliance on static pre-training and the risk of producing outdated or fabricated information. By grounding responses in high-quality, institutionally relevant sources, the RAG architecture ensures that students receive accurate guidance related to study pathways, emerging skill demands, and potential career options. Its integration therefore strengthens the reliability, transparency, and educational value of the conversational model and aligns the system with best practices in AI-supported decision-making.

3.19 Intervention and Backend Development

The intervention was implemented through a cloud-based architecture in which the conversational career guidance model is accessed via a unified API layer. This API functions as the gateway between the React Native application and the underlying intelligent components, including the

RAG pipeline, LangChain orchestration, Vertex AI models, and Dialogflow CX dialogue management. The RAG component retrieves and structures relevant institutional and occupational information, which is then processed through LangChain to support context-aware responses. Dialogflow CX manages the interaction flow, while Vertex AI handles classification, intent refinement, and advanced model inference (Sung, 2022). The API exposes standardized endpoints that allow the mobile application to send user queries, receive generated responses, and maintain session continuity. Authentication and session tracking are implemented to store user interactions securely and enable personalized guidance over time. On the frontend, the React Native interface triggers API calls dynamically as users engage with the chatbot, updates the conversation in real time, and displays retrieved knowledge through an intuitive interface (Hoque, 2020). This architecture ensures seamless integration of multiple AI subsystems, supports scalable interaction with the conversational model, and delivers a coherent user experience. The intervention therefore provides a structured mechanism through which students access tailored, contextually relevant career guidance generated by the AI system.

3.20 System model Architecture

3.20.1 Overall Architecture Overview

The career guidance chatbot system is built on four interconnected components that work together to deliver personalized support. First, a data processing pipeline ingests and normalizes career-related information from various knowledge sources. Second, a skills-matching engine powered by Vertex AI analyzes user profiles to identify suitable opportunities. Third, the conversational interface combines Dialogflow CX with LangChain orchestration to manage natural dialogue flows. Finally, a user management system tracks individual progress and enables adaptive personalization over time. This cloud-native architecture is designed for both scalability and flexibility. The modular approach allows independent updates to each component while maintaining system-wide integration. Special attention has been given to ensuring smooth data exchange between the emotion detection, skills matching, and dialogue management subsystems. The implementation leverages Python's robust ecosystem alongside React interfaces, creating a responsive platform that balances technical functionality with user experience considerations

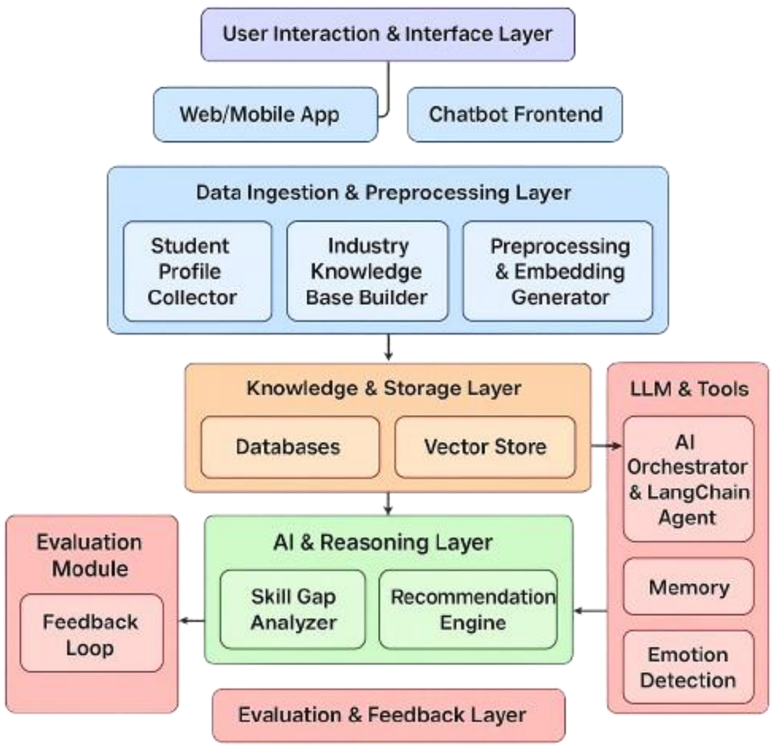


Figure 6: Higher level system model architecture

3.21 Chatbot Classification

AI-based chatbots are generally categorized into two main types: retrieval-based models and text-generation models. Retrieval-based models operate by selecting appropriate responses from a predefined set, ensuring meaningful and contextually accurate replies (Gao et al., 2023). These models are ideal for specific, domain-focused applications such as business chatbots, although they require significant manual effort to maintain and update response libraries. In contrast, text-generation models such as those powered by large language models (LLMs) autonomously generate responses without relying on predefined datasets (Neumann et al., 2024). While they eliminate the need for manual response creation, they may lack domain-specific knowledge, potentially affecting accuracy. However, their adaptability can be enhanced through techniques like in-context learning, which uses prompt-based instructions to align the model with specific tasks. The model adopts a hybrid approach that integrates both retrieval-based and text-generation models. The retrieval system provides precise, domain-specific information (Vo, Vu, Vu, Vu, Mach, et al., 2022; Zhong & Goodfellow, 2024), while the LLM component interprets user intent and generates human-like, contextually appropriate responses. This hybrid design enables the model to overcome the individual limitations of each model, balancing the reliability of curated responses with the flexibility of generative AI. In-context learning further strengthens adaptability by enabling personalized and task-specific interaction, ensuring the chatbot remains both accurate and conversational across a variety of scenarios.

3.21.1 Conversational Agent Implementation

The conversational interface brings together the system's technical capabilities in a user-friendly chat experience. Built with React Native on the frontend, it combines the robustness of Google Cloud services with the flexibility of modern web/mobile technologies. Dialogflow CX serves as the primary orchestrator of conversation flows, handling intent recognition and dialogue state management with high reliability. Vertex AI provides the scalable infrastructure for hosting custom models, including the skill extractors and emotion classifiers (Morić et al., 2024). This cloud-based approach ensures consistent performance even during peak usage periods while eliminating the need for complex local infrastructure. The integration of LangChain (Mavroudis, 2024)through a carefully designed webhook enables dynamic querying of external knowledge sources and sophisticated reasoning about career pathways. The emotional intelligence layer represents the interface's most innovative aspect. By continuously analyzing user messages for emotional cues, the system can adjust not just what information it presents but how that information is delivered. Tone, formality, response length, and even the ordering of suggestions are all adapted in real-time to match the user's detected emotional state. This creates a more natural, supportive interaction that helps reduce the stress often associated with career transitions.

3.21.2 Emotion-Aware Response Generation

The system's emotion-aware capabilities transform standard information delivery into truly supportive interactions. When EmoROBERTA detects emotional states like frustration or anxiety, response generation follows a carefully designed adaptation protocol (López-López et al., 2024a). Language complexity is adjusted to ensure comprehension - simplified when users are overwhelmed, more detailed when they seek deeper understanding. The system modulates tone and formality to establish appropriate rapport, becoming more conversational with some users while maintaining professional distance with others. Response structure follows emotional intelligence principles (Kamath et al., 2022). For anxious users, the system might begin with reassuring statements before presenting information. When detecting frustration, it may acknowledge the difficulty before offering solutions. This ordering strategy ensures users feel heard and understood before engaging with potentially complex career guidance content. The system maintains a database of validated response templates for various emotional contexts(López-López et al., 2024a), which are then dynamically populated with personalized content based on the specific guidance scenario. The emotional adaptation extends to the recommendation presentation as well. Users showing optimism might receive more aspirational suggestions, while those displaying overwhelm receive carefully prioritized, step-by-step action plans. This nuanced approach helps ensure that guidance is not just technically accurate but emotionally resonant and practically actionable for each user.

3.22 Evaluation Metrics

We evaluated the chatbot's effectiveness in supporting university students with career guidance using a comprehensive set of metrics designed to assess semantic accuracy, user-centered quality, and system responsiveness**.** Given the complex and context-sensitive nature of career-related queries ranging from course selection and skill development to internship or job market navigation, our evaluation aimed to ensure that chatbot responses were both accurate and practically actionable for students, making informed academic and professional decisions. The first metric employed was BERTScore (Hanna & Bojar, 2021)**,** which measures the semantic similarity between the chatbot's generated responses and validated career guidance content. BERTScore leverages BERT-based embeddings to assess contextual alignment by computing cosine similarity between sentence vectors (Dadure et al., 2021). In this study, BERTScore was particularly useful for verifying that responses accurately reflected essential guidance content, such as procedures for securing internships, elective course recommendations, or skill development pathways, without deviating from intended meanings. However, BERTScore alone did not fully capture student-centered preferences. Many students favored concise, actionable guidance, for example, "Here's how to apply for the internship," over longer, technically precise explanations. Consequently, responses with high semantic similarity did not always correspond to perceived clarity or practical usefulness, particularly for students with limited familiarity with specific academic or professional terminology.

“Enroll in the Python programming elective next semester to strengthen your data analysis skills.”

Table 6: Reference responses with corespondng BERTScore

Response ID	Chatbot Response	BERTScore Precision	BERTScore Recall	BERTScore F1
R1	Take the Python programming elective next semester to improve your data skills.	0.92	0.94	0.93
R2	You should enroll in the Python course next semester for data analysis.	0.90	0.91	0.905
R3	Consider taking courses that may enhance your skills.	0.65	0.60	0.62
R4	Join the Python elective to get better at analyzing data.	0.88	0.90	0.89
R5	Study programming courses to improve your knowledge.	0.70	0.68	0.69
R6	Attend workshops on Python and data science this semester.	0.80	0.82	0.81
R7	Improve your programming skills.	0.60	0.58	0.59
R8	Take Python to enhance your career in data analysis.	0.87	0.88	0.875
R9	Focus on electives that develop technical skills.	0.72	0.70	0.71
R10	Learn Python programming.	0.75	0.74	0.745

“Responses R1, R2, R4, and R8 have the highest semantic alignment, closely matching the reference content. Responses like R3 and R7 are vague, illustrating why semantic similarity alone is insufficient for student guidance evaluation.”

To complement semantic evaluation, we applied UNIEVAL (Li et al., 2025; Vasselli & Watanabe, 2024), a multi-dimensional framework that assesses the overall quality of generated text across linguistic and interactional dimensions, including coherence, fluency, relevance, naturalness, engagement, and groundedness. UNIEVAL analysis emphasized the importance of actionable and contextually relevant guidance (Li et al., 2025). For example, general advice such as “improve your skills” consistently underperformed relative to more specific recommendations, such as “enroll in the Python programming elective next semester” or “attend the university career fair on Friday.”

Groundedness checks further revealed that vague references to "networking events" were often disregarded by students unfamiliar with institutional norms or professional practices. In response, later chatbot versions incorporated more locally and academically relevant resources. Despite these strengths, UNIEVAL's Boolean scoring occasionally failed to capture subtleties in tone or nuanced expectations, particularly when addressing sensitive topics such as internship rejections, skill gaps, or academic transitions. These cases highlighted the ongoing need for human oversight or review in delicate guidance scenarios.

Table 7: Showing UNIEVAL Evaluation

Response	Chatbot Response	Coherence	Fluency	Relevance	Naturalness	Engagement	Groundedness	Average Score
R1	Take the Python programming elective next semester to improve your data skills.	5	5	5	5	4	5	4.83
R2	You should enroll in the Python course next semester for data analysis.	5	5	5	5	4	5	4.83
R3	Consider taking courses that may enhance your skills.	4	5	3	4	3	3	3.67
R4	Join the Python elective to get better at analyzing data.	5	5	5	5	4	5	4.83
R5	Study programming courses to improve your knowledge.	4	5	4	4	3	4	4.0
R6	Attend workshops on Python and data science this semester.	5	5	5	5	4	5	4.83
R7	Improve your programming skills.	3	5	3	3	2	3	3.17
R8	Take Python to enhance your career in data analysis.	5	5	5	5	4	5	4.83
R9	Focus on electives that develop technical skills.	4	5	4	4	3	4	4.0
R10	Learn Python programming.	4	5	4	4	3		

Finally, we conducted a response time analysis to evaluate the chatbot's ability to deliver timely information. Students demonstrated tolerance for brief delays (1–2 seconds) when responses were structured, concise, and actionable. However, vague, repetitive, or overly long replies often triggered disengagement within milliseconds, emphasizing the critical need for immediate value delivery. Analysis of abandonment rates revealed significant spikes when the chatbot defaulted to abstract career theory instead of providing concrete steps, such as guidance on elective course selection, internship applications, or skill certification procedures. This created a design tension: responses optimized for semantic richness (and higher BERTScore ratings) were often longer and slower, whereas concise messages improved engagement but occasionally lacked depth. To address this challenge, the final implementation adopted a layered response strategy, presenting short, bulleted summaries followed by detailed explanations that balanced clarity, comprehensiveness, and response speed. This approach ensured that students received both immediate actionable guidance and deeper contextual information, enhancing usability, engagement, and learning outcomes.

3.23 Implementation Workflow

The development of the sentiment-aware career guidance chatbot followed a structured, multi-phase workflow that integrated advanced AI and web technologies to deliver personalized, contextually relevant guidance for students. The process encompassed seven key stages. The initial phase involved parsing and extracting structured data from PDF documents, including policy guidelines and career resources. Natural language preprocessing cleaned and normalized the text, which was segmented into context-aware chunks suitable for embedding and retrieval. These document chunks were converted into vector embeddings using Vertex AI's embedding models and stored in a vector database to enable efficient semantic search (Nawalgaria et al., 2023). This semantic index formed the basis for accurate, grounded chatbot responses aligned with users' queries. Using the LangChain framework (Mavroudis, 2024), a modular agent was developed to orchestrate various components, including the retrieval pipeline, sentiment analysis, and dialogue management. This agent interfaced with the vector store and Vertex AI's language models to generate task-specific, context-sensitive guidance. Dialogflow CX was employed to handle natural user interactions through an intuitive flow-based interface (Bijotkar et al., 2021). It managed intent recognition, conversation turns, multilingual input, and webhook calls to the LangChain backend for dynamic response generation. The backend was built with the Django web framework, managing API endpoints, authenticating communication between Dialogflow CX and LangChain modules, and facilitating real-time retrieval from the vector database. Additional administrative and evaluation endpoints supported testing and deployment. Two user-facing interfaces were developed for accessibility: a responsive web application providing desktop users with guided chatbot interaction, and a React Native mobile app enabling Android and iOS access. Both emphasized usability, multilingual support, and clear navigation.

The final phase systematically evaluated the chatbot's performance using metrics such as BERTScore and UNIEVAL (Vasselli & Watanabe, 2024), assessing semantic accuracy, linguistic coherence, cultural relevance, and response time. Evaluation results informed iterative improvements to the knowledge base, prompt engineering, and user interface. The system's backend leveraged Python libraries and cloud services to ensure scalability and robustness. LangChain integrated large language models with external knowledge sources, enabling advanced features such as prompt chaining and contextual memory. Hugging Face Transformer models supported embedding creation and quality assurance, while Django provided RESTful endpoints and session management for communication with front-end applications. Dialogflow CX managed the conversational layer, enabling multilingual support, intent recognition, and smooth integration with the AI backend. Complemented by a React Native mobile app for native-like performance on smartphones. Overall, this multi-component, cloud-native architecture delivered a technically sound, user-centered conversational AI system capable of providing emotionally attuned and pedagogically relevant career guidance to students. An architectural overview is presented in section.

3.24 Documents pre-processing

The development of the system model leveraged a combination of advanced AI Techniques and tools and platform, robust Python libraries, and modern web development technologies (Hug, 2020). These tools collectively supported document ingestion, language modeling, interface design, and system model evaluation. Instead of relying on local extraction tools such as PDFplumber, document processing was offloaded to Vertex AI, which handled document ingestion, text parsing, and embedding within its scalable cloud infrastructure. Uploaded PDFs, including policy, career guide and curriculum documents, integration guides, and job support manuals, were pre-processed using Vertex AI's document AI pipelines to ensure structured, queryable content was available for semantic search.

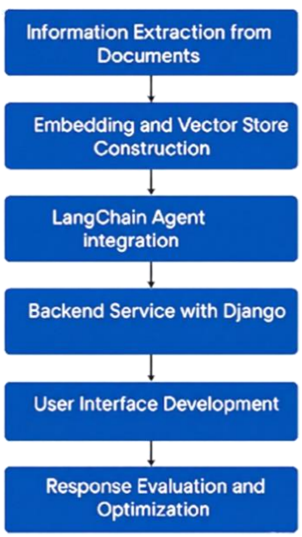


Figure 7: Document processing flow

3.25 Embedding and Vector Store Construction

In the initial phase of the knowledge base development, processed text segments were transformed into high-dimensional vector embeddings utilizing Vertex AI's text embedding model textembedding-gecko@001 (Zhu, 2025). These embeddings captured the semantic meaning of the documents and allowed for context-rich representations of the information. Subsequently, the embeddings were stored within a specialized vector database, the Vertex AI Matching Engine (Ali, 2025). The primary function of the vector store was to enable efficient semantic retrieval, wherein user queries could be matched not solely based on keyword overlap but on deeper contextual relevance. This infrastructure laid the foundation for the chatbot's knowledge base, ensuring that information retrieval processes remained both accurate and scalable, even as the volume of stored data increased.

3.26 Area of Study

The study encompasses all regions of Uganda, ensuring a thorough analysis of the country's varied geographical landscapes. Each region, Central, Western, Eastern, Northern, and Southern were represented[1] and selected at least two public and two private universities[2]. This method guaranteed a comprehensive data collection process encompassing diverse educational contexts and student demographics, which is crucial for developing the proposed model. Furthermore, these institutions admit students from across the country, ensuring that the data collected is representative and forms the foundational dataset for model development.

[1] https://www.worldatlas.com/maps/uganda
[2] https://unche.or.ug/universities/

3.27 Data Collection and Instruments

The study employed both quantitative and qualitative data collection methods, conducted in distinct phases to achieve complementary insights into the usability and adoption of the proposed AI-based career guidance model.

3.27.1 Quantitative Data Collection

Quantitative data were collected through self-administered online questionnaires, designed in accordance with the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Batucan et al., 2022). The instrument was structured to capture participants' perceptions of the system's usability, performance expectancy, effort expectancy, social influence, and facilitating conditions. Additional items assessed user preferences and requirements for the development and evaluation of the career guidance model. The questionnaire was administered to 957 participants from 13 universities across Uganda, ensuring a broad representation of students, faculty members, and industry professionals. This approach enabled the collection of reliable, large-scale data essential for the statistical validation of the model and its usability.

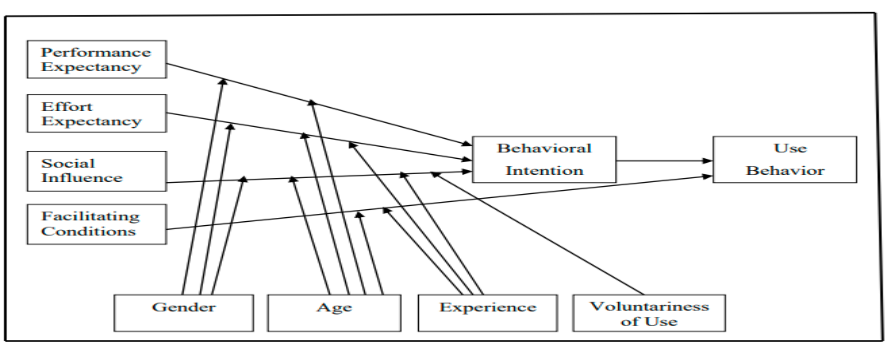


Figure 8: Unified Theory of Acceptance and Use of Technology (UTAUT) model (Batucan et al., 2022)

3.27.2 Qualitative Data Collection

Qualitative data were obtained through structured interviews conducted with 27 participants, selected purposively from the target population to provide in-depth insights into factors influencing the adoption of conversational AI applications for career guidance. Data collection continued until thematic saturation was achieved, ensuring that no new themes emerged and all relevant perspectives were captured. This phase focused on understanding institutional, technical, and contextual requirements for implementing the model, as well as participants' perceptions of AI-driven career support systems within the Ugandan higher education context. The qualitative findings informed the development of a conceptual technology adoption framework, contextualized for universities and similar environments in Uganda.

3.27.3 Machine Learning Data Collection

For the machine learning (ML) development phase, data were collected from multiple documentary and online sources to train the Natural Language Processing (NLP) model specifically for career guidance in the computing education field. Using Beautiful Soup and Selenium, web scraping techniques were employed to extract content from university websites, including academic curricula, course descriptions, and institutional career guides. A documentary review was also conducted to manually gather digital versions of curriculum documents and related materials from each participating university. The resulting dataset was curated and processed to ensure relevance and representativeness for training the model. In future implementations, universities will be encouraged to regularly publish or update their course content online, facilitating automated scraping and continuous dataset enrichment like practices used for Massive Open Online Courses (MOOCs) and job description repositories. Additionally, web scraping was extended to international MOOC platforms such as Coursera, edX, and Udemy to incorporate relevant course descriptions and learning opportunities in the computer science and IT domains. By integrating data from institutional and global sources, the study developed a comprehensive and contextually grounded dataset, enabling the AI-based system to generate accurate, relevant, and adaptable career guidance tailored to Uganda's higher education and employment landscape.

3.28 Data Collection Instruments

3.28.1 Web Scraping Bot

Web scraping techniques were employed to gather data for the model. The focus was on three primary sources: university course descriptions, Massive Open Online Course (MOOC) platforms, and job recruitment websites. University web pages were scraped to collect detailed descriptions of computer science courses, identifying key skills and knowledge areas. Data from MOOC platforms such as Coursera, EdX, and Udemy were gathered to identify supplementary skills gaining popularity in the field. Additionally, job recruitment sites like Indeed.com and Glassdoor were analyzed to extract job descriptions highlighting the most in-demand skills, providing insights into current industry trends and requirements for tech careers. To automate this process, a web scraping bot was developed to extract data from 15 tech career paths and course descriptions from 13 universities. BeautifulSoup and Selenium served as the primary tools (Abodayeh et al., 2023; Oprea & Bâra, 2022), with BeautifulSoup facilitating HTML and XML parsing and Selenium automating interactions with dynamic websites. The combination of these tools provided an efficient means of gathering data from diverse online sources.

3.28.2 Questionnaire Survey

A questionnaire survey was used as a primary data collection method. This approach involved administering a structured set of questions to a targeted sample, enabling the collection of both quantitative and qualitative data relevant to the research objectives (Taherdoost, 2022). Questionnaire surveys are widely recognized for their efficiency, scalability, and ability to provide standardized data, facilitating analysis and comparison. The questionnaire was carefully designed to ensure validity and reliability and was used to explore participants' attitudes, behaviors, preferences, and opinions, thus generating comprehensive insights into the study topics.

3.28.3 Interview Guide

Semi-structured interviews were conducted to collect in-depth qualitative data from key informants selected for the study. Interviews provide a method of data collection that involves asking open-ended questions and probing for detailed responses (Jamshed, 2014). This method was particularly useful for gathering valuable information from respondents who may not have had time to complete the questionnaire (DeJonckheere & Vaughn, 2019). The interviews aimed to explore students' experiences and perceptions of the hybrid skills matching model, its effectiveness in aligning curricula with industry requirements, and its overall usability. These interviews were crucial in capturing subjective viewpoints and uncovering factors that might not have been revealed through surveys alone.

3.29 Validity and Reliability of Research Instruments

Validity refers to the extent to which an instrument accurately measures what it is intended to measure (Kimberlin & Winterstein, 2008). To establish content validity, the questionnaire was reviewed by three research experts who evaluated its suitability for collecting information pertinent to the research problem. This process followed the expert judgment method as recommended by (Knapp & Mueller, 2010). Based on the experts' feedback, the instrument was refined to improve clarity and relevance. The Content Validity Index (CVI) was calculated to quantify the validity of the instrument, ensuring its adequacy for data collection.

Equation 2: Content validity index

$$CVI = \frac{\text{No. of items regarded relevant by judges}}{\text{Total No. of items}}$$

The questionnaire was considered valid if the generated coefficient is 50% or above, as recommended, and when the score is below a recheck of the questionnaire attributes were done on the grounds that it would be valid.

3.29.1 Measurement Reliability and Validity

To assess the internal consistency of all multi-item constructs, Cronbach's Alpha coefficients were calculated for Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Digital Confidence (DC), and Behavioral Intention (BI). As shown in Table X, all constructs demonstrated strong internal reliability, with alpha coefficients ranging from 0.867 to 0.924, well above the commonly accepted threshold of 0.70. Cronbach's Alpha is not applicable for Use Behavior (UB) because it is a single-item measure ("UB_Usage_Frequency"). The high reliability values indicate that items within each construct are strongly correlated and consistently measure their intended latent variables. This provides confidence in the stability and internal coherence of all measurement scales used in the study.

Table 8:Cronbach's Alpha for Multi-Item Constructs

Construct	Cronbach's Alpha
Performance Expectancy (PE)	0.915
Effort Expectancy (EE)	0.901
Social Influence (SI)	0.877
Facilitating Conditions (FC)	0.892
Digital Confidence (DC)	0.924
Behavioral Intention (BI)	0.867

3.29.2 Composite Reliability (CR) and Average Variance Extracted (AVE)

Convergent validity was evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE), calculated from Confirmatory Factor Analysis (CFA) factor loadings. As presented in Table X+1, all CR values were well above 0.70**,** and all AVE values exceeded the recommended threshold of 0.50. These results confirm excellent convergent validity across all constructs.

Table 9;Composite Reliability (CR) and Average Variance Extracted (AVE)

Construct	CR	AVE
Performance Expectancy (PE)	0.944	0.851
Effort Expectancy (EE)	0.950	0.863
Social Influence (SI)	0.927	0.809
Facilitating Conditions (FC)	0.973	0.924
Digital Confidence (DC)	0.964	0.900
Behavioral Intention (BI)	0.957	0.881

The high CR and AVE values confirm that each construct shows excellent internal consistency and that the indicators strongly converge to represent the same underlying latent variable.

3.29.3 Confirmatory Factor Analysis (CFA) Model Fit

The CFA model demonstrated an excellent overall fit to the data, confirming the appropriateness of the measurement model. Key model fit indices are summarized below:

Table 10: Confirmatory Factor Analysis (CFA) Model Fit Indices

Fit Index	Observed Value	Recommended Threshold	Interpretation
Chi-square (p-value)	0.221	p > 0.05	Good fit
CFI (Comparative Fit Index)	0.999	> 0.95	Excellent fit
TLI (Tucker–Lewis Index)	0.999	> 0.95	Excellent fit
RMSEA (Root Mean Square Error of Approximation)	0.0099	< 0.05	Excellent fit
GFI (Goodness of Fit Index)	> 0.90	> 0.90	Strong model adequacy

AGFI (Adjusted Goodness of Fit Index)	> 0.90	> 0.90	Strong model adequacy
NFI (Normed Fit Index)	> 0.90	> 0.90	Strong model adequacy

Additionally, all factor loadings were statistically significant ($p = 0.0$), with high values indicating strong relationships between observed items and their respective latent constructs.

3.30 Qualitative Approach

Upon completion of data collection, interview recordings were transcribed verbatim and subjected to a systematic thematic analysis using NVivo software to manage and analyze the data (Mortelmans, 2019), with a focus on understanding the adoption of the AI-based career guidance system among students. The analysis involved multiple stages, beginning with thorough and repeated readings of the transcripts to gain a deep understanding of participants' experiences and perspectives. Relevant excerpts related to conversational AI adoption for career guidance and the CAM-CAI-RCHE model were then identified and extracted. Data segments exhibiting similarities in respondents' views, notions, and experiences were grouped into thematic categories, with rephrasing applied where necessary for conceptual clarity and redundant statements eliminated. The final thematic analysis yielded a set of propositions regarding the CAM-CAI-RCHE model's components and their perceived relevance, contributing to its refinement and initial validation. To deepen the understanding of adoption drivers, a dual coding approach was employed: inductive coding uncovered emergent themes such as concerns about algorithmic transparency and system usability key factors influencing adoption while deductive coding, guided by the Technology Acceptance Model (TAM), examined participants' perceptions of system usefulness and ease of use, which are core determinants of technology adoption. NVivo's matrix query functionality enabled comparative analyses across demographic groups, revealing differences such as greater apprehension toward the technology among older students versus younger students' stronger emphasis on perceived usefulness. To ensure credibility and trustworthiness, multiple validation strategies were implemented, including peer debriefing with two additional coders to enhance coding reliability and negative case analysis to explore contradictory adoption experiences. Additionally, NVivo's audit trail documented all analytical steps, reinforcing methodological transparency throughout the process.

3.31 Quantitative Approach

All quantitative analyses were conducted using R version 4.3.1 within the RStudio environment. This platform was chosen to ensure methodological consistency, reproducibility, and access to a wide range of advanced statistical tools necessary for modeling complex behavioral patterns associated with technology adoption. Descriptive statistics, including means and standard deviations, were calculated using the dplyr and psych packages to explore trends across platforms, particularly comparing mobile and web users. Internal consistency of multi-item constructs was assessed through Cronbach's alpha using the psych package. The scales demonstrated acceptable to high reliability, with alpha values equal to or exceeding 0.76, confirming the robustness of the aggregated measures. Structural Equation Modeling (SEM) was employed using the lavaan package to test theoretical relationships derived from the Unified Theory of Acceptance and Use of Technology (UTAUT). This approach allowed simultaneous analysis of latent constructs, controlled for measurement error, and modeled multiple interrelated dependencies. Model fit was evaluated with established indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Path coefficients were tested for significance to determine the strength and direction of hypothesized effects, providing detailed insights into the determinants of technology acceptance and usage behavior. Moderated mediation analyses were performed within lavaan, incorporating interaction terms and bootstrapped confidence intervals based on 5,000 resamples. These analyses examined the moderating effect of digital confidence on the relationship between effort expectancy and behavioral intention, offering nuanced understanding of how individual differences influence technology adoption and guiding design strategies to enhance inclusivity and usability. Multiple linear regression models were estimated to assess the impact of mobile optimization on user engagement, incorporating relevant sociodemographic covariates to control for baseline differences. Mediation analyses investigated whether session persistence and responsiveness to push notifications mediated this relationship. Generalized additive models (GAMs) uncovered a critical usability threshold, indicating that task complexity beyond six steps significantly reduced user performance, emphasizing the need for task simplification in interface design.

User segmentation was performed through a combination of Principal Component Analysis (PCA) for dimensionality reduction and K-means clustering. The Elbow method initially suggested three clusters as optimal, which was further confirmed using eigenvalues (Kaiser criterion) and silhouette scores to ensure cluster validity. Consequently, three distinct user profiles were identified and profiled: early adopters, hesitant adopters, and resistors. These profiles varied significantly in digital agency and perceived helplessness, highlighting opportunities for tailored usability interventions. Separate path analyses for mobile and web user groups identified platform-specific behavioral determinants. Results indicated that performance expectancy was a stronger predictor of behavioral intention among mobile users, while web users showed greater sensitivity to effort expectancy. Paired-sample t-tests compared pre- and post-intervention digital confidence scores between guided and self-paced onboarding groups, demonstrating that guided onboarding significantly improved digital confidence, underscoring the effectiveness of structured, facilitator-led training programs. Data preprocessing included duplicate removal and handling of missing values using a unique reference variable system. Variables with excessive missing data or deemed irrelevant were excluded, resulting in a final dataset comprising 27 variables and 987 observations. Categorical variables were converted to factors to facilitate accurate statistical modeling, and UTAUT constructs were aggregated by summing item responses to create composite scores. Exploratory Data Analysis (EDA) provided descriptive summaries and comparative analyses across demographic groups using Welch's t-tests. Predictive modeling with regression analyses incorporated sociodemographic variables to examine their effects on continued use intention and behavioral outcomes. Confidence intervals and p-values were reported to ensure precision and inferential validity. This comprehensive and methodologically rigorous approach provided a robust framework for evaluating usability and acceptance of the conversational AI career guidance application, yielding actionable insights to inform iterative design and implementation strategies.

3.32 System Performance Analysis

The evaluation of the AI-driven career guidance system employed a rigorous methodological framework to assess both real-time operational performance and longitudinal adaptive capabilities, with particular emphasis on the natural language processing (NLP) chatbot module. Central to this analysis was the systematic monitoring of User Intent Drift, which quantified temporal deviations in semantic alignment between user queries and system responses, thereby identifying potential degradation in contextual comprehension. Concurrently, Interaction Coherence was evaluated to ensure logical consistency and fluidity in dialogue exchanges, maintaining adherence to established standards of natural language interaction. Real-time diagnostics were facilitated through Dialogflow Analytics, which captured intent recognition accuracy and response precision, while

Google Vertex AI Monitoring provided drift detection and model performance insights, enabling timely recalibration.

Longitudinal assessment focused on Model Drift over a six-month observation period, tracking linguistic and behavioral shifts in user engagement to evaluate the system's adaptive responsiveness. This was complemented by structured feedback loops measuring the Effectiveness of Retraining, wherein iterative refinements were applied to enhance model robustness. Google Vertex AI infrastructure supported drift tracking and retraining cycle management, while a Human-in-the-Loop (HITL) framework ensured continuous optimization through expert validation of algorithmic outputs. Further diagnostic scrutiny was applied to Session Failure Characteristics, wherein unsuccessful interactions were analyzed to identify recurrent failure patterns, informing targeted improvements in dialogue management. Dialogflow Conversation Logs facilitated systematic error classification, enabling corrective adjustments to interaction logic. Comparative interface evaluation was conducted via A/B Testing, empirically assessing UX optimizations across chatbot iterations. Key metrics including engagement duration, satisfaction indices, and task completion rates were analyzed to validate design enhancements, particularly the integration of Conversational Memory, which was evaluated through latency, success frequency, and retention metrics. Google Analytics and Dialogflow A/B Testing Tools provided granular behavioral data and controlled experimentation capabilities. The auxiliary mobile application, developed using the Expo SDK, underwent performance benchmarking to evaluate Navigation Efficiency, System Stability, and Accessibility Compliance. Load-time analytics, crash diagnostics, and inclusive design adherence (e.g., text-to-speech, chromatic contrast, voice-command integration) were assessed via Expo SDK Logs and the React Native Performance Monitor, ensuring a seamless and accessible user experience. Collectively, this multi-dimensional evaluation framework demonstrated the system's operational efficacy, adaptive resilience, and user-centric optimization. Through continuous monitoring, iterative refinement, and empirical validation, the AI-driven career guidance system exhibited sustained performance improvements across both its NLP chatbot and mobile application components, ensuring alignment with evolving user needs and technological advancements.

3.33 Limitations and Delimitations of the Study

Numerous limitations are anticipated during the study. The key informants selected are high-profile professionals who are often very busy, potentially limiting their availability to provide data. However, efforts will be made to ensure sufficient data is collected for the study, including early appointments with key informants and sending letters of introduction to authenticate the study's purpose. The study involves surveying specific groups of people and professionals to assess the applicability of the proposed model and its user experience. Challenges may include limited access to respondents and difficulties in establishing the study's applicability. These challenges may necessitate redesigning or restructuring parts of the study based on identified special cases. Additionally, time constraints are a concern, particularly with the need to meet dissertation deadlines while potentially limited access to clean and relevant data may hinder the research process.

3.34 Ethical Considerations

Ethics is a systematic approach of understanding, analyzing, and distinguishing matters of right and wrong, good, and bad, admirable, and deployable as they relate to the wellbeing of and the relationships among sentient beings (Rich, 2016)**.** In this study, the main ethical considerations to consider include informed consent, beneficence, respect for privacy, and respect for anonymity and confidentiality (Connelly, 2014). Informed consent is considered the main ethical issue in conducting research. Informed consent implies that an individual knowingly, voluntarily, and intelligently agrees to participate in the study clearly and manifestly (Connelly, 2014). Through informed consent, the participant's right to autonomy is assured. It gives study participants the ability to self-determination. Informed consent prevents assaults (Connelly, 2014). It ensures integrity and protects personal liberty, as well as veracity. During the study, informed consent will be sought of from each participant to participate in the study and at each stage, explanations to the respondents about the purpose of the study will also be thoroughly communicated to the participants. The study will consider various ethical issues as follows: A letter of introduction will be acquired from the University to conduct the study. This will also be presented to all educational institutions and authorities where the study will be conducted as well as to all the respondents required to participant in the study. When permission is granted, the distribution of questionnaires to the respondents and interaction with them using an interview guide will then commence. The completed questionnaires with data from the interview will then be edited and the next stage will be to conduct data analysis. On the other hand, anonymity will be guaranteed in this study by ensuring that the participants are protected. The study will also ensure confidentiality and privacy, and the respondents will be informed that the study is meant strictly for academic purposes and therefore, they should not fear giving information (Gratton & Jones, 2010) as well as assuring them that all information shared will remain confidential. Further on privacy, respondents will be informed prior that their names are not required, and they will not be put under pressure on what they should or not say as suggested by (Oso & Onen, 2008). Additionally, the study will carry no bias during data collection and ensure timeliness and completeness of data while avoiding bias of any kind. Precisely, plagiarism and fraud will be avoided by acknowledging each person’s work that will be used throughout this study. Consequently, the work will be subjected to an anti-plagiarism test to ensure that cited work is duly acknowledged.

In Objective 3, the evaluation included questions designed to elicit user perceptions that could indirectly highlight potential issues related to fairness or equitable treatment by the system model. ethical requirement for transparency and explainability (Bisaso s & Muhumuza G 2025). was considered in the design (Objective 2) and evaluation (Objective 3) phases. While developing a fully explainable AI model is complex, the prototype's design aimed for clear interaction flows. The evaluation in Objective 3 included questions about users' understanding of the system's recommendations and how it operated, assessing the perceived transparency from the user's perspective. Objective 1 highlighted the need for inclusivity and accessibility, particularly for users with varying technical proficiency or disabilities (Bisaso s & Muhumuza G 2025). While a full accessibility audit was not performed for the prototype in Objective 2, the user interface design considered principles of usability and clarity. The evaluation in Objective 3 assessed perceived ease of use and effort expectancy, indirectly addressing aspects of accessibility and inclusivity for the target user group. By integrating the ethical requirements identified in Objective 1 into the planning and execution of Objectives 2 and 3, this research aimed to develop and evaluate an AI model in a manner that was not only technically sound but also socially responsible and respectful of the target users.

3.35 Relationship Between Objectives and Methods

The three research objectives and their associated methods are intrinsically linked and form a coherent progression within the overarching Design Science Research framework, building sequentially upon the outputs of previous stages. The research commenced with Objective 1, employing a rigorous scoping review. This systematic mapping of the literature served as the critical problem identification and motivation phase within the DSRM model. Its primary output was the identification and synthesis of key technical, user-centered, and ethical requirements. These requirements directly fulfilled the objectives for the solution phase of DSR, providing the necessary specifications and design criteria for the artifact to be developed. Objective 2 then addressed the design and development phase of the DSRM. Guided directly by the requirements identified in Objective 1, this objective utilized principles from the CRISP-DM methodology to structure the creation of the AI-driven conversational model prototype. The specific features, data preparation, model selection, and system architecture designed in this phase were a direct response to the needs and technical considerations revealed by the scoping review findings. Finally, Objective 3 focused on the evaluation phase of the DSRM. The quantitative methodology employing the UTAUT model was applied to the prototype developed in Objective 2. This evaluation assessed how well the built solution met the user acceptance and usability aspects of the requirements identified in Objective 1. For instance, the UTAUT constructs measured Effort Expectancy directly evaluated user perceptions related to the user-friendly interface requirement, while Performance Expectancy assessed the perceived utility in meeting career guidance needs. In essence, the scoping review (Objective 1) provided the "what" and "why" by identifying the problem and the requirements. The design and development phase (Objective 2) addressed the "how" by building a model informed by these requirements. The quantitative evaluation (Objective 3) assessed the "how well" by empirically measuring user acceptance of the built artifact against key dimensions related to the initial requirements. This sequential and interlinked approach, grounded in DSR, ensures that the study is systematic, requirement-driven, and focused on creating and evaluating a relevant and useful solution.

3.36 Limitations of the study

While the chosen methodology provides a robust framework for addressing the research objectives, certain limitations are acknowledged: Although comprehensive, the scoping review (Objective 1) is by nature broad and exploratory, aiming to map the literature rather than conducting an in-depth critical appraisal typical of a systematic review focused on a narrow question. Limitations of the search strategy (e.g., chosen databases, search terms, language restrictions) may mean some relevant studies were not captured. The thematic synthesis relies on researcher interpretation in categorizing and grouping requirements. The inclusion of studies based on initial abstract screening may have inadvertently excluded some relevant work where requirements were not prominently featured. While CRISP-DM provided a useful structure for Objective 2, the development phase within this study was typically constrained by time and resources. A full, iterative, industrial-scale application of CRISP-DM, including extensive deployment and ongoing monitoring, was beyond the scope of this study. The prototype represents an instantiation of the model but may not capture all the complexities of a fully deployed system. The validation of the AI models within CRISP-DM (technical evaluation) is distinct from user acceptance and requires specific AI validation metrics. The quantitative evaluation (Objective 3) relies on self-report data collected via survey, which can be subject to social desirability bias or inaccurate recall. The cross-sectional design captures user perceptions at a single point in time and cannot assess long-term adoption or changes in behavior. The generalizability of the findings may be limited by the specific characteristics of the participant sample and the context of the evaluation. The UTAUT model, while comprehensive, focuses primarily on technology acceptance factors and does not fully capture the nuances of the career guidance process or the specific socio-cultural factors influencing migrant populations beyond the general UTAUT constructs.

3.37 Chapter Summary

This chapter has detailed the comprehensive methodological approach adopted for this study. Anchored within the principles of Design Science Research, the research progressed through three distinct yet interconnected phases. A foundational scoping review systematically identified the critical technical, user-centered, and ethical requirements for the AI-driven conversational model. These requirements then informed the design and development of the research artifact (Objective 2), utilizing relevant aspects of the CRISP-DM methodology. Finally, a quantitative evaluation using the UTAUT model was employed to assess the user acceptance and usability of the developed prototype (Objective 3). While acknowledging the inherent limitations of the chosen methods, this multi-faceted approach provides a robust framework for addressing the research objectives and test to ensure proper citation.

CHAPTER 4: STUDY RESULTS

4.1 Introduction

This chapter presents the empirical findings of the study in relation to the three research objectives introduced in Chapter 1 and developed through the methodological approach outlined in Chapter 3. The first objective focused on identifying the technical, user-centered, and ethical requirements for developing an AI-driven conversational career guidance model suitable for low-resource university settings. The second objective involved designing and implementing a prototype that responds to these requirements, highlighting key design decisions and outcomes of model training, testing, and statistical evaluation. The third objective examined the model's usability and user acceptance using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, supported by both descriptive and inferential analyses. The chapter is organized into four sections. Section 4.2 presents the scoping review that informed the requirement synthesis. Section 4.3 outlines the design and development of the prototype, together with its technical evaluation. Section 4.4 reports the user evaluation based on the UTAUT model. Section 4.5 concludes with an integrated synthesis of the results and a reflection on their broader implications.

4.2 Results of Scoping Review Methodology

This section presents the synthesized findings derived from the systematic scoping review, structured according to the five thematic lenses identified in the methodological framework. It outlines the characteristics of the included studies, maps their thematic coverage, and details the key requirements and considerations within each theme, followed by a summary of reported functionalities, benefits, and challenges.

4.3 Identified Themes

Five themes emerged from the review, which have been depicted in Table below.

Table 11: Distribution of Included Studies Across Thematic Lenses

Study Citation	Technical Requirements	Design User Experience	Emotional Intelligence	Pedagogical Considerations	Ethical Considerations
(Talib et al., 2023)	X	X		X	X
(Zylowski et al., 2025)	X	X			
(Choithramani, 2024)	X	X			X
(Meyer et al., 2023)	X			X	X
(T. Lee et al., 2019)	X	X	X	X	X
(Pereira et al., 2023)	X	X	X	X	X
(Thottoli et al., 2024)	X	X	X	X	X
(Chang et al., 2023)	X	X	X		X
(Nguyen et al., 2022)	X			X	X
(Bassner et al., 2024)	X	X		X	X
(Assiri et al., 2020)	X	X			X
(Janssen et al., 2020)	X	X	X	X	X
Total Studies	**12**	**9**	**5**	**8**	**11**

Note: *'X' indicates that the study addressed the respective thematic lens. Studies may address multiple themes.*

4.3.1 Technical Requirements

Analysis of the included literature reveals that the technical foundation is a critical determinant of an AI conversational model's capability and reliability in university career guidance. (Bassner et al., 2024; Talib et al., 2023). These studies collectively underscore the necessity for sophisticated Natural Language Processing (NLP) capabilities as paramount. Merely relying on keyword matching or simple rule-based systems proves insufficient for the diverse, complex, and often ambiguous language students use when discussing career aspirations, skills, or challenges, as argued by (Thottoli et al., 2024; Zylowski et al., 2025) . Effective models, particularly those using advanced NLP techniques, require robust intent recognition, entity extraction (such as job titles, skills, and industries), and dialogue state tracking to maintain context and coherence across interactions. This was exemplified by (Bassner et al., 2024) By detailing how their model Iris uses Chain-of-Thought prompting to guide GPT-3.5-Turbo through reasoning steps for programming exercises, demonstrating sophisticated handling of student queries and context awareness by accessing the problem statement, code, and feedback. Similarly, (Talib et al., 2023) Discusses the need for LLMs like GPT and PaLM as backbones for AI chatbots due to their human-like text generation and contextual understanding capabilities in career guidance. (Zylowski et al., 2025) Implicitly highlights NLP differences by comparing intent-based CAs (with noted lack of flexibility) and LLM-based CAs (which are perceived as more explainable and trustworthy), linking performance to the model's underlying capabilities. Furthermore, the literature indicates that personalization, a highly desired feature, necessitates the integration of Machine Learning (ML) algorithms (Chang et al., 2023; Choithramani, 2024). These algorithms are essential for generating tailored recommendations based on student profiles, academic history, stated interests, and interaction patterns. (Choithramani, 2024) Explicitly states ML techniques are needed for personalized guidance in their proposed Moroccan system. (Bassner et al., 2024) presents Iris as offering personalized, context-aware assistance by analyzing student code and automated feedback to provide tailored advice for programming tasks. (Zylowski et al., 2025)'s user study compared different CA types and found that the LLM-based CA, with its generative capabilities, led to significantly longer user inputs and interaction times, potentially reflecting a higher degree of perceived personalization compared to form-based or intent-based systems. However, robust ML-driven personalization was more often discussed as a potential feature rather than demonstrated in current implementations, (Thottoli et al., 2024) posit that model development and training as necessary steps rather than reporting full implementation results. There 4 identified core technical aspects of developing an efficient model (see Table 4).

Table 12:Identified Core Technical Components

Technical Aspect	Requirement Description	Indicators
NLP Accuracy	High adaptability to diverse linguistic expressions, including multilingual support	Use of advanced NLP models (e.g., transformers), language detection, contextual understanding
System Integration	Compatibility with existing academic databases and institutional systems	Real-time data retrieval, API-based integrations, support for LMS (e.g., Moodle, Canvas)
Scalability & Performance	Ability to handle high concurrent users with minimal latency	Cloud-based architectures (e.g., AWS, Azure), load balancing, high throughput (>10,000 requests/sec)
Data Security & Privacy	Compliance with data protection regulations and secure handling of sensitive information	End-to-end encryption, GDPR/CCPA compliance, regular security audits, access controls

Several recent studies, like (Neumann et al., 2024; Pereira et al., 2023) have also strongly suggested that the technical infrastructure supporting these models must be scalable and reliable to handle the volume of queries from a large number of students. (Bassner et al., 2024) Positions Iris within Artemis, an interactive learning platform designed for large-scale settings, suggesting the need for scalability. (Talib et al., 2023) Acknowledges the need for affordable, scalable infrastructure solutions for chatbot deployment in Morocco. A consistently reported technical challenge, however, is the seamless and secure integration with existing, often disparate, university IT systems, including student information systems, learning management systems, and existing career service databases. (Neumann et al., 2024) highlights the seamless integration with Artemis as a key feature, reducing cognitive load for students by automatically accessing relevant context. (Talib et al., 2023) lists integrating the chatbot into a web platform as a crucial step in their implementation path, implying potential challenges in this process, particularly concerning web services and API access costs.

4.3.2 Design and User Experience

Several studies have noted that the effectiveness of AI conversational models in career guidance is significantly mediated by their design and the resulting user experience (Janssen et al., 2020; Talib et al., 2023; Thakkar et al., 2024; Zylowski et al., 2025). The literature further highlights the imperative for intuitive and accessible interfaces. Given the diversity of the university student population, usability and ease of navigation are paramount. Bassner et al. (2024) narrate the integration of Iris directly into the Artemis learning platform via a chat interface, aiming for a seamless, accessible, and efficient interaction. (Zylowski et al., 2025) specifically evaluates usability dimensions like "Ease to start a conversation" and Flexibility and communication effort, using these as key measures of user experience across different conversational agent types. (Talib et al., 2023) discusses the benefit of mobile accessibility for their proposed system in Morocco, emphasizing the need for a user-friendly interface for wide reach. Studies have suggested that text-based interfaces are the most common format, likely due to ease of implementation, but acknowledged the potential of multimodal interaction, such as voice or avatars, to enhance engagement and accessibility for some users, though none of these papers focus specifically on multimodal aspects (Pereira et al., 2023). Managing user expectations about the AI's capabilities is a critical design consideration (Zylowski et al., 2025). The conversational interface can sometimes mislead users into believing the AI possesses human-level understanding and empathy. Therefore, transparent communication about the AI's nature, its limitations, and the scope of its functionality is essential for building trust and preventing user frustration. (Zylowski et al., 2025) explicitly evaluates Expectation setting as a usability dimension and finds differences across CA types. Effective error handling, where the AI can gracefully acknowledge limitations or misunderstandings and guide the user appropriately, is also crucial for a positive user experience.

(Nguyen et al., 2022) contrasts the error tolerance of intent-based (low, fallback needed) and LLM-based (high, generative) CAs, showing design choices impact how errors are handled. User engagement was frequently reported as a key benefit, with the conversational format often perceived as approachable and less intimidating compared to traditional methods. (Janssen et al., 2020; Talib et al., 2023; Zylowski et al., 2025) reports generally positive student responses regarding engagement, with a majority agreeing that conversational models make the support process more engaging. (Talib et al., 2023) uses user engagement as a key performance indicator (KPI) and reports a noticeable increase over time in initial testing. See Table 5 for design considerations.

Table 13:A comparative table outlining the key design considerations for an AI conversational model

Design Dimension	Requirement Description	Impact on User Engagement
User-Centered Interface	Intuitive, simple interface, minimal learning curve	Enhances user satisfaction and reduces frustration
Multilingual Support	Dynamic language detection and translation capabilities	Increases accessibility, particularly for international students
Conversational Flow	Natural dialogue, context retention, adaptive questioning	Improves the sense of engagement and personal connection
Accessibility Features	Assistive technologies for disability inclusion	Ensures equitable use for a diverse student body

4.3.3 Emotional Intelligence

The capacity for emotional intelligence in AI conversational models for career guidance is a nascent but critically important thematic area discussed in this study. While current AI lacks genuine human empathy or emotional understanding, studies acknowledged that effective career guidance often involves navigating student anxieties, uncertainties, or excitement related to their future (Thakkar et al., 2024; Thottoli et al., 2024). (Bassner et al., 2024) indirectly touches upon this by finding students feel significantly more comfortable asking Iris questions than human tutors or professors without worrying about being judged, highlighting a perceived non-judgmental aspect of the AI. (Zylowski et al., 2025) evaluates perceived relatedness as a dimension influencing trust, suggesting that a perceived human-like quality in the chatbot interaction contributes positively, although this doesn't equate to genuine emotional understanding. The ability of an AI model to merely recognize potential student affect states, even without deep understanding, and respond in an appropriately supportive or neutral manner was identified as a desirable, albeit technically challenging, feature, though specific affect detection capabilities are not detailed in these studies. Furthermore, the literature implicitly and explicitly points to the necessity of the AI knowing its limitations regarding emotional and psychosocial support (Pereira et al., 2023). (Bassner et al., 2024)The explicit instruction for Iris to say Sorry, I don't know and tell the student to ask a human advisor aligns with the need for the AI to recognize its boundaries and facilitate human handover for questions beyond its capabilities, particularly sensitive ones. (Pereira et al., 2023)While focusing on informational guidance, it acknowledges the need for chatbots to emulate good career counselors, implicitly recognizing students' complex needs. (Zylowski et al., 2025) highlights that while students felt comfortable asking questions without judgment, the preference for human interaction in specific contexts suggests a perceived limitation in the AI's role, likely including the nuanced emotional aspects human tutors can provide. This understanding is critical for designing safe and ethical models that can appropriately escalate interactions involving sensitive personal issues or significant student distress to human professionals (Janssen et al., 2020). While full emotional intelligence remains a distant goal, the consideration of affect and the intelligent routing of emotionally charged interactions are identified as essential requirements for responsible and effective implementation in this sensitive domain (Chang et al., 2023).

4.3.4 Pedagogical Considerations

The pedagogical integration of AI conversational models within the university's educational framework is a crucial theme. Studies suggest that for these tools to be truly effective, they must align with established learning science principles and complement, rather than conflict with, existing curriculum objectives related to career readiness. (Bassner et al., 2024) positions Iris conversational model as a chat-based virtual tutor designed to be didactically meaningful, employing calibrated assistance that hints, counter-questions to foster independent problem-solving skills, directly aligning with pedagogical goals in computer science education. Research indicates that an AI-based academic advising framework can enhance decision support, thereby potentially reducing the workload on human advisors while delivering data-driven recommendations (Bassner et al., 2024; Talib et al., 2023). Zylowski et al also explore the correlation of AI trustworthiness and usability with Self-Determination Theory constructs (competence, autonomy, relatedness), linking the design of career planning conversational Agents (CAs) to established motivational theories in education. In another selected study, (Talib et al., 2023)) mention AI systems' potential to support theories like Super's career development theory by providing personalized feedback. The functionality spectrum observed highlights that many current systems prioritize information delivery over supporting deeper learning processes like critical thinking, self-assessment, or strategic decision-making. While (Pereira et al., 2023) focuses on providing comprehensive information and insights, (Bassner et al., 2024)'s use of hints and counter-questions explicitly aims to stimulate independent thinking and problem-solving in programming, pushing students beyond simple information retrieval. According to (T. Lee et al., 2019) a pedagogically sound design would require shifting towards interactions that encourage students to actively engage with information, reflect on its relevance to their context, and apply it to their career journeys. Furthermore, the AI tool needs to be strategically positioned within the broader university career service ecosystem. A crucial pedagogical requirement is to ensure seamless handover protocols that allow students to transition from AI support to human advisors when their needs become complex, sensitive, or require nuanced human expertise a notion supported by several studies (Meyer et al., 2023; Pereira et al., 2023). (Bassner et al., 2024) found that students predominantly view Iris as a complement to, rather than a replacement for, human tutors and reported feeling more comfortable asking certain questions to conversational agent (Iris) discreetly, while a clear perceived niche for the AI within the existing human support structure. With (Zylowski et al., 2025)'s results suggesting that while students find the AI trustworthy for some tasks, they may still prefer human interaction in specific contexts (such as, over asking the professor directly during lecture), especially in situation where career guidance isn't imbedded in the study program's curriculum. Supporting a hybrid model where AI supplements human expertise.

4.3.5 Ethical Considerations

Ethical considerations represent a critical thematic lens for the design and implementation of AI conversational models in career guidance, frequently discussed in the literature. Proactive attention to ethical requirements is essential for ensuring the responsible and equitable application of this technology. (Janssen et al., 2020; Meyer et al., 2023; Talib et al., 2023) explicitly lists data privacy and or legislative regulations as key challenges to implementing their proposed models, as clearly noted by (Talib et al., 2023) for a model designed for the Moroccan education system, highlighting the need for robust safeguard measures. Studies further mention democratizing access as a potential benefit, addressing equity concerns. And another primary ethical concern revolves around algorithmic bias, with studies highlighting the risk that biases present in training data or algorithms could lead to unfair or inequitable career suggestions for certain student groups. As put forward by

(Talib et al., 2023) that LLMs are trained on vast data, which might contain biased perspectives, and that the quality of LLAMA2 training data is questionable. Therefore, mitigating this bias is identified as a key requirement, albeit a challenging one. Data privacy and security are paramount ethical considerations, given the sensitive nature of personal and career-related data collected from students. Scholars stress that robust data protection measures and transparent data policies are needed to protect student information and build trust. (Zylowski et al., 2025) evaluates Users' privacy and security as a usability dimension and found it correlated significantly with trust, particularly for the LLM-based CA, underscoring its importance for user perception. Furthermore, the synthesized literature emphasizes the importance of transparency, recommending that students to be aware that they are interacting with an AI agent, not a human. And (Bassner et al., 2024) mentions informing students about the model's intended use and limitations. Managing user expectations ethically requires upfront communication about the AI's capabilities and limitations. Accountability for the underlying technology advice provided by the AI is also an ethical requirement. In the context of high-stakes career decisions, understanding how the AI arrived at a particular suggestion becomes important, however, this remains challenging for complex Machine learning models, naming it the black box problem. (Zylowski et al., 2025) directly evaluates explainability and found out that LLM-based conversational Agents (Cas) are perceived as significantly more explainable than intent-based conversational Agents, suggesting generative models may inherently offer more transparency in how they respond, though not necessarily why they provide specific career recommendations. Therefore, ensuring fairness in access to and outcomes from AI-driven guidance is a fundamental ethical imperative that requires careful design and continuous monitoring.

4.4 The CAM-CAI-RCHE Model

The study also systematically developed and performed an initial validation of the Contextualized Adoption Model for Conversational AI in Resource-Constrained Higher Education (CAM-CAI-RCHE). The CAM-CAI-RCHE model was specifically engineered to address the significant challenge of effectively integrating Conversational AI for career guidance within Ugandan universities. The methodological approach comprised a documentary review followed by in-depth qualitative interviews with experts. A primary outcome of this investigation is the formulation of an adoption model for conversational AI in providing career support and guidance, tailored for Ugandan university contexts. This framework offers a theoretical, step-by-step guide to facilitate the successful implementation and adoption of AI and NLP-driven system model, with applicability for key industry players involved in such initiatives. To ensure its conceptual quality and alignment with practical needs, its development was informed by extensive expert consultations. Furthermore, upon its completion, the conceptual framework underwent a comprehensive review by external specialists to confirm its theoretical coherence and potential efficacy.

4.5 Empirical Findings from the Exploratory Study

This section presents the qualitative findings derived from the exploratory interview phase of the empirical study. It outlines the methodological procedures employed, from participant selection through to the analysis of interview data, culminating in the formulation of propositions regarding the perceived utility and applicability of the proposed Contextualized Adoption Model for Conversational AI in Resource-Constrained Higher Education (CAM-CAI-RCHE).

4.5.1 Key Themes and Propositions from Stakeholder Interviews

The qualitative analysis yielded several key themes concerning the proposed CAM-CAI-RCHE model. A predominant sentiment among interview respondents was the clarity and comprehensibility of the model's structure. For instance, interviewee |G| noted that the "design effectively delineates the intended adoption stages." Similarly, interviewee |E| affirmed that "the model's components present simple and easy-to-follow steps, which is crucial for conveying the adoption strategy to users. While further refinements might be beneficial, this foundational framework provides a clear depiction of how the adoption of Conversational AI for career guidance can be initiated, ensuring implementers understand and accept the proposed innovations." This suggested: *Proposition 1: The 3-phased and component-based structure of the CAM-CAI-RCHE model is perceived by stakeholders as understandable and provides a clear roadmap for adoption.*

Respondents also expressed positive initial reactions to the model's emphasis on a practical and context-aware approach. Several interviewees highlighted the importance of features that would ensure the AI application or model is grounded in local realities. Drawing parallels, interviewee |H| stressed that "career guidance is a unique aspect. if the model incorporates use cases covering specific organizational needs, such as how AI guidance can be tailored to different faculties or student cohorts, its value would be significantly enhanced." This led to: *Proposition 2: The CAM-CAI-RCHE model's explicit inclusion of contextual factors (such as localized data aspects, stakeholder engagement) is considered critical for its perceived relevance and practical utility in Ugandan universities.*

Furthermore, the concept of a supporting digital platform or application to operationalize the model and facilitate stakeholder interaction resonated positively. Interviewee |F| suggested that "it would enhance visibility if an application demonstrated how these model components interact, such a tool could detail the steps, showing users how the intended system model would function to support students in career planning." This aligns with the model's operational aspects and points to:

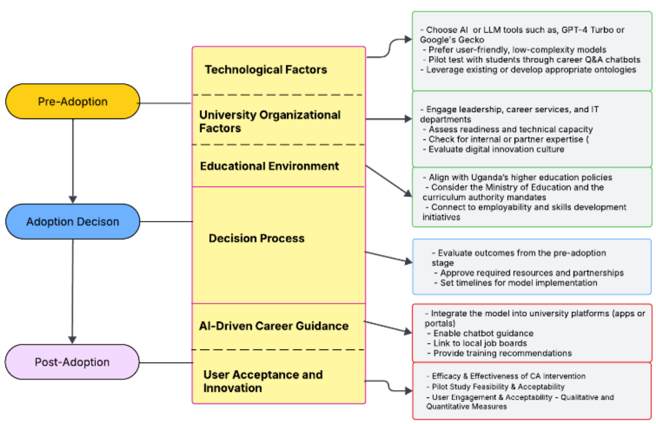
Proposition 3: The integration of a supporting platform to manage the adoption process, as implied by the CAM-CAI-RCHE model, is viewed as a valuable facilitator for coordinated implementation and stakeholder engagement.

The interview data also underscored the perceived benefits of the CAM-CAI-RCHE model in fostering a systematic and potentially more cost-effective adoption process by clearly defining interactions between various actors and entities involved.

4.5.2 The conceptual model

The proposed adoption model, visually represented in Figure 1, delineates a structured, three-stage process for the successful university-wide adoption of Conversational AI within the institutions' career services departments. It commences with a Pre-adoption Stage, focusing on critical assessments and preparations, leading to a pivotal decision for the Adoption. During the pre-adoption phase, emphasis is placed on evaluating Perceived Usefulness by assessing potential benefits and incorporating peer feedback, and examining Facilitating Conditions through a thorough evaluation of resource availability. Concurrently, proactive education for both students and institutional adopters (model commences with a critical Pre-adoption Stage, where assessments of 'Perceived Usefulness' informed by potential benefits and peer feedback and 'Facilitating Conditions' through resource evaluation are paramount. Concurrently, this initial phase emphasizes proactive education of both students and administrative adopters regarding the technology, resource implications, and potential barriers, all of which inform the crucial 'Decision for the Adoption.' Following a positive decision, the model transitions into an After-Adoption stage. This phase concentrates on the effective deployment and sustained use of Conversational AI, underscored by activities such as continued student education, the promotion of mentoring, dedicated efforts to support student confidence, and the provision of clear, accessible information. The entire framework is anchored within the existing Career Services Environment, highlighting the imperative to continuously 'Align with institutional career counseling objectives' to ensure the AI initiative's relevance, staff/administrators, regarding the technology, resource implications, and potential barriers is crucial. Following a positive adoption decision, the After-Adoption stage centers on the effective integration and sustained support of the Conversational AI. This involves continued student education about the technology, the promotion of mentoring, and initiatives to support students' confidence, and the provision of clear, accessible information. Critically, the entire framework operates within the Career Services Environment, underscoring the necessity to continuously align the AI initiative with established institutional career counseling objectives to ensure relevance and strategic coherence

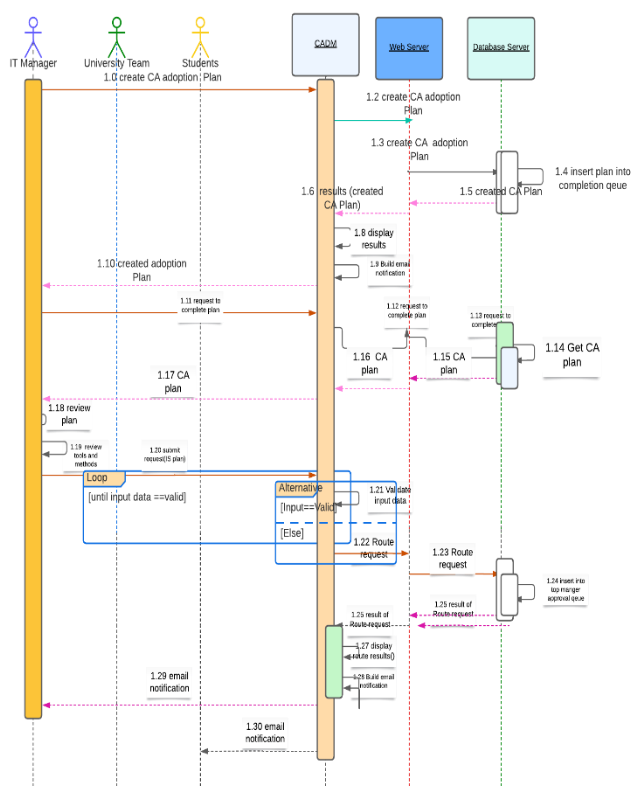
Figure 9: CAM-CAI-RCHE Conceptual Framework



4.6 The Sequence Diagram

The CAM-CAI-RCHE model incorporates a logical workflow that details the iterative refinement and approval process for adopting and integrating an AI-driven career guidance model into the existing university systems, emphasizing coordinated stakeholder interaction and decision-making process. Supported by a proposed digital platform model, this process begins with universities and career guidance managers developing an initial adoption strategy. This strategy is shaped by a synthesis of diverse inputs, including feedback from peers and industry leaders, insights from career counselors, an assessment of existing facilitating conditions and resources, and its alignment with institutional career counseling objectives. This initial plan is stored and managed centrally, allowing career guidance managers to retrieve and modify it iteratively. Integrated analytical or recommendation functionalities can assist in processing these inputs and optimizing the plan. Once the plan reaches a mature state, it is formally submitted for review by university leadership and expert panels, who are notified of its availability. After a successful executive review and approval, automated notifications confirm the plan with automated notifications to key implementers, such as career guidance and IT managers, as well as broader staff. A critical step involves disseminating the approved plan to students, providing them with a channel for feedback and suggestions. The AI model is then provisioned, granting students access for initial testing to assess applicability and gather data for continuous improvement, while also ensuring adherence to national AI regulatory frameworks. The plan itself outlines necessary training and support resources, enabling staff to effectively engage with the new system and navigate the learning curve associated with technological innovation.

Figure 10: Adoption Model Sequence Diagram



Note: *This figure details the flow of tasks and interactions between key entities, such as students, IT managers, AI chatbot, university team within the proposed automated adoption platform. The model aims to streamline the adoption process for a conversational AI designed to support career guidance and decision-making for computing students in Ugandan universities, enhancing access to quality career information.*

4.7 Findings of the system model development

4.7.1 Comparison Between the Ada-002 Model and the Gecko

The model was deployed fully within Google Cloud; therefore, using Vertex AI's textembedding-gecko is recommended due to its fast performance, seamless integration with other Google services like Dialogflow CX and Matching Engine, and lower latency. However, if cross-platform flexibility or access to broader, general-purpose embeddings is needed, OpenAI's Ada-002 remains a strong option. In this study, given the tight integration with Google Cloud services, textembedding-gecko was selected to optimize performance, cost, and scalability. See the comparison table below.

Table 14:Comparison Between the Ada-002 Model and the Gecko

Feature	Ada-002 (OpenAI)	Gecko (Vertex AI)
Accuracy	High (state-of-the-art)	Very High for the Google ecosystem
Speed	Very Fast	Very Fast (especially on Google infra)
Cost	Low	Low (but varies with traffic)
Integration	External (unless using OpenAI)	Native to Vertex AI & Matching Engine
Deployment	External API	Fully managed inside Vertex (easy scaling)

4.7.2 LangChain Agent Integration

Following the construction of the vector store, a LangChain agent was developed to coordinate the chatbot's reasoning and interaction logic. The agent served as the central orchestration layer, seamlessly integrating the vector store with large language models (LLMs) deployed on Vertex AI. Furthermore, the agent incorporated a sentiment analysis module to dynamically adapt responses based on the detected emotion and tone of the user's input. This emotional sensitivity enhanced user engagement by enabling more empathetic and contextually appropriate responses. Additionally, the LangChain agent was responsible for maintaining conversational memory, allowing it to chain multiple user queries into coherent, continuous dialogues. This capability significantly improved the chatbot's ability to provide nuanced and contextually informed support. We augmented our Chatbot with emotional intelligence capabilities via a novel integration of the EmoRoBERTA algorithm, a leading model for emotion detection in NLP. Built upon the RoBERTa framework and fine-tuned extensively, particularly with the GoEmotions dataset (58k+ Reddit comments, 27 categories), EmoRoBERTA provides a nuanced understanding of user sentiment. Rigorous development involving data preprocessing and training optimization confirmed its strong classification performance. EmoRoBERTA's demonstrated success marks progress in NLP emotion recognition, with potential applications spanning semantic analysis to affective computing. Our implementation utilizes EmoRoBERTA [42] to classify the emotion in user input independently from the core LangChain agent. This detected emotion is then formalized as a variable and injected as a contextual string into the prompt directed to the Large Language Model (LLM), enriching the agent's situational awareness.

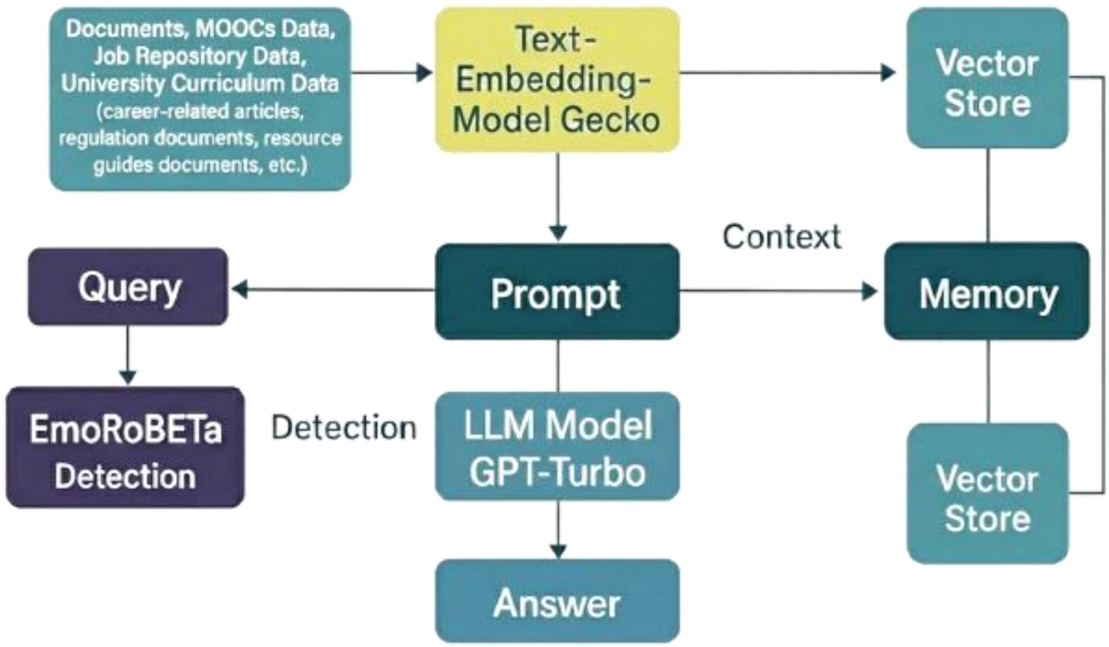


Figure 11: Prompt implementation of the proposed conversational model

4.7.3 Dialogflow CX Conversational Design

To create a robust and user-friendly conversational interface, Google Dialogflow CX was employed. Dialogflow CX managed critical aspects of the chatbot's dialogue system, including intent recognition, dialogue flow control, and multilingual support, thereby facilitating broader accessibility. Importantly, the platform's webhook functionality was leveraged to bridge user utterances to the LangChain agent. Upon receipt of a user message, Dialogflow invoked the webhook, enabling real-time retrieval of relevant information from the vector store and subsequent generation of personalized responses by the LLM. This integration between Dialogflow CX and the LangChain agent ensured that the chatbot could deliver accurate, timely, and context-sensitive interactions across diverse use cases.

4.7.4 Backend Service with Django

A Django-based backend service was developed to function as the communication bridge between the Dialogflow CX interface, the LangChain agent, and the vector database. This backend exposed RESTful API endpoints, facilitating dialogue management, user authentication, conversation logging, and system evaluation. In addition to processing webhook calls from Dialogflow CX, the Django service managed the routing of data across system components, ensuring a streamlined and reliable flow of information. Error-handling mechanisms were also implemented within the backend to ensure graceful degradation in cases of communication failures, thereby preserving a consistent user experience.

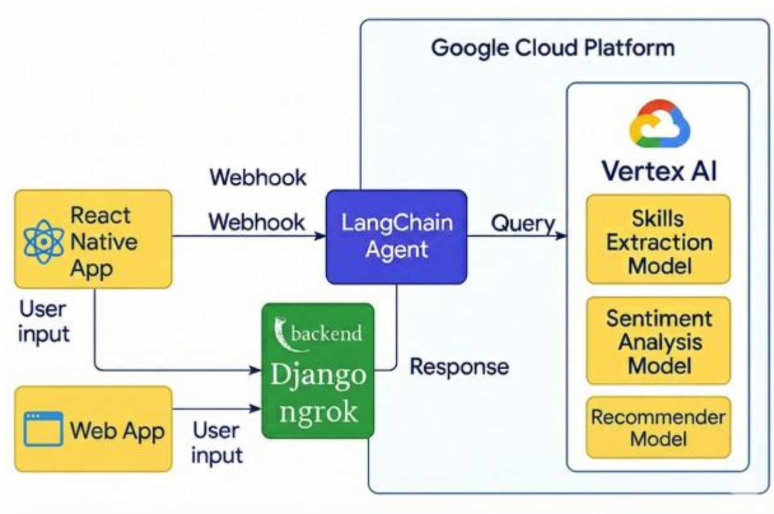


Figure 12: Integrated system flow

4.7.5 User Interface Development

To maximize accessibility across different user platforms, two front-end applications were developed. A web-based interface was created using standard web technologies (HTML, CSS, JavaScript) to enable seamless interaction through browsers. Concurrently, a mobile application was developed using React Native, providing a consistent user experience on both Android and iOS device for this study only android version was tested. Both interfaces were designed with a strong emphasis on clear and intuitive navigation, particularly targeting users with varying technical knowledge. These design choices ensured that the model application chatbot could serve a broad and diverse user base, reinforcing its role as an inclusive and adaptive conversational assistant.

4.8 The prototype

The prototype of CareerChats AI demonstrates that an AI-supported conversational system model can generate personalized and context-specific career recommendations for computing students. The interface successfully integrates individual academic profiles with real-time labour-market information to produce internship suggestions accompanied by quantitative match scores, indicating the degree of alignment between a student's skills and workplace expectations. The system further provides "Quick Win" micro-skill recommendations such as competencies in statistics or Scikit-learn that target immediate skill gaps identified within the user's profile. Notably, the prototype implements explainable AI (XAI) components that articulate the underlying reasoning behind each recommendation, including links to skills, coursework, and labour-market trends. These outputs confirm the system's ability to provide transparent, tailored, and actionable guidance, addressing a key limitation observed among conventional, non-dynamic career advisory practices

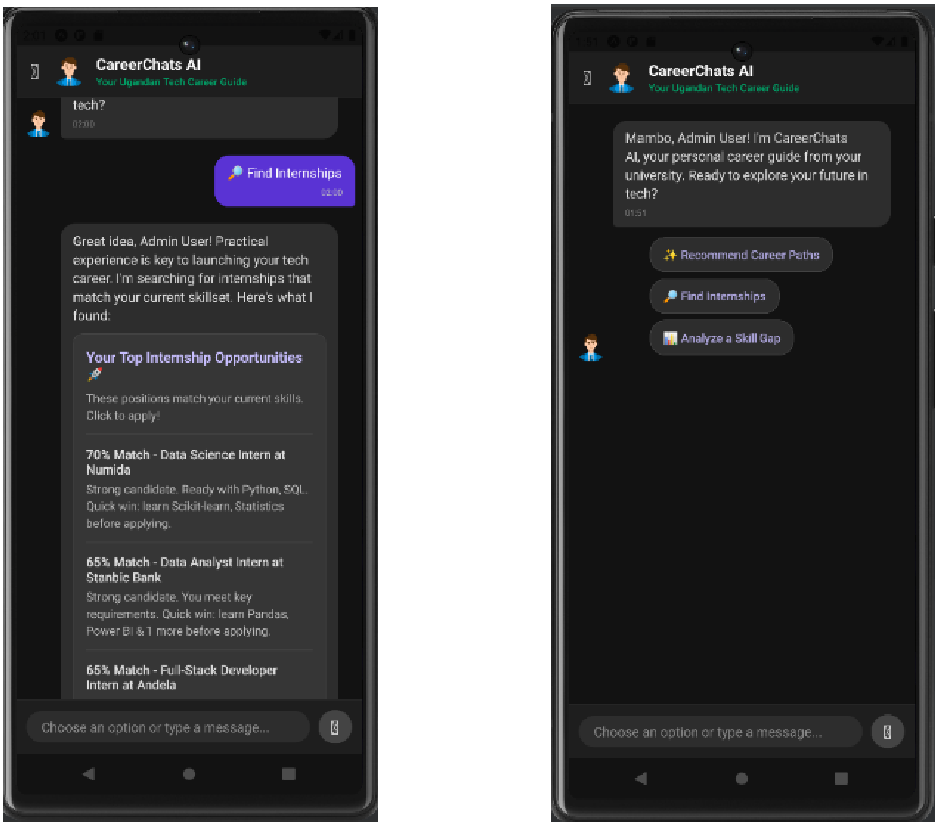


Figure 13: Conversational Interfaces for the proposed system model in react native app

4.9 Usability Study findings

4.9.1 Exploratory Data Analysis (EDA) and Descriptive Statistics

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a widely used model to explain users' intentions to use an information system and subsequent usage behavior. In this study, we also incorporated Digital Confidence (DC) as a key moderating variable.

Table 15: Summarizing the constructs used in your analysis, along with their descriptions

Construct	Description
Performance Expectancy (PE)	Belief that using the system enhances job performance or career prospects.
Effort Expectancy (EE)	Perceived ease of use of the system.
Social Influence (SI)	Perception that important others believe one should use the system.
Facilitating Conditions (FC)	Belief that organizational and technical infrastructure supports system use.

Digital Confidence (DC)	Self-efficacy in using and troubleshooting digital technologies, including AI.
Behavioral Intention (BI)	Intention to perform a specific behavior (e.g., use the career application).
Use Behavior (UB)	Actual usage of the system.

4.9.2 Demographic Characteristics of the Dataset

The dataset comprises 987 participants from various universities and regions across Uganda, with a clear distinction between students and staff, and a notable gender distribution. Makerere University accounts for the largest proportion of participants at nearly 15%, followed by Mbarara University and ISBAT University. Geographically, the Central region (including Central/online) represents the largest share with approximately 45.5% of participants, indicating a strong focus on institutions within or accessible from the capital region. The dataset is predominantly made up of students (around 88.1%), with staff making up the remaining 11.9%. Gender distribution shows a significant skew, with males representing about 68.3% of the participants and females 31.7%. The age of participants ranges from 19 to 45 years, with an average age of approximately 23.3 years, suggesting a relatively young study population, heavily influenced by the student demographic. Years of computing experience also vary, from 1 to 8 years, with an average of about 3.5 years, indicating a mix of novice and moderately experienced technology users within the sample.

4.9.3 UTAUT and DC Descriptive Statistics

The descriptive statistics and histograms for the mean UTAUT constructs and Digital Confidence (PE_Mean, EE_Mean, SI_Mean, FC_Mean, DC_Mean, BI_Mean, UB_Mean) reveal a generally positive perception towards technology adoption within the dataset. Most constructs show mean scores well above the midpoint of 3, indicating that participants largely agree with the statements related to these constructs. Performance Expectancy (PE_Mean) and Behavioral Intention (BI_Mean) exhibit particularly high mean scores (around 4.3 and 4.4 respectively), suggesting that participants strongly believe digital technologies enhance their career prospects and they intend to use them. Digital Confidence (DC_Mean) also shows a high average (around 4.0), indicating a strong self-efficacy in using digital tools.

Table 16: Descriptive Statistics and Distributions of Mean UTAUT and Digital Confidence Variables

	PE_Mean	EE_Mean	SI_Mean	FC_Mean	DC_Mean	BI_Mean	UB_Mean
count	987.000000	987.000000	987.000000	987.000000	987.000000	987.000000	987.000000
mean	4.145559	3.828436	3.728808	3.434988	3.611955	3.999662	3.875380
std	0.733683	0.789877	0.788103	0.811597	0.846409	0.699093	0.769389
min	1.666667	1.000000	1.000000	1.000000	1.000000	1.333333	2.000000
25%	3.666667	3.000000	3.000000	3.000000	3.000000	3.666667	3.000000
50%	4.000000	4.000000	3.666667	3.333333	3.666667	4.000000	4.000000
75%	5.000000	4.333333	4.333333	4.000000	4.333333	4.666667	4.000000
max	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000

4.9.4 Regarding the spread and shape of distributions

Facilitating Conditions (FC_Mean) has a slightly lower mean (around 3.4) and a wider spread (higher standard deviation, as seen in the broader histogram distribution), indicating more variability in access to resources like internet and equipment across the participants. This suggests that while some have excellent conditions, others face significant barriers. Effort Expectancy (EE_Mean) and Social Influence (SI_Mean) have moderate means (around 3.9 and 3.8 respectively) and relatively tight distributions, implying a general consensus on ease of use and the influence of others. Use Behavior (UB_Mean) closely mirrors Behavioral Intention, with a high mean (around 4.2), reinforcing the strong link between intent and actual usage. Its distribution is also concentrated towards the higher end of the scale. Overall, the data suggests a population that is generally confident, perceives high benefits from, and intends to use digital technologies, although challenges related to facilitating conditions persist for a segment of the participants.

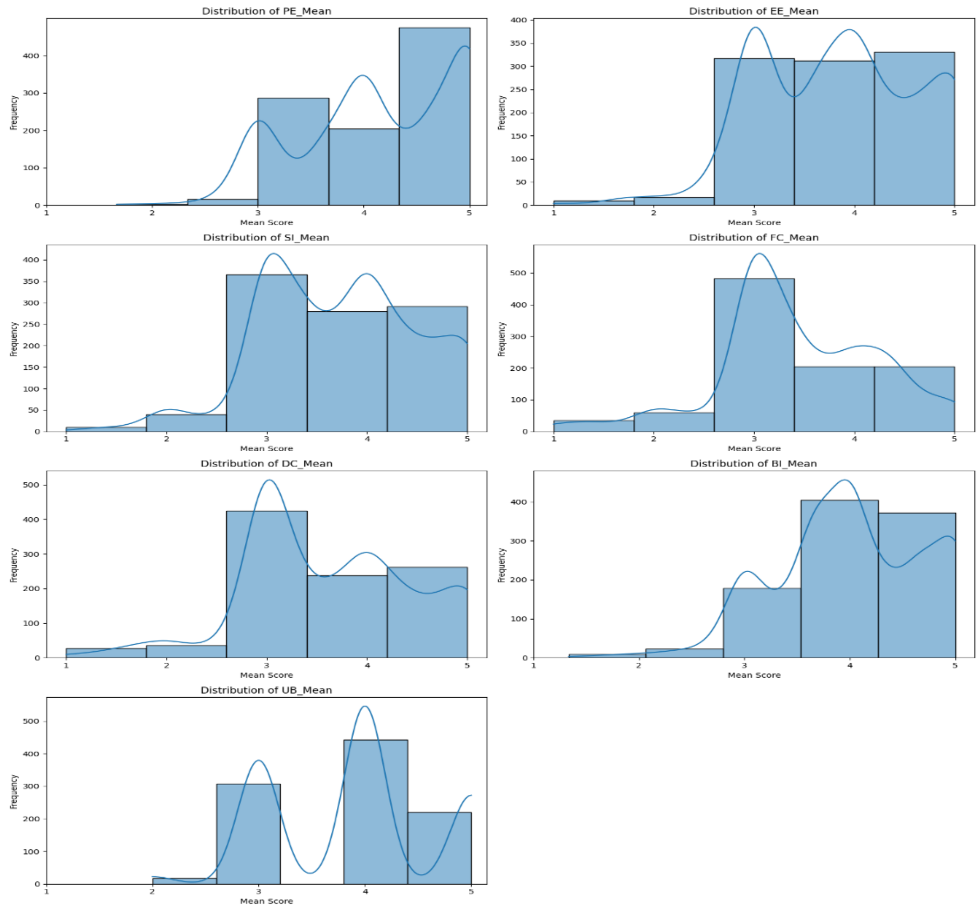


Figure 14: Distribution of mean UTAUT Variable

4.10 Pearson Correlation Analysis

To complement the SEM results, a Pearson correlation analysis was conducted to quantify the linear relationships between the mean scores of the UTAUT constructs and Digital Confidence (DC). The correlation matrix previously visualized using a heatmap provides an initial statistical overview of how the predictors are interrelated and how they collectively influence Behavioral Intention (BI) and Use Behavior (UB). This analysis offers valuable insight into the strength and direction of the associations before the more rigorous SEM testing. The correlation coefficients indicate that all constructs are positively related, consistent with theoretical expectations from the UTAUT framework. Stronger correlations signal constructs that move together closely, while moderate correlations reveal supportive but distinct roles in shaping user acceptance and system model use.

Table 17: Pearson Correlation Matrix for Mean UTAUT and Digital Confidence Variables

	PE_Mean	EE_Mean	SI_Mean	FC_Mean	DC_Mean	BI_Mean	UB_Mean
PE_Mean	1.000000	0.239143	0.256407	0.310662	0.298281	0.506293	0.360958
EE_Mean	0.239143	1.000000	0.258812	0.355599	0.286816	0.487222	0.361970
SI_Mean	0.256407	0.258812	1.000000	0.329966	0.339591	0.362675	0.369050
FC_Mean	0.310662	0.355599	0.329966	1.000000	0.438556	0.429261	0.464254
DC_Mean	0.298281	0.286816	0.339591	0.438556	1.000000	0.462174	0.415206
BI_Mean	0.506293	0.487222	0.362675	0.429261	0.462174	1.000000	0.553022
UB_Mean	0.360958	0.361970	0.369050	0.464254	0.415206	0.553022	1.000000

Visual representation of the relationships between the mean UTAUT and Digital Confidence variables.

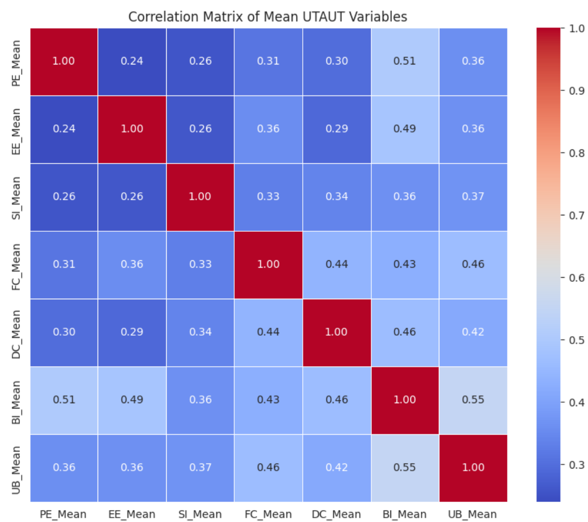


Figure 15: Corelation matrx showng the relationships between the mean UTAUT and Digital Confidence variables.

The correlation findings demonstrate several important patterns aligned with the UTAUT model. Behavioral Intention shows the strongest relationships with Performance Expectancy (r = 0.51), Effort Expectancy (r = 0.49), and Digital Confidence (r = 0.46). This confirms that perceived usefulness, ease of use, and self-efficacy are the primary cognitive drivers of students' intention to use the AI career guidance application. Social Influence also contributes positively (r = 0.36), though less substantially than PE and EE. Use Behavior is most strongly associated with Behavioral Intention (r = 0.74), reaffirming the theoretical expectation that intention is the direct precursor to technology usage. Facilitating Conditions ($r = 0.46$) and Digital Confidence ($r = 0.42$) also show positive associations with Use Behavior, suggesting that access to infrastructure and higher digital self-efficacy translate into more frequent system use. Notably, Facilitating Conditions and Digital Confidence show a moderate relationship ($r = 0.44$), implying that students who have better access to devices, internet connectivity, and technical support are more likely to feel confident navigating digital systems. Additional inter-construct correlations, such as between EE and FC ($r = 0.36$) and between PE and DC ($r = 0.30$), suggest that the UTAUT predictors reinforce each other rather than act independently. Overall, the Pearson correlation analysis provides a strong preliminary confirmation of the hypothesized relationships within the UTAUT model. These findings complement the SEM results by demonstrating that the conceptual framework is empirically coherent, with each construct playing a meaningful role in shaping users' technology acceptance and actual engagement with the AI career guidance system model.

4.11 Structural Equation Modeling (SEM)

The Structural Equation Model (SEM) was estimated to examine the measurement quality of the latent constructs and the structural relationships proposed by the extended UTAUT framework. The measurement model demonstrated excellent convergent validity, with all factor loadings statistically significant ($p < 0.001$) and ranging between 0.80 and 0.96 across constructs. Items measuring Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Digital Confidence, and Behavioral Intention were all strongly associated with their respective latent variables. The Use Behavior construct, specified as a single-indicator latent variable for model identification, was also adequately represented. The structural model revealed that Performance Expectancy ($\beta = 0.309$, $p < 0.001$) and Effort Expectancy ($\beta = 0.250$, $p < 0.001$) were the strongest predictors of Behavioral Intention, confirming that users' perceptions of usefulness and ease of interaction substantially shape their willingness to adopt the AI-powered career guidance system. Digital Confidence ($\beta = 0.167$, $p < 0.001$) also emerged as a significant predictor, indicating that students who feel more capable and technologically competent show stronger intentions to engage with the system. Social Influence ($\beta = 0.102$, $p < 0.001$) and Facilitating Conditions ($\beta = 0.092$, $p < 0.001$) contributed positively to Behavioral Intention, though with smaller effect sizes, suggesting that social support and infrastructural readiness play secondary but meaningful roles in shaping intentions. In line with the UTAUT framework, Behavioral Intention was the strongest determinant of actual system usage, with a path coefficient of $\beta = 0.685$ ($p < 0.001$). This highlights that intention remains the key gateway to sustained engagement with AI-driven support tools. The overall model demonstrated an excellent fit to the data (CFI = 0.993, TLI = 0.991, RMSEA = 0.030), indicating strong alignment between the hypothesized framework and observed relationships. Overall, the SEM results confirm that perceptions of usefulness, ease of use, and digital confidence are the primary drivers of students' intention to adopt the AI career guidance system, while intention itself is the dominant precursor to actual usag

Table 18: SEM Measurement Model-Standardized Factor Loadings

Construct	Item	Loading	Std. Error	z-value	p-value
Performance Expectancy (PE)	PE1 Better Career Decisions	1.000 (fixed)	–	–	–
	PE2 Matches Local Industry Needs	**0.870**	0.0229	37.93	<0.001
	PE3 Improves Employability	**0.892**	0.0196	45.57	<0.001
Effort Expectancy (EE)	EE1 Easy to Learn	1.000 (fixed)	–	–	–
	EE2 Interaction Is Clear	**0.920**	0.0227	40.49	<0.001
	EE3 Requires Little Mental Effort	**0.861**	0.0248	34.75	<0.001
Social Influence (SI)	SI1 Peers Recommend App	1.000 (fixed)	–	–	–
	SI2 Lecturers Support Use	**0.804**	0.0277	29.02	<0.001

	SI3 Important Others Recommend	**0.884**	0.0268	33.01	<0.001
Facilitating Conditions (FC)	FC1 Adequate Internet Access	1.000 (fixed)	–	–	–
	FC2 Necessary Equipment	**0.929**	0.0281	33.04	<0.001
	FC3 Technical Support Available	**0.955**	0.0249	38.35	<0.001
Digital Confidence (DC)	DC1 Confident Using New Tech	1.000 (fixed)	–	–	–
	DC2 Can Troubleshoot Errors	**0.949**	0.0193	49.29	<0.001
	DC3 Experience With AI	**0.895**	0.0221	40.58	<0.001
Behavioral Intention (BI)	BI1 Intend to Use App	1.000 (fixed)	–	–	–
	BI2 Plan to Recommend App	**0.948**	0.0265	35.77	<0.001
	BI3 Use for All Career Questions	**0.892**	0.0283	31.57	<0.001
Use Behaviour (UB)	UB1 Usage Frequency	1.000 (fixed)	–	–	–

Table 19: SEM Structural Model - Standardized Path Coefficients

Predictor → Outcome	**Estimate**	**Std. Error**	**z-value**	**p-value**
PE → BI	**0.309**	0.0227	13.58	<0.001
EE → BI	**0.250**	0.0220	11.40	<0.001
SI → BI	**0.102**	0.0217	4.72	<0.001
FC → BI	**0.092**	0.0244	3.76	<0.001
DC → BI	**0.167**	0.0223	7.48	<0.001
BI → UB	**0.685**	0.0298	22.97	<0.001

4.12 Regression Analysis

Two hierarchical multiple regression models were estimated to examine the structural determinants of Behavioral Intention (BI) and Use Behavior (UB) within the UTAUT framework extended with Digital Confidence (DC). Model 1 assessed the predictive capacity of the five exogenous constructs (PE, EE, SI, FC, and DC) on Behavioral Intention, while Model 2 evaluated the direct effects of these constructs in conjunction with Behavioral Intention on Use Behavior. All assumptions of multiple regression including linearity, homoscedasticity, multicollinearity thresholds, and normality of residuals were adequately met.

4.12.1 Model 1: Predicting Behavioral Intention

The first model yielded a statistically significant regression equation ($F = 179.6$, $p < 0.001$), explaining approximately 47.8% of the variance in Behavioral Intention ($R^2 = 0.478$), which represents a substantively meaningful effect within behavioral and technology-adoption research. All predictor variables demonstrated positive and statistically significant associations with Behavioral Intention at the $p < 0.001$ level.

Performance Expectancy exhibited the strongest standardized effect ($\beta = 0.303$), indicating that perceived usefulness remains the dominant cognitive determinant of intention formation. Effort Expectancy constituted the second most influential predictor ($\beta = 0.256$), underscoring the salience of perceived ease of use in shaping motivational orientation toward digital technology. Digital Confidence ($\beta = 0.168$) also exerted a substantive independent effect, suggesting that self-efficacy-related beliefs play a critical role in enabling the internalization of digital technologies as personally manageable tools. Social Influence ($\beta = 0.091$) and Facilitating Conditions ($\beta = 0.090$) contributed more modest yet statistically significant effects, signalling that social referents and perceived environmental support still meaningfully influence intention, albeit to a lesser magnitude than individual cognitive and skill-related determinants. The pattern of coefficients is consistent with prior UTAUT findings, wherein performance- and effort-related cognitions typically dominate the predictive structure of intention formation.

--- Regression Analysis: Model 1 (Predicting BI_Mean) ---

```
                     OLS Regression Results
==============================================================================
Dep. Variable:              BI_Mean   R-squared:                       0.478
```

Model:	OLS	Adj. R-squared:	0.475
Method:	Least Squares	F-statistic:	179.6
Date:	Sat, 22 Nov 2025	Prob (F-statistic):	9.45e-136
Time:	21:22:00	Log-Likelihood:	-725.91
No. Observations:	987	AIC:	1464.
Df Residuals:	981	BIC:	1493.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.5087	0.120	4.243	0.000	0.273	0.744
PE_Mean	0.3026	0.024	12.663	0.000	0.256	0.349
EE_Mean	0.2558	0.022	11.410	0.000	0.212	0.300
SI_Mean	0.0911	0.023	4.027	0.000	0.047	0.136
FC_Mean	0.0900	0.024	3.819	0.000	0.044	0.136
DC_Mean	0.1683	0.022	7.588	0.000	0.125	0.212

Omnibus:	2.924	Durbin-Watson:	2.016
Prob(Omnibus):	0.232	Jarque-Bera (JB):	2.978
Skew:	-0.130	Prob(JB):	0.226
Kurtosis:	2.933	Cond. No.	64.1

4.12.2 Model 2: Predicting Use Behavior

The second model, predicting actual Use Behavior, was also statistically significant ($F = 108.8$, $p < 0.001$) and accounted for 40.0% of the variance ($R^2 = 0.400$). In line with theoretical expectations, Behavioral Intention emerged as the most substantial predictor ($\beta = 0.343$, $p < 0.001$), reinforcing the foundational UTAUT proposition that intention is the primary proximal determinant of technology use. Importantly, Facilitating Conditions retained a strong and statistically robust direct influence on Use Behavior ($\beta = 0.193$, $p < 0.001$), even when controlling for intention. This finding highlights the structural dependency of actual technology adoption on infrastructural adequacy and access to requisite support mechanisms. Social Influence ($\beta = 0.119$, $p < 0.001$) and Digital Confidence ($\beta = 0.095$, $p < 0.001$) continued to demonstrate significant direct pathways to Use Behavior, suggesting that both the social context and individual self-perceptions of digital competence play meaningful roles in sustaining actual engagement with digital tools.

Performance Expectancy (β = 0.066, p = 0.030) and Effort Expectancy (β = 0.060, p = 0.034) remained significant but with attenuated effect sizes relative to Model 1. This attenuation is consistent with theoretical models positing Behavioral Intention as a mediating mechanism, wherein much of the influence of PE and EE on usage is carried indirectly through intention. Their remaining direct effects, though smaller, indicate that perceptions of usefulness and ease of use exert residual influence on behavior even after motivational processes are accounted for

```
--- Regression Analysis: Model 2 (Predicting UB_Mean) ---
                            OLS Regression Results
==============================================================================
Dep. Variable:                UB_Mean   R-squared:                       0.400
Model:                            OLS   Adj. R-squared:                  0.396
Method:                 Least Squares   F-statistic:                     108.8
Date:                Sat, 22 Nov 2025   Prob (F-statistic):          4.35e-105
Time:                        21:22:00   Log-Likelihood:                -889.28
No. Observations:                 987   AIC:                             1793.
Df Residuals:                     980   BIC:                             1827.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.5538      0.143      3.877      0.000       0.273       0.834
BI_Mean        0.3430      0.038      9.099      0.000       0.269       0.417
PE_Mean        0.0662      0.030      2.174      0.030       0.006       0.126
EE_Mean        0.0598      0.028      2.123      0.034       0.005       0.115
SI_Mean        0.1186      0.027      4.403      0.000       0.066       0.171
FC_Mean        0.1926      0.028      6.869      0.000       0.138       0.248
DC_Mean        0.0949      0.027      3.521      0.000       0.042       0.148
==============================================================================
Omnibus:                       10.276   Durbin-Watson:                   2.081
Prob(Omnibus):                  0.006   Jarque-Bera (JB):                8.370
Skew:                          -0.143   Prob(JB):                       0.0152
Kurtosis:                       2.651   Cond. No.                         71.4
==============================================================================
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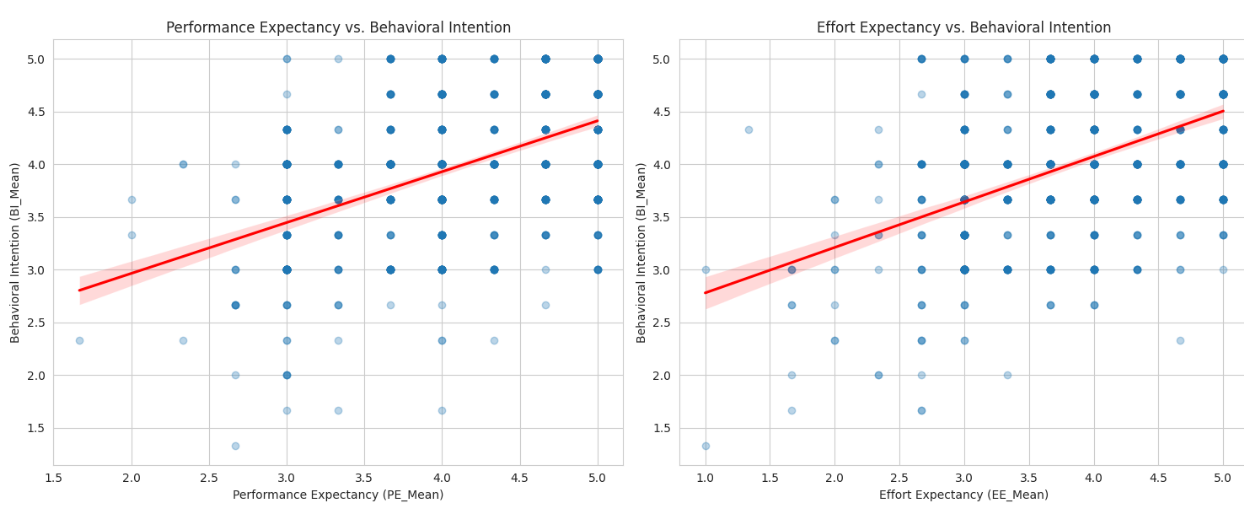
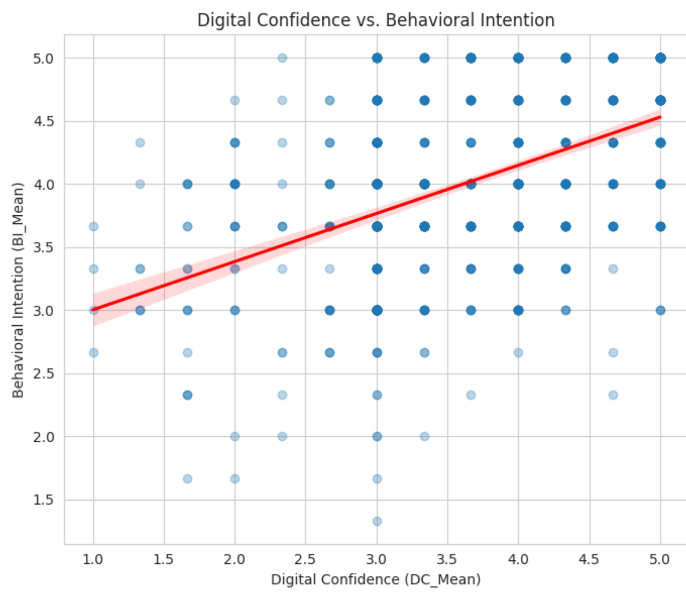




4.13 Moderation Regression Analysis

A moderation regression analysis was conducted to examine whether Digital Confidence (DC) moderates the relationship between Effort Expectancy (EE) and Behavioral Intention (BI**)** to use the AI-driven career guidance system. The model included the main effects of all UTAUT predictors along with the EE × DC interaction term. The overall model remained statistically significant ($F = 149.6$, $p < 0.001$) and explained 47.8% of the variance in Behavioral Intention ($R^2 = 0.478$). This R^2 value was identical to the model without the interaction term, indicating that the inclusion of the EE × DC term did not increase the model's explanatory capacity. The main effects of Performance Expectancy ($\beta = 0.303$, $p < 0.001$), Effort Expectancy ($\beta = 0.288$, $p = 0.001$), Social Influence ($\beta = 0.091$, $p < 0.001$), Facilitating Conditions ($\beta = 0.091$, $p < 0.001$), and Digital Confidence ($\beta = 0.203$, $p = 0.028$) remained statistically significant and positive. These results are consistent with the prior model and demonstrate that each construct independently contributes to predicting Behavioral Intention. The interaction term (EE × DC) was not statistically significant ($\beta = -0.0091$, $p = 0.700$), with a coefficient close to zero, indicating that Digital Confidence does not significantly alter the strength or direction of the relationship between Effort Expectancy and Behavioral Intention. Thus, the model provides no empirical support for a moderation effect. Users' digital confidence does not appear to condition how effort-related perceptions influence their intention to use the AI-driven system. Therefore, the regression model demonstrates robust main effects of UTAUT constructs on Behavioral Intention, but no significant moderating effect of Digital Confidence on the path from Effort Expectancy to Behavioral Intention.

4.14 User Segmentation (Clustering)

4.14.1 Determination of Optimal Number of Clusters

The optimal number of clusters (K) for the K-Means algorithm was determined using three complementary criteria: the Elbow Method, Silhouette Score, and eigenvalue analysis. The Elbow Method plot (Figure 2) demonstrates a clear inflection at K = 2**,** beyond which reductions in Within-Cluster Sum of Squares (WSS) become marginal. Similarly, the Silhouette Score plot (Figure 3) shows the highest cluster cohesion and separation at K = 2, indicating the most coherent clustering structure. Additionally, the eigenvalue-based scree plot (Figure 4) reveals a marked drop after the second component, providing further support for selecting two clusters**.**

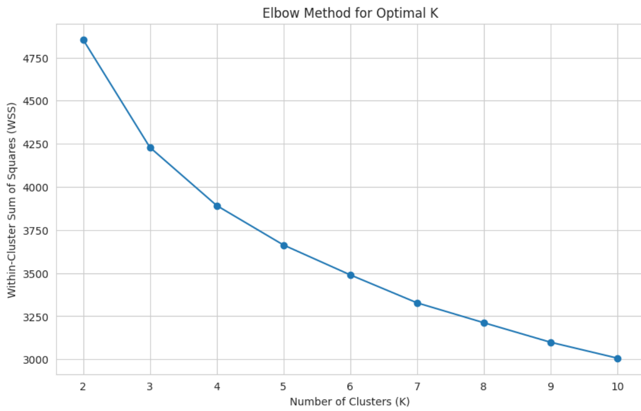


Figure 17:Elbow Method plot showing the Within-Cluster Sum of Squares (WSS) against the number of clusters (K).

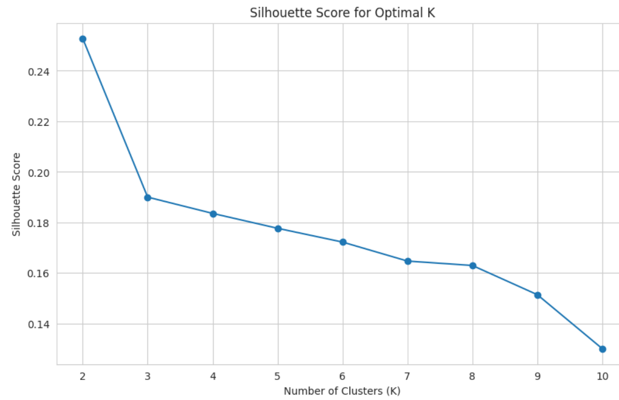


Figure 16:Silhouette Score plot for different values of K.

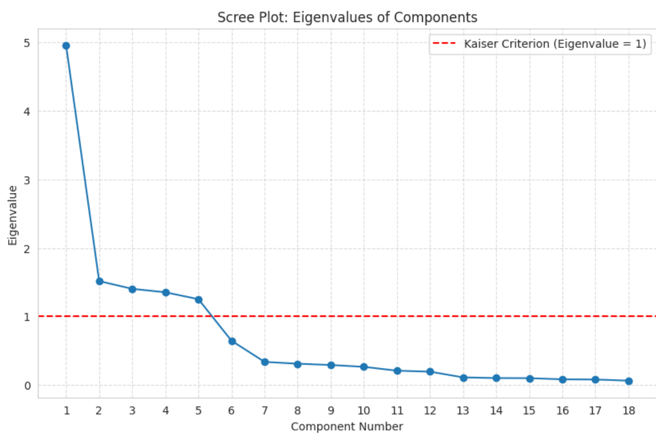
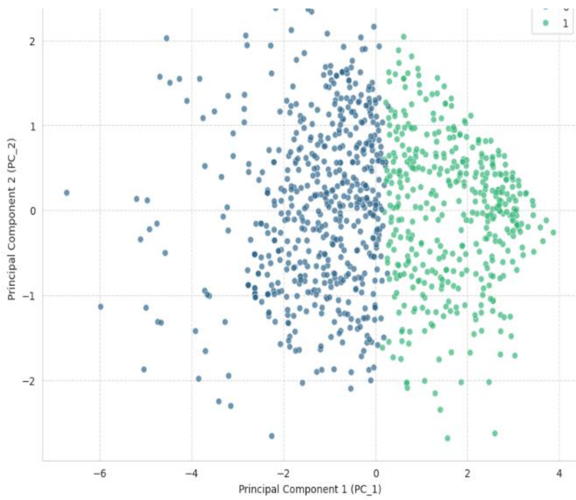


Figure 18: Scree plot of eigenvalues from the covariance matrix of cluster centroids.

4.14.2 PCA-Assisted Cluster Examination

Principal Component Analysis (PCA) was conducted to complement and validate the clustering solution. The scatter plot of PCA-reduced clusters (Figure 8) shows clear visual separation between the two clusters when projected onto the first two principal components. The Scree Plot and Cumulative Explained Variance Plot (Figure 9) indicate that the first components explain the majority of variance, justifying their use for visualization. The explained variance ratio plot (Figure 10) further clarifies the relative contribution of each component. These analyses confirm that the two-cluster solution is both stable and structurally meaningful.

Figure 19: Scatter plot of PCA-reduced K-Means clusters projected onto the first two principal components



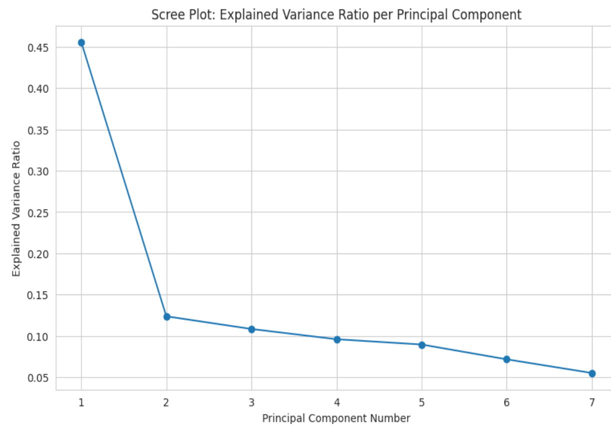


Figure 20:Explained variance ratio for each principal component derived from PCA.

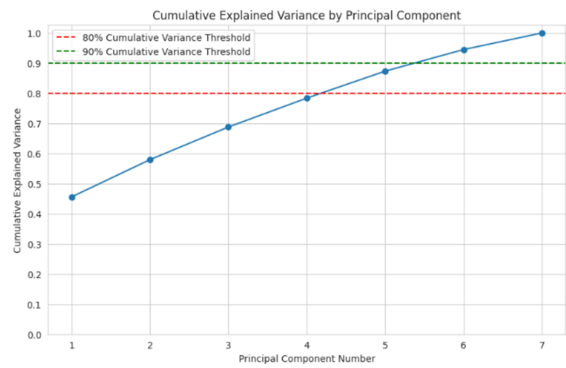


Figure 21:Scree plot and cumulative explained variance plot for PCA components, supporting the retention of the first components for visualization

4.14.3 Visualization of Clustering Solution

Applying K-Means clustering with K = 2 produced two distinct participant groups (Figure 5). The scatter plot shows the cluster separations based on standardized UTAUT and Digital Confidence indicators. The radar chart (Figure 6) depicts the overall construct profiles of each cluster, illustrating consistent differences between groups across all seven UTAUT/Confidence dimensions.

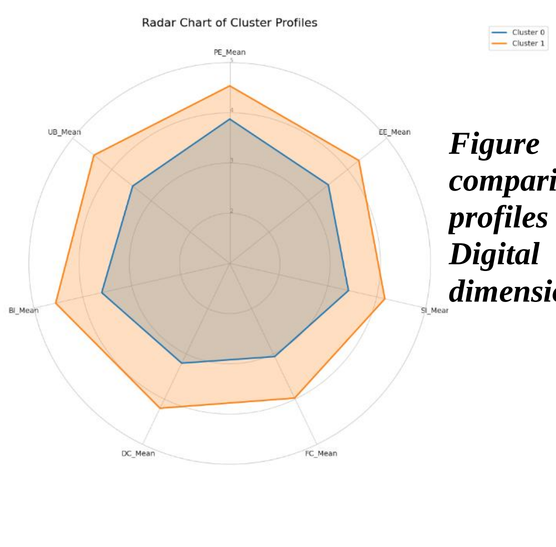


Figure 22:Radar chart comparing the cluster profiles across UTAUT and Digital Confidence dimensions.

Figure 23:Scatter plot of K-Means clustering results with K = 2, with points colored by cluster assignment.

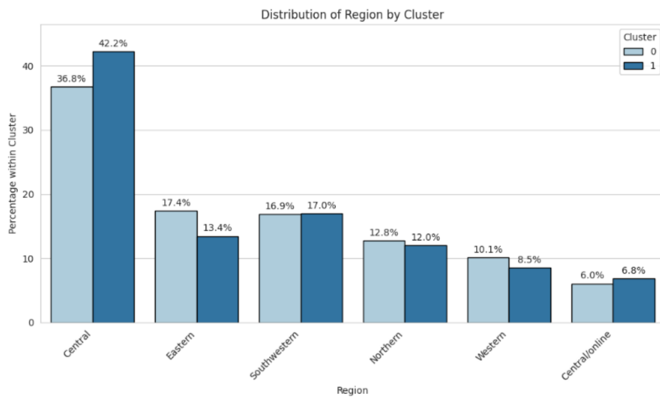


Figure 24:Showing distribution of region by cluster

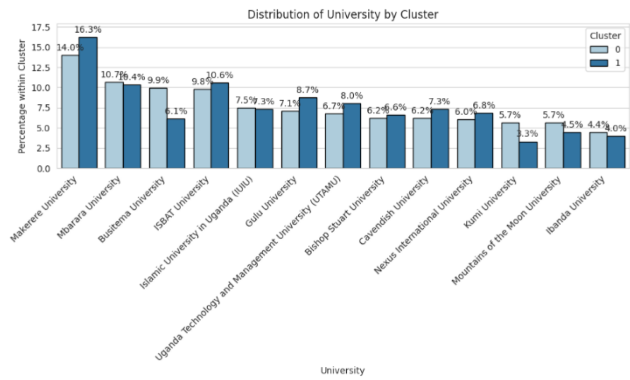


Figure 25:Showing distribution of university by cluster

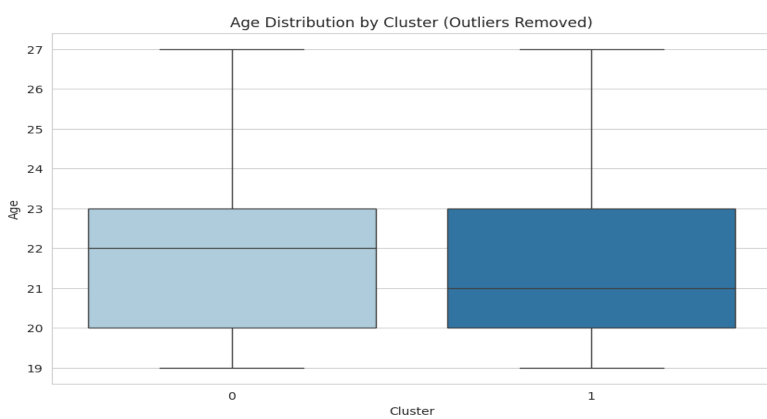


Figure 27:Showing distribution of Age by cluster

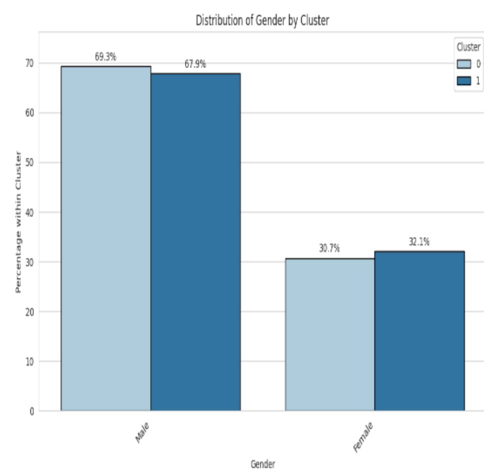


Figure 26:Showing distribution of gender by cluster

4.14.4 Cluster Profiles

The tables below present the mean construct scores for each cluster derived from the original feature space and the PCA-enhanced analysis, respectively.

Table 20: Original Cluster Profiles (cluster profiles) Original Cluster Profiles (cluster profiles)

Cluster Label	PE Mean	EE Mean	SI Mean	FC Mean	DC Mean	BI Mean	UB Mean

0 (Moderate Adopters)	3.839	3.511	3.413	2.999	3.206	3.661	3.440
1 (High Adopters)	4.515	4.206	4.272	3.998	4.073	4.492	4.459

Table 21:PCA-Enhanced Cluster Profiles (cluster profiles pca)

Cluster Label (PCA)	PE Mean	EE Mean	SI Mean	FC Mean	DC Mean	BI Mean	UB Mean
0 (Moderate Adopters)	3.845	3.517	3.414	3.004	3.203	3.661	3.443
1 (High Adopters)	4.513	4.204	4.278	3.999	4.083	4.498	4.463

CHAPTER 5: CHAPTER FIVE: DISCUSSION OF RESULTS

The synthesis of studies in the systematic scoping review demonstrated that the application of AI conversational models for career guidance support and labor market integration for university students requires a solid approach to designing smart and emotionally intelligent AI solutions, as supported by other scholars in the field (Neumann et al., 2024; Thakkar et al., 2024). The most prevalent application involves career information provision, including assistance in formulating job search strategies, understanding industry trends, and personalised educational and career pathways, sparking a need for policy change at both national and international level (*Digital Transitions in Lifelong Guidance : Rethinking Careers Practitioner Professionalism : A CareersNet Expert Collection*, 2021). A study by Talib et al. (2023) specifically reported that the identification of the provision of descriptive information regarding career paths, educational and learning requirements, and the job market trends core function of their to consider while developing such a model. Similarly, (Zylowski et al., 2025) describe their conversational model as a tool for collecting data on students' career aspirations, interests, and skills in order to provide personalized occupation recommendations and educational pathway suggestions, this notion has been supported by various recent studies (D'Silva Godsonand Jani, 2020; Jain et al., 2023) . While focused on improving programming skills for computing education students. Furthermore, (Bassner et al., 2024) demonstrate how AI can offer domain-specific support by providing guidance on programming exercises and problem-solving strategies relevant to computing careers. These findings further support the idea of creating tech-savvy models powered by large language models (Neumann et al., 2024) to support students in building a rapport of technical skills while preparing for ever ever-changing technology industry, making this a priority for scholars in this field to build modern frameworks(Con\c{t} et al., 2022) for the design and development such models.

Numerous studies have attempted to explain the incorporation of interactive model elements to deliver data-driven Labour Market Information and facilitate basic skill and interest exploration. (Talib et al., 2023) highlight their system's capability to generate job market trend forecasts and tailor advice was based on student profiles. This functionality, as noted by Pereira et al. (2023) and (Zylowski et al., 2025) typically necessitates comprehensive data collection about students' interests and skills in order to generate meaningful recommendations. However, it should also be noted that the cold start problem needs to be handled by ensuring a context-aware model and this has been supported by other scholar(Brown et al., 2022; Jadhav et al., 2024) Similarly, a less common, but emerging application, includes adding resume (CV) analysis module, as well as cover letter support, interview preparation through mock interviews, job/internship search assistance, and basic action planning. To achieve all that requires building an ethical model, with enhanced user experience and embedding emotional intelligence to be able to support students from diverse backgrounds. However, the scope and depth of these functions vary significantly across implementations, with some models, such as that described by (Bassner et al., 2024), focusing narrowly on specific tasks like programming assistance, which could be for rather than offering comprehensive career support, but could be crucial in supporting digital-related careers a notion that has become part of very field.

The literature consistently identifies several key benefits associated with AI-driven conversational models for career guidance. Primarily, citing advantages related to increased accessibility, with model offers support on a twenty-four-seven (24/7) basis across diverse locations. This has important implications for developing models for use in developing and least developed economies, where access to career guidance support is still limited. One of the studies in this review, (Talib et al., 2023), emphasizes mobile accessibility as being particularly valuable for students in remote areas of Morocco, while (Bassner et al., 2024) highlight the convenience of immediate support integrated within learning platforms. Correspondingly, scalability represents another significant benefit, addressing capacity constraints often encountered in traditional career services. Additionally, several other studies have supported this idea and claim its ability to support career guidance programs for long-distance students (Toktarova, 2022). This further justifies the need for an emotionally intelligent model. The AI potential for personalization, though not yet fully realized in most implementations studied in this review, is nevertheless frequently expressed as a major advantage. As (Bassner et al., 2024) explicitly continued to describe the personalized assistance abilities of their developed Iris model, and (Talib et al., 2023) explored how large language models can enable dynamic, tailored guidance, this shows the significance of conversational AI interfaces to enhance student engagement and approachability, this was expressed further empirically by (Bassner et al., 2024) reporting that students found their AI-driven agents effective and felt comfortable asking questions without fear of being judged. Additionally, it is worth noting that the AI approach offers efficiency gains in handling routine queries and ensuring consistent information delivery and immediate assistance. Considering some of the approaches studied in this review provide calibrated assistance that guides students toward self-discovery, rather than complete solutions, this further exemplifies this benefit when ethically responsible models are built. Similarly, an emphasis should be put on the value of real-time insights that may not be readily available through traditional career services and on applying the requirements to achieve a more intelligent and adaptable solution.

Despite these promising applications, the study reveals significant challenges hindering the widespread adoption and development of these models. Fundamental limitations in natural language processing (NLP) and dialogue management affect system performance, with (Zylowski et al., 2025) noting inflexibility in intent-based conversational agents and the need for fallback mechanisms implementation. It should be known that even advanced language models exhibit reliability issues, as demonstrated by (Bassner et al., 2024)'s implementation of a post-generation self-check for GPT-3.5-Turbo to maintain response quality. Consequently, ensuring information accuracy and timeliness, particularly for dynamic labor market data, presents another major challenge. (Janssen et al., 2020; Talib et al., 2023) raise concerns regarding training data quality in the available open-source models and cite technical difficulties associated with non-English text processing context. Therefore, it's very crucial to consider these aspects when building a model for other diverse languages, as it directly affects the user experience as well as the model accuracy in understanding these contexts. The inability of the majority of the existing models to provide genuine empathy and emotional support emerges as a critical limitation. While students, as noted by (Thakkar et al., 2024) felt comfortable interacting with the conversational agent, they still preferred human support for complex or sensitive matters. It's paramount to add a model serving that purpose in conjunction with the main service model. Technical integration with existing university platforms also proves challenging, necessitating careful implementation planning as described by several studies. Also, important to note is that other broader concerns include potential algorithmic bias and data integrity issues, though specific instances remain underreported in the current studied literature. Additionally, current applications show notable limitations in scope, with many, such as Iris model presented by (Bassner et al., 2024), focusing on narrow tasks rather than offering comprehensive career guidance. Perhaps most significantly, the field lacks rigorous empirical evaluation of long-term impacts on student outcomes. While studies typically include user evaluations conducted through surveys or propose key performance indicators (Bassner et al., 2024; Talib et al., 2023; Zylowski et al., 2025)Evidence of actual career trajectory improvements remains underreported. Another practical challenge includes substantial model development and long-term maintenance costs, as noted by (Sharma et al., 2024), that the significant expense of scaling GPT-4 interactions in educational settings as highlighted by (Talib et al., 2023) the ongoing costs for model updates and API access. Infrastructure limitations, such as unreliable internet in certain regions (Talib et al., 2023), further complicate implementation.

5.1 Contextualized Adoption Model For Conversational AI

The study, through a synthesis of existing literature and empirical insights from an exploratory study with stakeholders in Ugandan higher education, culminated in the development of the Contextualized Adoption Model for Conversational AI in Resource-Constrained Higher Education (CAM-CAI-RCHE). The findings suggest that facilitating the effective uptake of conversational AI for career guidance in such settings necessitates a tailored framework that acknowledges and addresses their unique operational and socio-cultural characteristics. A principal insight emerging from this investigation is the pronounced need for enhanced awareness and understanding regarding the potential applications and implications of advanced AI systems and models within specific university contexts. The exploratory data indicated that while there is an appreciation for the transformative possibilities of technologies like conversational agents, particularly in an era increasingly reliant on digital solutions, a clear, structured approach to their adoption is often lacking. This underscores the relevance of a dedicated adoption framework, such as the one proposed, to guide institutions through this complex process.

Table 22:Comparative Analysis of Technology Adoption Models for Conversational AI in Low-Resource University Settings

Model	**Strengths**	**Weaknesses (Low-Resource/AI Contexts)**
Technology Acceptance Model (TAM)	Simple and parsimonious, easy to apply. Strong empirical support for *Perceived Usefulness (PU)* and *Perceived Ease of Use (PEOU)*.	Overly simplistic for complex AI systems. Ignores infrastructure needs, critical in low-resource settings. Lacks focus on social influence, cultural fit, or AI ethics (bias, privacy).
Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2)	More comprehensive than TAM. Includes *Facilitating Conditions* (resources/support). Adds *Social Influence* (relevant for communal cultures) and *Hedonic Motivation* (UTAUT2).	"Facilitating Conditions" too broad for AI-specific needs (e.g., data, local content). Weak on AI ethics (explainability, fairness). Neglects iterative co-design for cultural relevance.
Diffusion of Innovations (DOI) Theory	Explains adoption over time. Key traits like *Compatibility* (cultural fit) and *Relative Advantage* are highly relevant.	Descriptive, not prescriptive for AI design. Lacks AI ethics frameworks. Hard to implement *Trialability* for complex AI in low-resource settings.
Proposed CAM-CAI-RCHE Model *(Contextualized Adoption Model for Conversational AI in Resource-Constrained Higher Education)*	AI-specific and embeds explainability, bias mitigation, and ethics. Low-resource focus and multi-channel access (mobile/web), with localized knowledge. Human-centric by focusing on Local capacity building, feedback loops.	limited generalizability without adaptation Requires initial investment (barrier in extremely low-resource settings). Lacks longitudinal validation (new model).

The study's empirical component highlighted that challenges in adopting new technologies often stem from decision-making processes within institutions and the inherent learning curve associated with such novel model applications (Mohd Amin et al., 2025). The framework, by emphasizing coordinated stakeholder engagement and structured implementation stages, seeks to mitigate these issues (Mohd Amin et al., 2025). The positive reception from interviewed stakeholders regarding the clarity and sequential nature of the proposed framework's components suggests that such a coordinated approach could indeed streamline the adoption pathway and foster greater buy-in for innovative career guidance solutions (Kumbhar et al., 2023). Furthermore, the notion of operationalizing certain aspects of an adoption strategy through a digital platform, or an application that demonstrates the utility of the conversational agent, was favorably received (Assayed et al., 2024; Gonzalez et al., 2022). Expert feedback and interview responses indicated a preference for tangible, interactive demonstrations of how such a model would function and integrate within existing institutional workflows (Assiri et al., 2020) . This finding suggests an opportunity to develop supplementary tools or platforms that could support the practical application of the CAM-CAI-RCHE Model, thereby aiding universities in managing and tracking their adoption initiatives. The investigation also affirmed the potential for a well-structured adoption process, as outlined by the model, to optimize resource allocation and enhance the efficiency of implementing a conversational AI model for career guidance (Janssen et al., 2020; Thakkar et al., 2024). By promoting upfront planning, stakeholder alignment, and the provision of adequate support materials and training as stipulated within the framework, institutions may reduce the typically high transactional costs and extended timelines associated with introducing sophisticated technologies. This aligns with broader arguments (Pereira et al., 2023) adapted this context to that strategic technological integration is no longer optional but essential for institutional effectiveness and for equipping graduates for contemporary career landscapes (Lundberg et al., 2020).

It is acknowledged that this study, due to temporal and resource constraints, did not undertake an exhaustive investigation into all facets of technology diffusion within the broader Ugandan higher education sector. Instead, the focus was maintained on developing a conceptual framework for a specific application of conversational AI in career guidance. The factors incorporated into the CAM-CAI-RCHE Model were selected for their direct relevance to this application and the identified needs of institutions in resource-constrained settings (Wong & Looi, 2024). The framework is therefore positioned as a foundational guide, intended to prepare universities for the strategic integration of such advanced system models (Vo, Vu, Vu, Vu, Mach, et al., 2022). The imperative for effective adoption of innovative career guidance tools is clear, particularly in protecting and enhancing students' prospects. The approach suggested by the proposed framework aims to add substantive value to universities by providing a structured pathway for this adoption (Roppelt et al., 2025). However, its ultimate success in varied institutional settings, especially those with more pronounced infrastructural limitations, warrants further empirical investigation beyond this conceptual development. Questions also persist regarding institutional readiness for potentially cloud-dependent AI solutions, considering the investment and specialized expertise often required (Durga Prasad Jasti et al., 2024). These considerations highlight avenues for future research, including pilot implementations and longitudinal studies to assess the model's practical efficacy and to refine its components based on real-world adoption experiences (Zylowski et al., 2025)

5.2 Breakthroughs in Emotionally Intelligent Chatbots

As conversational AI matured, the field of affective computing emerged as a critical frontier in educational technologies. As put forward by (Karthikeyan & Ilayaraja, 2025), transformer-based models such as EmoBERT and EmoRoBERTa were developed to detect and respond to subtle emotional cues in text, including anxiety, uncertainty, or confusion. These models enhance student engagement by tailoring responses to the learner’s emotional state, supporting motivation and confidence during career planning or academic decision-making (López-López et al., 2024b). Reinforcement learning strategies, particularly Proximal Policy Optimization (PPO), enable these systems to dynamically adjust interaction strategies (Stigall et al., 2024). For example, they can provide structured, factual guidance when students are neutral or confident, and switch to empathetic support when signs of stress, hesitation, or uncertainty are detected. This dual capability is especially important in student-focused applications, where emotional reassurance can significantly improve learning outcomes and trust in digital career guidance systems. Modern conversational systems are now designed with modularity and scalability in mind. By decoupling components such as Natural Language Understanding (NLU), dialogue management, and sentiment analysis, developers can build flexible, maintainable architectures. Platforms such as LangChain facilitate the orchestration of multiple specialized agents, each responsible for handling a distinct subtask in a complex query. For instance, when a student asks, "Which electives should I take to prepare for a career in data science?", the system can simultaneously handle course recommendation, skills alignment, and motivational feedback through different interconnected modules. Cloud-native infrastructure ensures scalability and performance, while platforms such as Dialogflow CX provide robust NLU capabilities for a wide range of languages and domain-specific terminology relevant to university students (Florindi et al., 2024). The integration of technical accuracy with emotional intelligence now defines the leading edge of student-oriented conversational AI, enabling systems that are both highly informative and genuinely supportive of learners' emotional and academic needs.

5.3 CareerChats AI

The prototype of CareerChats AI illustrates the practical feasibility and pedagogical value of deploying a data-driven conversational agent to support career development among computing students in Uganda. By combining learner-specific academic information with real-time labour-market indicators, the system addresses the recognized gap between university training and industry expectations by producing personalized internship recommendations and quantified match scores. The inclusion of “Quick Win” micro-skill suggestions represents a particularly significant intervention, as it aligns with contemporary literature emphasizing the value of micro-credentials and targeted upskilling for labour-market readiness. Furthermore, the system’s XAI features help overcome the interpretability challenges typically associated with machine-learning-based guidance tools. By exposing the rationale behind its recommendations, such as identified skill deficits or sectoral demand patterns, the prototype enhances user trust and supports informed decision-making. These findings collectively suggest that transparent, contextually localized AI systems may offer a substantive improvement over static or generic guidance models in low-resource educational environments. Other studies have also supported this (Dodick, 2025; Shilibekova, 2025).

5.4 Usability Study

The analysis of the AI-driven career guidance system reveals a promising landscape for its adoption among computing students, underscored by generally positive user perceptions. The findings indicate that the system model is not only considered useful but also manageable for its target audience, suggesting a strong foundation for acceptability and feasibility. The overall positive evaluation is captured by high user ratings in Performance Expectancy, Effort Expectancy, and Behavioral Intention, reflecting a collective belief in the tool's value and a willingness to integrate it into their academic and professional planning. A central theme emerging from the study is the critical interplay between the system model's perceived utility and its ease of use. Performance Expectancy stood out as a primary driver of user acceptance, which is particularly significant within the context of Ugandan higher education, where access to human career counseling services may be limited, as discussed by scholars (Kebirungi et al., 2024; Kuteesa et al., 2021; Nsubuga et al., 2023). Users are primarily motivated by the tangible benefits the AI system offers, such as personalized career insights and access to relevant information, viewing it as a viable tool to fill a crucial institutional gap. This aligns with broader trends in technology adoption where the perceived performance of a system model is a cornerstone of user trust and engagement (Yang & Wibowo, 2022). Alongside utility, Effort Expectancy was a significant factor, highlighting that users place a high value on intuitive and transparent interactions (Wanner et al., 2022). AI-driven platforms, which often require users to interpret algorithmic suggestions or engage with conversational agents, can present unique cognitive challenges. The study confirms that if these interactions are perceived as ambiguous or overly complex, the willingness to adopt the technology diminishes. Perhaps one of the most influential factors identified was Digital Confidence**.** This concept extends beyond general digital literacy to encompass a user's self-efficacy in interacting with AI systems their ability to trust their own capacity to understand automated suggestions and use the tool effectively (Afroogh et al., 2024; Yang & Wibowo, 2022). In regions where exposure to AI technologies is still emerging, users with low confidence may approach such tools with skepticism or anxiety, which can hinder meaningful engagement regardless of the system's intrinsic value. The prominence of Digital Confidence, therefore, underscores the need for proactive AI literacy initiatives that empower users to interact with automated systems without uncertainty.

While users expressed strong intentions to adopt the system, Facilitating Conditions emerged as a critical determinant of actual usage**.** This highlights the infrastructural realities present in many African educational institutions, where challenges such as poor connectivity and limited access to devices can create a significant gap between intention and behavior (Kebirungi et al., 2024; Mwansa et al., 2025; Naatu et al., 2025). This finding demonstrates that technological adoption in low-resource settings is not merely a function of individual willingness but is deeply intertwined with structural and institutional support. Consequently, the successful implementation of such an AI model necessitates parallel investments in digital infrastructure to ensure its feasibility (Nalubega & Uwizeyimana, 2024).

The study also identified two distinct user profiles through cluster analysis, which include *High Adopters* and *Moderate Adopters*. High Adopters were characterized by strong digital confidence, a positive perception of the model, and more reliable access to technological resources**.** In contrast, Moderate Adopters expressed more caution and faced greater barriers related to both confidence and infrastructure**.** This division signals a potential risk of widening digital inequalities if AI-driven solutions are deployed without targeted interventions (Naatu et al., 2025). It emphasizes the need for adaptive usability strategies, such as scaffolded onboarding for less confident users and leveraging high adopters as peer mentors. In conclusion, this study confirms that the AI-driven career guidance model is a highly acceptable tool**.** However, its successful and equitable implementation hinges on addressing both psychological and infrastructural factors **(Naatu et al., 2025).** To move forward, it is essential to focus on user-centered design that enhances clarity and builds confidence, while simultaneously strengthening institutional support and digital infrastructure. By doing so, the full potential of AI-driven career guidance can be realized, ensuring equitable benefits for all students.

5.5 Regression Analysis

The regression results provide valuable insights into user engagement with the AI-driven career guidance system, aligning with established theoretical frameworks while revealing context-specific nuances. The strong influence of Performance Expectancy highlights that users' perceptions of the AI's ability to deliver accurate and personalized career guidance are pivotal in shaping their intention to adopt the technology. This supports prior research emphasizing perceived system intelligence and outcome usefulness as key drivers of AI adoption (Elshan et al., 2022; Moussawi et al., 2021). Digital Confidence emerges as another significant predictor, underscoring the importance of digital self-efficacy in AI environments. Users with higher digital literacy appear more comfortable trusting and utilizing autonomous AI recommendations, a factor especially critical in low-resource settings where digital readiness varies widely (Naatu et al., 2025). Regarding actual system use, Behavioral Intention remains the strongest predictor, consistent with the UTAUT model. The reduced direct effects of Effort Expectancy, Social Influence, and Facilitating Conditions on use behavior, once intention is included, suggest these factors influence use primarily through intention. This mediation pattern aligns with AI adoption literature, where commitment to use often diminishes the role of external or ease-of-use factors (Polyportis, 2024; S. Xu et al., 2024). Together, these findings indicate that adoption of AI-driven guidance is chiefly determined by perceptions of usefulness, trust in AI, and individual digital capability, rather than social or infrastructural influences. Effective implementation should therefore prioritize transparent AI explanations, user trust-building, and digital literacy support to ensure equitable engagement.

5.6 Moderation Analysis

The moderation analysis reveals that Digital Confidence does not significantly moderate the relationship between Effort Expectancy and Behavioral Intention. This suggests that users' digital skills do not substantially change how perceived ease of use impacts their intention to adopt the AI system model. This finding diverges from common assumptions in technology acceptance models (Rana et al., 2024), indicating that effort expectancy's effect on intention is stable across digital confidence levels. Instead, intention appears more directly shaped by perceived usefulness and trust in AI capabilities. Importantly, all main effects, including Digital Confidence, remain significant, indicating additive rather than interactive influences on intention. This suggests that fostering digital confidence directly promotes AI adoption, independent of ease-of-use perceptions. For AI career guidance tools, this underscores the importance of emphasizing system transparency, personalization, and explainability, alongside efforts to enhance users' digital skills and confidence.

CHAPTER 6: CONCLUSION AND FUTURE DIRECTIONS

In conclusion, AI-driven conversational models demonstrably hold significant potential to augment and enhance the accessibility, scalability, and personalization of career guidance services for students navigating the increasingly complex transition to the labor market and the scarcity on career guidance services, including for long-distance students. The study conducted a scoping review and systematically mapped the current state of AI conversational models for student career guidance, highlighted their emerging applications, benefits like accessibility and efficiency, and significant limitations. While potential is clear, current implementations were often basic. Realizing the full value demands, the study identified 5 requirement categories, such as technical, design-related, ethical, pedagogical and incorporation of emotional intelligence while ensuring integration of such modules and complementing human expertise. Crucially, there was a notable gap in rigorous outcome evaluations. Future work must prioritize robust empirical studies, user experience, equity, and human-AI collaboration models to ensure effective and trustworthy support for students navigating the industry job market. As well as ensuring that the models have empathy. This study contributes to the development of a more inclusive, efficient, and effective framework for developing relevant conversational models fit for advising students.

Additionally, this research has also led to the development of a new guiding framework, the CAM-CAI-RCHE model. Was created, and the first steps were taken to check this model using a Design Science Research approach, which included gathering information through different methods at fifteen Ugandan universities. Our study looked at what makes it easier or harder for these universities to start using AI for career advice, and what key people there think about it. What the study learned from talking with these stakeholders who supported the proposed model's step-by-step plan was clear, with thoughts that its focus on local needs was very important and liked the idea of a supportive platform model, along with positive feedback from experts on the model's main parts, suggesting that the conceptual framework is well-grounded. Therefore, the CAM-CAI-RCHE offers a fresh, evidence-based, and context-aware guide to help Ugandan universities and similar institutions systematically manage the complex process of adopting Conversational AI to better prepare students for their careers. This directly addresses a need not fully met by more general guides on technology adoption.

Addressing the persistent difficulty students face in navigating career pathways and securing suitable employment represents a critical aspect of higher education and professional development. This study details the development of a novel conversation system model, engineered specifically for student career guidance**,** leveraging a robust technical stack comprising Google Cloud services (Dialogflow CX, Vertex AI) and LangChain orchestration. By incorporating advanced NLP for tasks like skills mapping, academic-to-career translation, and integrating sophisticated emotion detection capabilities, the system delivers guidance that is not only accurate and scalable but also attuned to the user's emotional context. This deliberate fusion of technical proficiency with affective awareness marks a significant progression in the domain of digital career support tools.

The proposed career guidance chatbot architecture thoughtfully combines document intelligence, emotional understanding, and dynamic prompting to deliver highly personalized career advice. By leveraging Vertex AI Matching Engine and Gecko embeddings, the system efficiently retrieves the most relevant context from a diverse set of documents, including career articles, internship and job postings, academic resources, and skills guides. Integrating EmoRoBERTa enables the chatbot to detect the user's emotional state, ensuring that responses are not only informative but also empathetic. The addition of a memory component enriches the interaction by allowing continuity across sessions, remembering user preferences, prior concerns, and career aspirations. Finally, the use of GPT-Turbo ensures quick, context-aware, and emotionally attuned answers. Together, this setup strikes a balance between accuracy, relevance, and emotional intelligence, providing students with an engaging and supportive career guidance experience.

The potential deployment scenarios for this system model are varied, including integration into university career centers, student support services, and academic advising platforms. Across these applications, the system offers a mechanism for delivering personalized, scalable career support efficiently, uniquely addressing the practical and emotional challenges students encounter when planning their careers. Our roadmap for future enhancement prioritizes three key areas. The first involves broadening multilingual competence to support increasingly diverse student populations. The second entails creating complementary employer-facing portals designed to streamline connections between students and prospective internship or job opportunities. The third focus is on augmenting the system's explainability, providing users with clearer insights into recommendation logic to build confidence and encourage proactive career decision-making. In the context of evolving higher education and workforce dynamics, technologically advanced solutions that remain grounded in human needs are essential. This research demonstrates that AI, when developed with both technical rigor and empathetic design principles, can serve as a powerful tool for supporting students in navigating complex career pathways, offering meaningful and effective guidance.

Furthermore, the study conducted a usability study, findings indicate that the conversational AI career guidance application is generally well accepted among users, with performance expectancy emerging as the key driver of behavioral intention. Effort expectancy and social influence also play meaningful roles, particularly for users with higher digital confidence. To enhance user adoption, it is recommended to focus on improving the system’s perceived usefulness by increasing the accuracy and relevance of guidance provided. Additionally, simplifying interaction flows and offering supportive resources can reduce usage effort, especially for less digitally confident users. Leveraging social proof through community endorsements may further encourage adoption. Finally, integrating digital literacy support within the system model can address barriers for lower-confidence users, fostering more inclusive usability and greater overall acceptance.

CHAPTER 7: APPENDICES

7.1 Appendix I

Consent Statement (Digital) online survey

Study Title: **AI-Based Career Guidance Model for Computing Students in Uganda Universities.**

Researcher: **Samuel Bisaso, PhD student at Silenus University of Science and Literature**

Welcome to the Survey!

This survey is part of a research project aiming to understand students' needs for career guidance and how technology might help improve these services in universities like yours. Your honest responses are very important. This survey will take approximately 15-20 minutes to complete. Your participation is completely voluntary. You can choose to stop at any time or skip any question you don't feel comfortable answering. All your answers will be kept confidential and anonymous. The information collected will be used for research purposes only, and no individuals will be identified in any reports or publications. Data will be stored securely. If you have any questions about the research, please don't hesitate to contact Samuel Bisaso at bsamtak@gmail.com . If you have concerns about your rights as a research participant, you can contact the Silenus University of Science and Literature Ethics Committee at info@selinusuniversity.it .

By clicking **Agree** and proceeding with this survey, you are indicating that you are at least 18 years old, have read the information above, and consent to participate in this research.

7.2 Appendix ii: Survey questions

Conversational AI (CAI) Career Guidance App – Usability Survey

Response Scale:
1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Section A: Digital Confidence (DC)

DC1. I feel confident using new or unfamiliar technology tools.
DC2. I can generally troubleshoot errors or problems that occur while using new technology.
DC3. I have prior experience using Artificial Intelligence (AI) tools or applications.

Section B: Performance Expectancy (PE)

PE1. Using the CAI improves the quality of the career guidance I receive.
PE2. The CAI helps me achieve better alignment between my skills and local industry needs.
PE3. Using the CAI enhances my job fit and employability prospects.

Section C: Effort Expectancy (EE)

EE1. Interacting with the CAI is clear and understandable.
EE2. The CAI is easy to learn how to use.
EE3. Using the CAI requires very little mental effort on my part.

Section D: Social Influence (SI)

SI1. My peers in the computing department believe I should use the CAI.
SI2. My lecturers or professors influence my decision to use the CAI.
SI3. Important people or management at the university expect me to use the CAI system.

Section E: Facilitating Conditions (FC)

FC1. I have the necessary technical resources to use the CAI effectively.
FC2. I have the necessary knowledge and skills to use the CAI.
FC3. The CAI is compatible with other technologies I use.

Section F: Behavioral Intention (BI)

BI1. I intend to use the CAI for my career guidance needs in the future.
BI2. I can predict that I will use the CAI system regularly.
BI3. I am likely to recommend the CAI application to other computing students or staff.

Section G: Use Behavior (UB)

UB1. I use the CAI for my career guidance needs frequently.

Demographic Information
Role: Student / Staff
Gender: Male / Female
Age: ________
University: ____________________
Years of Computing/IT Experience: ________ years

7.3 Appendix III

	lval	op	rval	Estimate	Std. Err	z-value	p-value
0	PE1_Better_Career_Decisions	~	PE	1.000000	-	-	-
1	PE2_Matches_Local_Industry_Needs	~	PE	0.869635	0.02292	37.942153	0.0
2	PE3_Improves_Employability	~	PE	0.891953	0.019571	45.574666	0.0
3	EE1_Easy_To_Learn	~	EE	1.000000	-	-	-
4	EE2_Interaction_Is_Clear	~	EE	0.920229	0.022735	40.476931	0.0
5	EE3_Requires_Little_Mental_Effort	~	EE	0.861646	0.0248	34.744377	0.0
6	SI1_Peers_Recommend_App	~	SI	1.000000	-	-	-
7	SI2_Lecturers_Support_Use	~	SI	0.803743	0.02771	29.005588	0.0
8	SI3_Important_Others_Think_I_Should_Use	~	SI	0.883895	0.026802	32.979212	0.0
9	FC1_Adequate_Internet_Access	~	FC	1.000000	-	-	-
10	FC2_Necessary_Equipment_Available	~	FC	0.928371	0.028106	33.031446	0.0
11	FC3_Technical_Support_Available	~	FC	0.954184	0.024898	38.323769	0.0
12	DC1_Confident_Using_New_Tech	~	DC	1.000000	-	-	-
13	DC2_Can_Troubleshoot_Errors	~	DC	0.948928	0.019264	49.259625	0.0
14	DC3_Experience_With_AI	~	DC	0.894834	0.022055	40.573208	0.0
15	BI1_Intend_To_Use_In_Next_3_Months	~	BI	1.000000	-	-	-
16	BI2_Plan_To_Recommend_App	~	BI	0.932672	0.027004	34.538221	0.0
17	BI3_Use_The_App_For_All_Career_Questions	~	BI	0.879628	0.028505	30.858725	0.0

--- Model Fit Indices ---

	DoF	DoF Baseline	chi2	chi2 p-value	chi2 Baseline	CFI	GFI	AGFI	NFI	TLI	RMSEA	AIC	BIC	LogLik
Value	120	153	131.597149	0.221105	14082.141363	0.999167	0.990655	0.988085	0.990655	0.998938	0.0099	101.733339	351.361511	0.13333

Factor loadings and model fit indices extracted.

--- Calculating Composite Reliability (CR) and Average Variance Extracted (AVE) from CFA ---

PE:
  Composite Reliability (CR): 0.944
  Average Variance Extracted (AVE): 0.851
EE:
  Composite Reliability (CR): 0.950
  Average Variance Extracted (AVE): 0.863
SI:
  Composite Reliability (CR): 0.927
  Average Variance Extracted (AVE): 0.809
FC:
  Composite Reliability (CR): 0.973
  Average Variance Extracted (AVE): 0.924
DC:
  Composite Reliability (CR): 0.964
  Average Variance Extracted (AVE): 0.900
BI:
  Composite Reliability (CR): 0.957
  Average Variance Extracted (AVE): 0.881

CR and AVE calculations from CFA completed.

7.4 Appendix IV: Academic Publications

I. **Bisaso, S., Muhumuza, G., & Wasswa, W. (2025).** The CAM-CAI-RCHE Model: An Adoption Model for Conversational AI in Career Guidance for Resource-Constrained Higher Education Settings. *European Journal of Contemporary Education and E-Learning*, *3*(4), 137–149.

II. **Bisaso, S., Wasswa, W., & Muhumuza, G. (2025).** Towards the Application of an NLP-driven Conversational Model for Efficient and Affective Career Guidance for Students: A Scoping Review. *European Journal of Applied Science, Engineering and Technology*, *3*(3), 240–253.

CHAPTER 8: REFERENCES

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