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Artificial Intelligence Adoption in Education A Study on Attitudes, Readiness, and Intention

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Abstract

This research conducts a comprehensive investigation into the impact of Artificial Intelligence (AI) on the educational landscape of the Kingdom of Saudi Arabia (KSA). Utilizing well-established theoretical frameworks such as the Theory of Planned Behaviour (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), and Technology Acceptance Model (TAM), the study employs primary data collected through a survey involving 198 participants, including students, faculty/teachers, and administrators in educational institutions. Data analysis, carried out using Eviews software, focuses on understanding the readiness for AI adoption in the educational context of KSA. The research addresses the absence of a comprehensive theoretical framework for guiding effective AI application in education. The survey, conducted through stratified random sampling, provides insights into participants' demographics and attitudes toward AI adoption. Findings reveal that approximately 35-40% of respondents expressing favourable attitudes, indicating the need for further exploration and educational initiatives. Regression analyses underscore the significance of factors such as attitude, knowledge, and usefulness in predicting AI adoption intention, demonstrating variations across gender, age groups, and professional roles. To address identified gaps, the study introduces an innovative AI Readiness Assessment Tool, designed based on TPB, UTAUT, and TAM frameworks. This tool evaluates individuals' preparedness for AI integration and provides a comprehensive assessment. The research proposes operational strategies and guidelines tailored for students, faculty, and administrators to enhance AI adoption in educational institutions. In conclusion, this research contributes a foundational theory for understanding AI's role in education in KSA, providing valuable insights and practical recommendations for educators, policymakers, and technologists. The study lays the groundwork for a modern, adaptive, and effective educational future aligned with the goals of Vision 2030.

Keywords
Artificial Intelligence; Teaching and Learning; TAM; UTAT; TPB.

1. Introduction
AI represents the transformative edge reshaping educational landscapes, promising innovative methodologies and personalized learning experiences. AI enables systems to simulate human intelligence, offering educators innovative tools to personalize learning experiences for students. In the rapidly evolving educational landscape of KSA, the integration of AI into teaching methodologies and learning systems holds unparalleled promise. Yet, despite its potential, the seamless integration of AI into educational practices remains impeded by a critical void, an absence of a comprehensive and cohesive theoretical foundation.

This study is aimed to bridge this gap by undertaking a accurate exploration aimed at constructing theories that explain AI's transformative role in enhancing pedagogy within the context of KSA. Within the educational ecosystem of the kingdom, AI represents an unprecedented opportunity to revolutionize traditional teaching and learning paradigms. However, its application remains fragmented, lacking a unified framework to harness its full potential.

At its core, this research seeks to explore the multifaceted dimensions of AI's application in Saudi Arabia's educational sector. By examining its public impression, ease of use, attitude towards it, impacts, advantages, and challenges, this study aspires to provide educators, policymakers, and technologists with invaluable insights. The overarching goal is to pave the way for an educational framework that is not only more engaging and efficient but also tailored to the specific needs and aspirations of Kingdom's educational aspirations.
This academic pursuit is strategically designed to address the intricate complexities and ambiguities that accompany AI's integration into Saudi Arabia's educational practices. While AI's influence grows across diverse sectors, its adaptation in education necessitates a well-defined and localized theoretical framework. This research aimed to fill this void by delving into the depths of AI's impact on pedagogy, crafting a robust framework tailored to the nuances of Saudi Arabia's educational landscape. Employing both theoretical exploration TPB, UTAUT, and TAM and survey methodologies, the study explores AI adoption potentials and challenges within KSA's education system. Building on the research findings, an AI-based assessment tool has been developed to evaluate users' AI adoption intentions, expectations, usefulness, and provide recommendations for improvement.

By exploring the contexts where AI demonstrates its greatest potential and discerning the challenges it might encounter within the Kingdom's unique educational framework, this study endeavours to elucidate effective methodologies. It seeks to shed light on public perception towards AI, and how AI can be optimally utilized to elevate teaching methodologies, augment learning experiences, and enhance educational outcomes in alignment with the Vision 2030 goals.

As Saudi Arabia progresses on its ambitious path of educational reform and technological advancement, this study stands as a guiding inspiration. It invites stakeholders to navigate the complexities, embrace the potential, and address the challenges that accompany the integration of AI and education within the unique context of the Kingdom. This study has potential to fasten the journey towards a more innovative, adaptive, and impactful educational landscape that underpin the transformative power of AI in enhancing teaching and learning experiences within Saudi Arabia.
AI is being used to improve pedagogy and make learning more engaging, interesting, and successful in the rapidly changing world of education. Integrating AI into teaching and learning is still in its early stages, facing challenges due to the lack of a comprehensive theoretical framework to guide its implementation. This research is positioned to address these difficulties, as summarized in the following problem areas:

- Lack of a comprehensive and cohesive theoretical foundation for integrating AI into educational practices.
- Insufficient understanding of the potential advantages and disadvantages associated with AI in the educational environment.
- Absence of AI assisted assessment tool in KSA that can determine the readiness toward AI usage and adoption in teaching and learning.

1.1 Objectives
This research aims to develop a robust theoretical framework that explains how AI can enhance teaching and learning. By investigating various AI applications and their impacts on pedagogy, we intend to provide valuable insights for educators, policymakers, and technologists, ultimately contributing to improving educational practices.

1. What are the educational contexts and scenarios where AI has shown the greatest potential, and equally, where it might face significant challenges or drawbacks?
2. How can we assess and measure the potential advantages and disadvantages of integrating AI into the educational environment?
3. How can we develop systematic guidelines and operational strategies for educators and policymakers to harness the potential of AI in education?

2. Literature Review
2.1 Teaching and Learning Styles
Teaching and learning process can be described as a transformative journey where knowledge is transmitted from educators to students. It involves the integration of multiple elements, including the identification of learning objectives by the instructor, the creation of teaching materials, and the execution of teaching and learning strategies (Munna & Kalam, 2021).

Successful teaching entails the application of suitable techniques and approaches to actively involve learners, support their learning, and enable them to attain their educational objectives. A teacher's responsibility is to establish a nurturing and encouraging learning atmosphere, offer guidance and constructive input, and assist learners in cultivating the competencies and knowledge essential for their success.

A teaching strategy pertains to the selection and diversity of instructional techniques employed during a teaching session, which can encompass activities such as group work, problem- solving, discussions, or hands-on practical exercises (Nicholls, 2002). He observed that in every teaching session, it is crucial to employ a variety of strategies to maintain student motivation and engagement. The “one-size-fits-all” approach frequently struggles to accommodate the diverse learning needs of students, leading to less than satisfactory outcomes (Pratama et al., 2023).

Learning is a sequence of events that fosters change through the accumulation of experiences, ultimately enhancing the potential for improved performance and future learning (Mayer, 2002). It is not an action imposed upon students; rather, it is an active process that students engage in themselves. Educators can enhance the learning process and optimize the students’ performance by creating teaching materials tailored to students according to their learning styles.

The concept of learning styles, being an essential and pivotal element in a student's educational development, has consistently been a topic of discussion in the field of education and pedagogy (Hu et al., 2021). Learning styles are generally described as the innate inclinations of individuals regarding how they participate in the learning experience (Ehrman & Oxford, 1990) and depict variations in individuals' learning approaches (Richardson, 2011). Visual learning styles, auditory learning styles, and kinesthetics learning styles are the three common learning styles considered during the teaching process.

In recent years, technological advancements have revolutionized education to bridge the gaps left by traditional strategies. The adoption of these technologies will enhance the methods of teaching and delivery (Pratama et al., 2023). AI technology is one of the most promising and influential developments in the education field. It is being used to improve pedagogy and make learning experience more engaging, and successful in the rapidly changing world of education.

2.2 Artificial Intelligence History in Education

The origins of AI date back to the 1950s when John McCarthy convened a two-month workshop at Dartmouth College in the United States of America (USA). It was in the proposal for this workshop in 1956 that McCarthy introduced the term "artificial intelligence" for the first time (Russel & Norvig, 2010, p. 17). In 1990, a broad meaning provided by Baker and Smith (2019) defined AI as “Computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving” (p. 10). AI a technology powered by algorithms that can make predictions, diagnoses, recommendations, and decisions, has become increasingly significant in the field of education. This is because of its ability to enhance learning in diverse educational settings (Limna, 2022). Additionally, it entails the replication of human-like intelligence functions in computer systems (Dong et al., 2020; Limna, 2022).

Furthermore, AI is characterized by a computer program's ability to learn and think. It includes any task in which a program performs actions that are typically associated with human intelligence (Mitchell, 2019). It can be observed that the integration of AI in education presents distinct opportunities, potential advantages, and associated challenges within the realm of educational practices (Ouyang & Jiao, 2021). One of the main objectives of AI in education is to deliver tailored learning assistance or guidance to individual students, taking into account their learning progress, preferences, or unique personal attributes (Hwang, 2014; Hwang et al., 2020).

However, due to the relatively recent introduction of AI in education, less-experienced instructors may face challenges in delivering timely and effective responses to the insights produced by AI applications (Chen et al., 2022). Academics, educators, policymakers, and professionals need to collaborate in addressing the novel possibilities and challenges brought by the AI revolution. Their combined efforts are essential in shaping the gain of necessary competencies and skills for all learners (Luan et al., 2020). In the context of education, AI technology encompasses several aspects of application that enhances the teaching and learning experience, including teacher feedback, automated grading systems, adaptive learning, and many more (Hwang et al., 2020; Yufeia et al., 2020).

2.3 Artificial Intelligence Applications in Education

Innovative technologies are reshaping the landscape of teaching and learning. The rapid development of AI technology in recent years has made the incorporation of AI in education increasingly clear and prominent. Both AI and education is primarily centered around the utilization of AI technology for aiding teaching, creating smart campuses, realizing intelligent approaches to learning, teaching, and administration (Huang et al., 2021). As mentioned by Zhang and Aslan, AI applications in education have been on the rise, showing great promise in delivering customized learning experiences, conducting real-time assessments, and enhancing meaningful interactions in online, mobile, or blended learning scenarios (2021). As mentioned by Zhang and Aslan, AI technology has been applied in the field of education in several aspects: an automatic grading system, teacher's feedback, virtual teachers, personalized learning, adaptive learning, and virtual reality (Yufei et al., 2020).

Automatic Grading System: an AI automatic grading system is a professional computer program that replicates a teacher's actions to assign grades to student tasks in an educational setting. It evaluates students' understanding, analyzes their responses, delivers feedback, and designs personalized training programs (Yufei et al., 2020).

Teacher’s feedback: modern technologies like AI-powered conversational robots, machine learning, and natural language processing present promising avenues for improving the quality of automated feedback (Peters, 2019). Feedback generated by teachers to students has been transformed from paper-based feedback to automated feedback empowered by AI technologies.

Virtual teachers: virtual teachers are created to fulfil their educational roles; any knowledge real teachers aim to convey to the students can be input into the virtual teacher without limitations. These virtual teachers are programmed to be proficient in multiple languages and can perform tasks beyond the physical capabilities of humans. They can verbally address students' requests in a second language, engage in interactive games, and even maintain conversations (Varzaru et al., 2022).

Personalized learning: personalized learning encompasses a range of educational approaches in which the pace of learning and instructional methods can be tailored to the specific requirements of each individual learner (Bailey, 2019). As a result, both fast and slow learners can persist in their education at their preferred speed (Yufei et al., 2020).
Adaptive learning: adaptive learning employs artificial intelligence to progressively gather and analyze student learning data. It identifies each student's unique learning styles and characteristics and, based on this analysis, automatically customizes the instructional content, methods, and pace to align with their individual needs (Wu, 2019).

2.4 Benefits and Challenges of Artificial Intelligence in Education

AI-powered technologies in education offer various benefits that can transform the teaching and learning experience for both students and educators. One of the key advantages of AI in education is personalized learning. It has the capacity to analyze student data and generate customized learning experiences tailored to individual learning styles, needs, and interests. In addition, AI solutions can provide valuable support to students facing disabilities, language barriers, and distinct learning requirements. For example, speech recognition software can be a valuable resource for students with hearing impairments or language challenges, while text- to-speech technology can help students who have visual impairments. AI has the capability to conduct comprehensive assessments of students' daily and exam performance using big data and machine learning. It can then offer individualized instructional support to address students' challenges and areas of difficulty (Bingham et al., 2018). Educators can also benefit by saving their time when automating administrative tasks like grading allows them to allocate more time to teaching, course planning, and mentorship. Moreover, AI offers opportunities for instructors to be productive and access resources to enhance their teaching skills and stay updated with the latest educational trends.

Although AI brings multiple benefits to the education field, there are challenges that need to be addressed when adopting AI technologies. The primary drawback of AI-based language learning tools is the absence of human interaction (Khanzode & Sarode, 2020). Effectively overseeing and protecting student data while adhering to privacy regulations poses a major concern. Differential access to technology and the internet among learners can influence their capacity to utilize AI learning tools. It is imperative to take into consideration the distinct needs and resources of all students and ensure that AI learning tools are accessible to everyone (Rebolledo Font de la Vall & González Araya, 2023). Teachers as well are challenged to obtain new digital teaching skills to effectively implement AI for educational reform. Furthermore, developers of AI teaching products should have a deep understanding of teaching methodologies to create products that are aligned with educators' instructional practices (Huang et al., 2021). In term of cost, adopting AI technologies could potentially be expensive, requiring a substantial initial financial commitment.

2.5 Artificial Intelligence Adoption by Post-millennials in Education
Post-millennials are the initial generation to have grown up with continuous access to digital technology, marking them as "digital-first". This unique background has instilled in them a natural attraction for AI technologies. This generation is highly likely to embrace AI in various aspects of their lives, encompassing both work and daily activities, owing to its potential to enhance their efficiency, connectivity, and information accessibility. Their strong inclination toward visual learning, swift information retrieval, and adept multitasking abilities positions them as an ideal generation to willingly adopt AI technologies (Chan & Lee, 2023).

2.6 Artificial Intelligence Applied Theories in Education
Many scholarly articles have explored the adoption of technology, with recent attention specifically focused on AI adoption within domains. Recognizing the factors that facilitate AI adoption across diverse contexts is of great importance to both researchers and practitioners. This knowledge can serve as a valuable guide for decision makers seeking to introduce AI into their institutions and increase adoption rates among individual users (Radhakrishnan & Chattopadhyay, 2020). The following theories are applied to understand the adoption of AI at both the organizational and individual levels.

Technology Acceptance Model (TAM): The Technology Acceptance Model as introduced by Davis in 1986, is employed to model user acceptance of information systems. It comprises two central factors: perceived ease of use and perceived usefulness. This theory explains the adoption of AI applications like autonomous vehicles (Zhang et al., 2020). The majority of studies have identified that perceived usefulness and perceived ease of use are robust indicators of the intention to use AI (Kelly et al., 2023).

Unified Theory of Acceptance and Use of Technology (UTAUT): This theory identifies four distinct constructs that act as direct factors influencing the acceptance and usage behaviour of users when it comes to technology adoption. These constructs include performance expectations, effort expectations, social Influence, and facilitating conditions. Additionally, the model considers gender, age, voluntariness, and experience as important moderators for these constructs (Venkatesh et al., 2003).

Theory of Planned Behaviour (TPB): Researchers have employed the theory of planned behaviour to explain the adoption of AI technologies by consumers. This theory underscores that behavioural intention, and the subsequent actual behaviours are influenced by key factors, namely attitude, subjective norm, and perceived behavioural control (Zhong et al., 2020).

2.7 AI Assisted Assessment Tool for Effective Pedagogy
An assessment tool is a systematic and standardized instrument or method utilized to consistently assess and measure specific attributes, skills, competencies, or behaviours of individuals (ElHady, 2023). A study to measure AI adoption has been made to propose a maturity level model that will be an indicator to evaluate individual's readiness to adopt AI (Bettoni et al., 2021). The assessment is based on distributed questionnaires where each question has a specific weight planned by the author to measure the readiness and assists a company in gaining insights into the areas where AI adoption is currently constrained or hindering its full potential utilization. In the field of pedagogy, there are multiple assessments that focus on assessing a particular element such as assessing complex assignment. Nevertheless, the researchers did not find any AI assisted assessment tool that aims to evaluate the level of knowledge, capability, and willingness to use and adopt AI in teaching and learning. The following Figure 1 displays the summary of the literature review including the key points and findings.

It's vital to acknowledge that AI implementation is a multifaceted endeavour. This goes beyond acquiring software and hardware to encompass setting up the necessary infrastructure and allocating resources over an extended period. Remarkably, the current research landscape lacks empirical assessments of AI adoption. Based on the research findings from the literature review, the following research gaps have been identified.

The first research gap focuses on KSA contextualized knowledge, and expectations in teaching and learning regarding AI assisted assessment and how this gap may vary depending on demographic factors like age, gender, and experience. To address this gap, research is needed to explore the extent of AI knowledge among students, faculty, and policy makers. The second research gap revolves around the absence of a reliable assessment predictive tool to evaluate the multifaceted factors that influence the adoption of AI. To advance the adoption of AI, it is crucial to have a comprehensive understanding of the factors that facilitate or hinder its implementation. The third research gap pertains to the literacy on role of AI assisted assessment tool in education and its alignment with Saudi Arabia's vision 2030. As KSA seeks to diversify its economy and invest in education, AI represents a transformative tool. Hence, research in this area will be essential and beneficial to ensure that AI technologies are harnessed in a way that supports the educational objectives of the vision. The researchers will study the factors that lead to the use and adoption of AI by post-millennials in the education domain within the context of KSA as shown in Figure 2 that explains the research gaps.

Figure 1. Literature Review Summary

The findings of these gaps are expected to produce an AI assisted assessment tool which will provide valuable insights for pedagogical institutions and decision-makers in devising effective AI adoption strategies, thereby bridging the existing gap in the ability to assess and plan for AI integration in KSA.

2.8 Theoretical Framework

Creating a comprehensive framework for technology adoption is a complex endeavour that often requires integrating multiple established models. TAM, TPB, and UTAUT are well-established models that offer valuable insights into the factors influencing technology adoption. In developing a framework that incorporates these models, the central aim is to offer a more holistic understanding of technology acceptance.

TAM focuses on perceived ease of use and perceived usefulness, TPB adds the dimension of behavioural intentions, perceived behavioural control and attitude, and UTAUT expands the view by considering performance expectancy and effort expectancy. By merging these models, the proposed framework would encompass a broad spectrum of variables, including gender, age, and experience to provide a more comprehensive perspective on AI use and adoption.

Performance Expectancy (PE): This concept is understood as the degree to which a user believes that adopting a new system would significantly improve their job performance (Venkatesh et al., 2003) and it is construed to be identical with perceived usefulness.

H1: performance expectancy significantly affects behavioural intention to use and adoption of AI in education.
Effort Expectancy (EE): This is defined as the degree of simplicity associated with the use of a new system as described by Davis in 1989 and it carries the same concept of perceived ease of use.

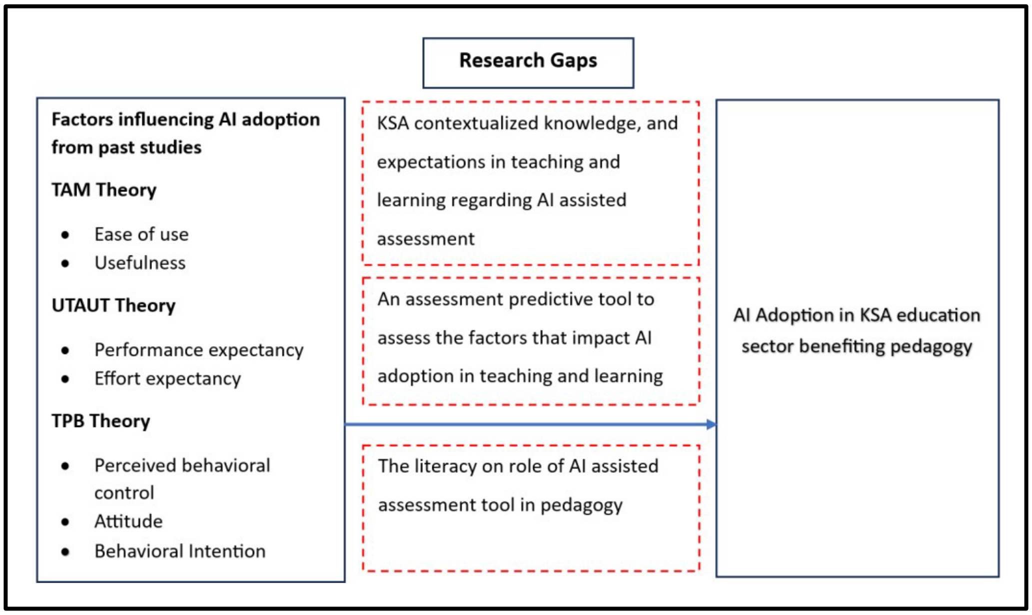

Figure 2. Research GAPs Model

H2: Effort expectancy significantly affects behavioural intention to use and adoption of AI in education.

Perceived Behavioural Control (PBC): Grouped factors related to knowledge, skills, and facilitative contextual factors into a category labelled as perceived behavioural control. It stands to reason that when individuals believe they have the capability to carry out an action and the necessary supporting conditions are in place, their intention to perform that action is likely to be stronger (Ajzen, 2020).

H3: knowledge significantly affects behavioural intension to use and adoption of AI in education.

Perceived Ease of Use (PEU): Perceived ease of use is described as the degree to which a consumer believes that utilizing a specific computer system is easy (Pillai & Sivathanu, 2020).

H4: perceived ease of use significantly affects attitude to use and adoption of AI in education.
Perceived Usefulness (PU): Perceived usefulness has been defined as the extent to which a consumer believes using a particular system would improve their performance of a specific task. Researchers found that this variable has a direct positive effect on adoption intention (Pillai & Sivathanu, 2020) and positive impact on Attitude (Lin et al., 2011). Taking these factors into account, the following hypothesis is formulated.
H5: perceived usefulness significantly affects attitude to use and adoption of AI in education.
Attitude (ATT): In TAM model, as proposed by Davis et al. (1989), it is posited that the assessment of Behavioural Intention (BI) is influenced by an individual's Attitude towards the use of a system.
H6: attitude significantly affects behavioural intension to use and adoption of AI in education.
Behavioural Intension (BI): Behavioural Intention (BI) is linked to the evaluation of an individual's strong intent within their specific context to carry out a particular behaviour as proposed by Fishbein and Ajzen in 1975.
H7: Behavioural intension positively affects the use and adoption of AI in education.

After thorough discussions regarding the model's development and a comprehensive explanation of the mechanisms behind hypothesis formation, Figure 3 illustrates the proposed theoretical framework for AI use and adoption.

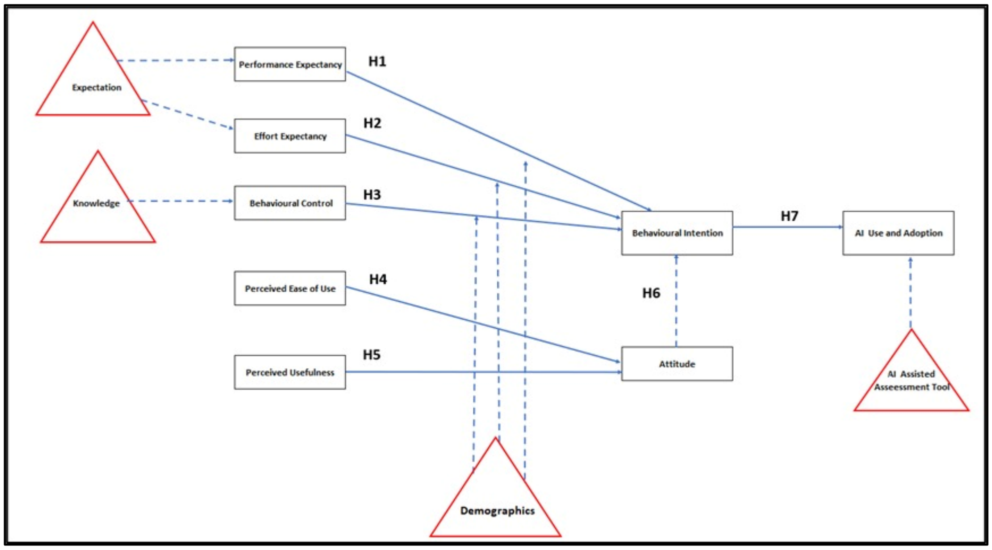

Figure 3. Proposed Theoretical Framework for AI Use and Adoption

3. Methods

This research is a basic study that apply quantitative research methods which rely on deductive logic and utilize formal hypotheses or models to clarify, predict, and ultimately establish causation (Hyde 2000; Johnson and Onwuegbunzie 2004; Morgan 2007). In this study, a conclusive descriptive research design was employed with quantitative data collection methods since descriptive study designs are effective in capturing a clear depiction of the characteristics inherent in the studied sample (Omair, 2015). Quantitative data is often considered more objective because it is based on numerical measurements and can be analysed using statistical techniques. The research strategy incorporated survey research which was administered to a diverse sample of students, teachers, and administrative employees to capture a broad spectrum of perspectives and experiences related to the usage and adoption of AI. The survey responses contributed to quantitative data analysis and reported the findings of the study.

In this study, the level of researchers' interference was limited to minimal degree which aimed to minimize any influence or intervention by the researchers. Data collection was conducted in a manner that does not disrupt or significantly alter the natural behaviour of the respondents. It enabled a transparent and structured approach to data collection and analysis while ensuring the research was aligned with the ethical principles of minimal interference.
This study was carried out in a non-contrived (Natural Environment) setting. This setting reflects the real-life context in which respondents' answers were made to provide insights into how AI can enhance teaching and learning from the perspective of students, teachers, and administrative employees and to what extent they were ready to use and adopt AI.

The unit of analysis is individual since it measures different answers of individuals to determine the level of their readiness to adopt and use AI in teaching and learning context. The study adopted a cross-sectional time horizon which means the primary data collection occurs within a specific time frame.

The study findings are instrumental in crafting a self-assessment tool to gauge user AI-readiness. Each parameter within the tool is allocated weights derived from both survey outcomes and literature review findings. Users are evaluated on a Likert scale ranging from 1 to 5, subsequently ranked from Poor to Excellent based on their scores. Furthermore, the assessment tool facilitates identifying areas for improvement. HTML was used for content structure, CSS for styling and layout, JavaScript for interactivity and functionality. The software "WebStorm" which is a powerful integrated development environment for JavaScript, HTML, and CSS was used for coding. The backend data processing aspect was check using python program. The assessment methodology is reliable as it leverages comprehensive literature, surveying and encompasses essential facets of human intelligence, including education, skills, knowledge, attitudes toward AI, and intentions to use it in the near future, ensuring robust conclusions. To achieve the objectives of the study, a methodology is developed which is shown in Figure 4.

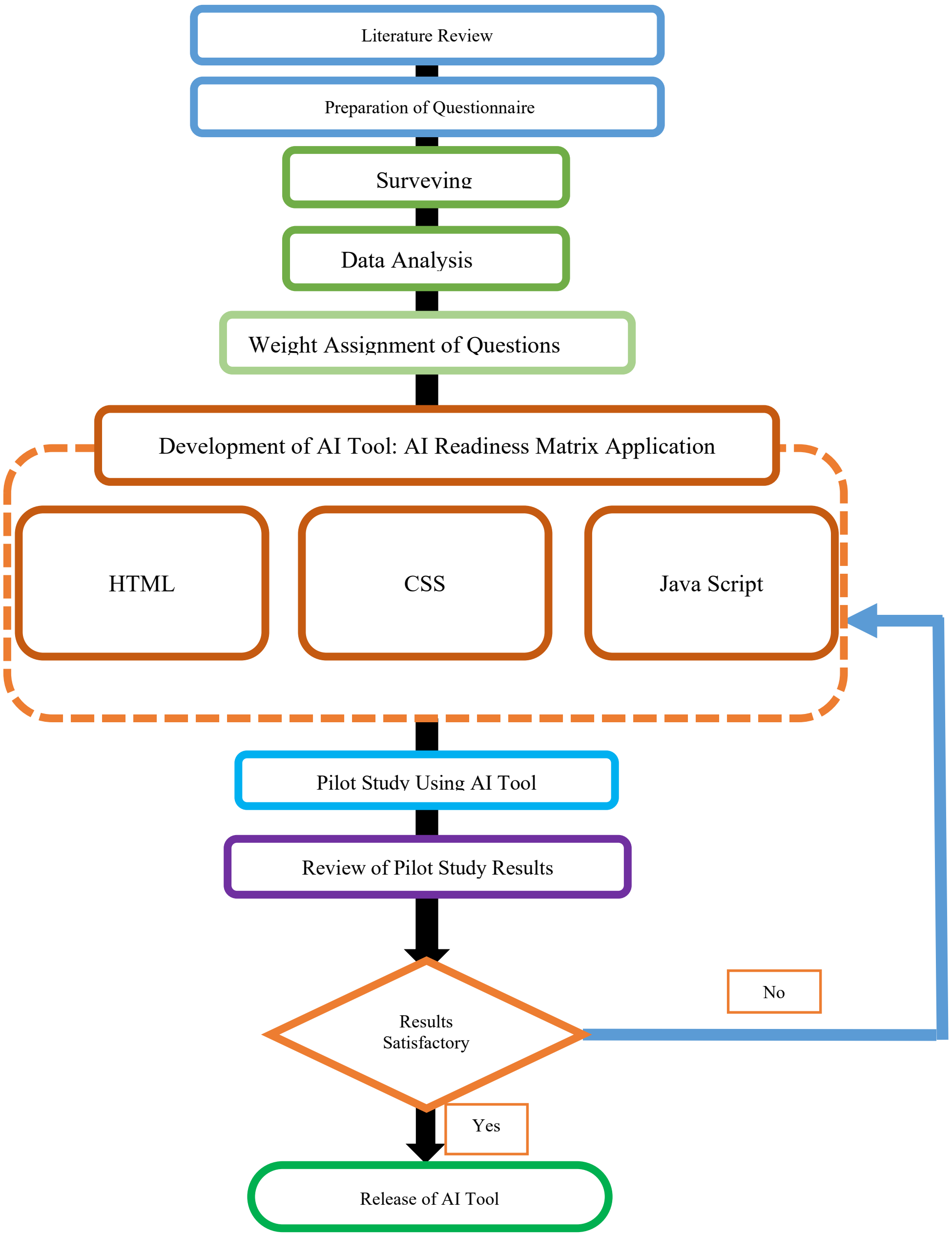

Figure 4. Methodology of the Development of AI-based Assessment Tool

In this study, the target population was Saudi Arabia that is estimated to be around 35.9 million as of 2023 ("Saudi Arabia – CIA", n.d.). Specifically, student, teachers and administrative employees in Saudi Arabians' educational institutions were targeted. The study focused on their readiness toward the usage and adoption of AI. The sample size determination utilized Abraham Wald's equation for estimating sample size from a constrained population, as outlined by Gil-Lacruz et al. (2020). The calculated sample size for the population was determined to be 385. However, due to the resource constraints, the researchers had targeted a sample of 200 participants while only 198 responses were received. Researchers ensured that the sample had knowledge about AI. The sampling technique used in this study was based on stratified random sampling where the respondents were divided into strata according to their category as students, teachers, or administrative employees from different age groups and gender. Sharma (2017) suggested that employing a stratified random sample produces a sample that effectively reflects the characteristics of the studied population as there was minimal missing data and it was suitable for this type of study where the respondent groups were known.

4. Data Collection

Data was gathered through an online survey using a structured research tool distributed through "SurveyMonkey" helping to reach diverse sample as identified. The findings were derived from a sizable sample that reflected the population with a sample size of 198 responses. This survey included a variety of representative questions related to specific hypothesis that assessed the participants readiness toward using and adopting AI. It encompassed various questions, including demographic information such as category, age, and gender, in addition to other questions organized into different sections. Each section contained several questions that were designed to study the aspects related to performance expectancy, effort expectancy, perceived behavioural control, perceived ease of use, perceived usefulness, attitude, and behavioural intension of students, teachers and administrative employees toward the usage and adoption of AI. All the questions in the survey, as shown in Annexure-A, were structured as closed-ended, utilizing a Likert Scale with five levels, ranging from "strongly disagree" to "strongly agree." The data collection was conducted anonymously to maintain a high level of confidentiality for both the study and its participants. Prior to conducting the survey, a pilot study with a small group of targeted samples of five respondents was conducted. This helped to identify some issues related to demographics response and were adjusted accordingly. In addition, it helped in questioning the wording, relevance, and clarity. It ensured that the questions were valid in capturing the intended information. The validation of measurements involved verifying internal consistency through the calculation of Cronbach Alpha values for each construct utilized in the model. All Average Variance Extracted (AVE) values were over 0.5 as indicated in Annexure-B. The Cronbach alphas was falling within the range reported in the study by Manis and Choi (2019) that supported the internal consistency. The questionnaire demonstrated an overall reliability of 0.96, indicating a highly reliable and consistent measurement tool.

To examine the relationship between the items of TPB, UTAUT and TAM and the readiness towards the usage and adoption of AI in educational institutions, this research had used several statistical techniques to analyze the results of the study. For example, descriptive statistics, regression analysis and coefficient correlation were employed to achieve the study's objectives. In addition, the hypotheses formulated in the theoretical framework section were tested using appropriate statistical tests to determine if they are significant. For the data analysis, the researchers used Eviews to conduct the analysis, define and assess the accuracy of the hypotheses proposed in this study.

The research was assessed as having no discernible ethical risks. The data collection process prioritized privacy, with a commitment to avoiding any negative impact on participants. Respondents were clearly informed that the study was exclusively for academic purposes and not for public disclosure, ensuring that their identity would not be required for providing information. Necessary ethics approval was secured from the research deanship of the university.

5. Results and Discussion

5.1 Descriptive Statistics

The survey utilized a stratified random sampling approach, ensuring a varied and representative selection of participants from different backgrounds, including students, faculty, and administrators. This approach aimed to capture unbiased perspective on AI adoption across diverse demographics. Figure 5 indicates that out of the 198 total respondents, a significant majority were females, constituting 71% of the surveyed population. Moreover, a substantial portion of participants, approximately 74%, are 26 years or older in age. Students' responses are higher than administrators and faculty with 45%, highlighting a predominant presence of mature individuals within the survey.

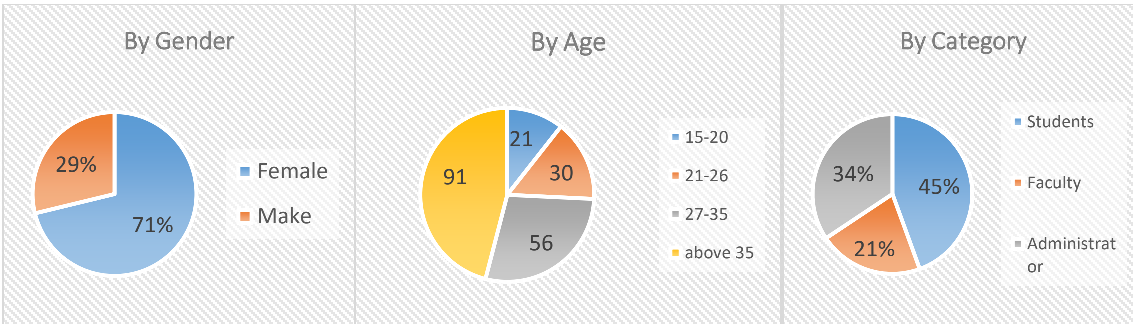

Figure 5. Survey Respondents

The survey conducted on AI adoption using established theoretical models revealed compelling insights into the attitudes and perceptions of students, faculty, and administrative staff within the institution. Employing TPB, UTAUT, and TAM frameworks allowed for a comprehensive analysis of various dimensions of AI acceptance.

Table 1 emphasizes a significant deficiency in robust positive feelings towards various aspects linked to AI. In particular, only around 35-40% of the surveyed individuals demonstrated favorable attitudes regarding AI adoption, knowledge, usefulness, and ease of use. The limited presence of positive responses suggests a prevailing sense of caution or hesitancy among respondents regarding the capabilities and practicality of AI technology. Consequently, it is apparent that further exploration and potential educational initiatives are required to cultivate more positive attitudes and understanding about the benefits and functionalities of AI among the surveyed sample.

Table 1. Positive Response for AI adoption

Theory	Factors	Average Responses
Theory of Planned Behaviour (TPB)	AI adoption (Behavioural Intention)	38%
	Attitude	37%
	Perceived Behavioural Control (Knowledge)	36%
Unified Theory of Acceptance and Use of Technology (UTAUT)	Effort Expectancy	38%
	Performance Expectancy	34%
Technology Acceptance Model (TAM)	Usefulness	35%
	Ease of Use	42%
	Total	198

Table 2 shows the categorized responses of students, faculty, and administration people towards AI adoption. It shows that the TPB demonstrated promising trends in behavioural intention and attitude toward AI adoption among the surveyed groups. The behavioural intention towards AI adoption shows that out of the respondents, 36%, 39%, and 41%, of the students, faculty, and administrative staff members showed positive inclination.

Furthermore, within the TPB framework, attitudes toward AI adoption were echoed consistently among the groups. Approximately 36% of students, 37% of faculty members, and 39% of administrative staff expressed positive attitudes toward AI integration. This uniformity signifies a cohesive positive outlook among the surveyed sample.

The UTAUT delved into the aspects of effort expectancy and performance expectancy, explaining subtle differences. Regarding effort expectancy, 35% of students, 43% of faculty, and 41% of administrative staff reported positive perceptions. Notably, the faculty segment displayed a relatively higher perception of effort expectancy compared to students, potentially indicating varying perceptions of the ease of incorporating AI technologies. Conversely, performance expectancy results revealed 33-35% positive responses, showcasing a relatively consistent perception across the segments.

Analysis through the TAM framework displays the perceived usefulness and ease of use of AI technologies with 37 to 49% positive responses. Notably, administrative personnel exhibited a slightly higher perceived usefulness compared to the other segments. Additionally, the ease-of-use aspect depicted considerable disparities among the surveyed sample with 37% to 49% positive responses, revealing a notable variance in faculty members' higher ease-of-use perceptions compared to students and administrative staff.

The study observed a general positive inclination toward AI adoption among all surveyed segments. However, nuanced differences in perceptions of effort, performance, usefulness, and ease of use between faculty, administrative staff, and students necessitate tailored approaches for successful AI integration within the institution. Analysis points out that the TAM framework is more applicable to study the perceived usefulness and ease of use of AI technologies. Understanding these variations could facilitate targeted interventions and training strategies to enhance AI acceptance and utilization across all segments.

Table 2. Response Distribution by Category

Response Category				
Theory	**Factor**	**Students**	**Faculty**	**Admin**
Theory of Planned Behaviour (TPB)	AI adoption (Behavioural Intention)	36%	39%	41%
	Attitude	36%	37%	39%
	Perceived Behavioural Control (Knowledge)	34%	39%	40%
Unified Theory of Acceptance and Use of Technology (UTAUT)	Effort Expectancy	35%	43%	41%
	Performance Expectancy	33%	34%	35%
Technology Acceptance Model (TAM)	Usefulness	34%	35%	37%
	Ease of Use	37%	49%	46%
Total		88	42	68

The survey yielded insightful data on AI adoption attitudes across different age demographics, as displayed in Table 3. Behavioural intention toward AI adoption had higher positive responses among older age groups (27 and above), ranging from 37% to 40%. Attitudes toward AI adoption followed a similar trend, with 36% to 39% positive responses among individuals over 27 years old. Perceived behavioural control exhibited a consistent trend. Results for effort expectancy showed positive responses ranging from 33% to 42%. Differences in performance expectancy perceptions were observed: 32% for ages 15-20, 36% for ages 21-26, 32% for ages 27-35, and 35% for individuals above 35 years. Perceived usefulness of AI showed a progressive trend with age: 32% for ages 15-20, 36% for ages 21-26, 33% for ages 27-35, and the highest perception of 37% among individuals above 35 years. Ease of use perceptions notably increased with age.

The data vividly illustrates age-related differences in AI adoption attitudes. Older age groups consistently displayed higher positive inclinations toward AI adoption across multiple theoretical models. The correlation between age and acceptance levels suggests that as age increased, so did the inclination toward embracing AI technologies. Analysis pints out that the TAM framework is more applicable to study the perceived usefulness and ease of use of AI technologies. These insights underscore the importance of tailored strategies considering age-specific expectations and perceptions. Understanding these age-based nuances could significantly influence the successful integration and acceptance of AI technologies within institutions.

Table 3. Response Distribution by Age Groups

Theory	Factor	15-20	21-26	27-35	>35
Theory of Planned Behaviour (TPB)	AI adoption (Behavioural Intention)	36%	36%	37%	40%
	Attitude	33%	35%	36%	39%
	Perceived Behavioural Control (Knowledge)	33%	35%	36%	39%
Unified Theory of Acceptance and Use of Technology (UTAUT)	Effort Expectancy	33%	36%	37%	42%
	Performance Expectancy	32%	36%	32%	35%
Technology Acceptance Model (TAM)	Usefulness	32%	36%	33%	37%
	Ease of Use	34%	40%	41%	47%
	Total	21	30	56	91

The survey data structured around prominent behavioural models reveal intriguing insights into AI adoption attitudes across different genders which is shown in Table 4. When examining behavioural intentions toward AI adoption, males reported a 37% inclination, while females expressed a slightly higher inclination at 39%. Attitudes toward AI adoption was closely aligned, with males indicating a 36% positive attitude and females at 37%. Perceived behavioural control, measured through knowledge, showed a similar alignment between genders, with both males and females reporting 36% and 37%, respectively. In terms of effort expectancy, both genders demonstrated closely matched perceptions, with males and females reporting 37% and 39%, respectively. Differences were observed in performance expectancy perceptions, where males reported 35% and females slightly lower at 34%. Perceived usefulness of AI showcased parity among genders, with both males and females expressing identical percentages at 35%. The ease-of-use factor revealed a slight variance, with males at 41% and females slightly higher at 44%. The data underscores a remarkable similarity in AI adoption attitudes between genders across various theoretical models. Both males and females showcased consistent inclinations toward AI adoption, demonstrating closely aligned behavioural intentions, attitudes, perceived behavioural control, and usefulness perceptions. However, nuanced differences emerged in perceived performance expectancy and ease of use. Males reported marginally higher expectations in ease of use (41%) compared to females (44%), whereas females indicated a slightly lower perception of performance expectancy (34%) in contrast to males (35%). These results highlight a convergence in AI adoption attitudes between genders while also pinpointing specific areas of divergence. Analysis pints out that the TAM framework is more applicable to study the perceived usefulness and ease of use of AI technologies. Understanding these nuanced differences is crucial in tailoring strategies to foster more comprehensive and inclusive AI adoption within the institution.

Table 4. Response Distribution by Gender

Theory	Factor	Male	Female
Theory of Planned Behaviour (TPB)	AI adoption (Behavioural Intention)	37%	39%
	Attitude	36%	37%
	Perceived Behavioural Control (Knowledge)	36%	37%
Unified Theory of Acceptance and Use of Technology (UTAUT)	Effort Expectancy	37%	39%
	Performance Expectancy	35%	34%
Technology Acceptance Model (TAM)	Usefulness	35%	35%
	Ease of Use	41%	44%
	Total	57	141

5.2 Regression Analysis

The regression analysis aimed at understanding the relationship between independent variables and dependent variables. Iindependent variables are Attitude (ATT), perceived behavioural control regards knowledge (KW), Effort Expectancy (EE), Performance Expectancy (PE), Usefulness, and Ease of Use (EU) in predicting AI adoption behavioural intention (BI). Screenshots of the regression analysis from Eviews software are given Annexure-C .

The regression analysis as displayed in Table 5 explores the determinants of AI adoption through three distinct models targeting the overall sample (Model 1), females (Model 2), and males (Model 3).

In Model 1, ATT and KW demonstrate statistically significant positive associations with AI adoption (Coefficients: 0.28*** and 0.33***, respectively, both with p-values < 0.01). Usefulness also exhibits significance (Coefficient: 0.22*, p-value < 0.05). The Adjusted R-squared for Model 1 is 0.68, based on 198 observations.

Model 2, focusing on females, highlights the significance of ATT and KW in predicting AI adoption (Coefficients: 0.42*** and 0.32***, respectively, both with p-values < 0.01). Additionally, Usefulness plays a crucial role (Coefficient: 0.28***, p-value < 0.01). Model 2 exhibits a slightly higher Adjusted R-squared of 0.70, based on 141 observations.

Conversely, Model 3, concentrating on males, presents nuanced findings. EE emerges as a key predictor with a significant positive association (Coefficient: 0.49***, p-value < 0.01). ATT and PE do not show statistical significance. Model 3 has an Adjusted R-squared of 0.72, based on 57 observations.
In summary, the analysis underscores the varied impact of psychological and usability factors on AI adoption across the entire population and gender subgroups, shedding light on nuanced patterns that may inform targeted strategies for fostering AI adoption.

Table 5. Regression Results Comparison by Overall Sample vs. Gender

Dependent Variables (AI adoption)			
Independent Variables	**Model 1 (All)**	**Model 2 (Female)**	**Model 3 (Male)**
Attitude (ATT)	0.28*** (0.08)	0.42*** (0.08)	-0.32 (0.19)
Perceived Behavioural Control explained by Knowledge (KW)	0.33*** (0.10)	0.32*** (0.10)	0.48 (0.30)
Effort Expectancy (EE)	0.11 (0.08)	0.00 (0.08)	0.49*** (0.18)
Performance Expectancy (PE)	0.06 (0.09)	0.03 (0.09)	0.36 (0.25)
Usefulness	0.22* (0.11)	0.28*** (0.12)	0.16 (0.23)
Ease of Use (EU)	0.08 (0.13)	0.09 (0.14)	-0.14 (0.32)
Adj. R square	0.68	0.70	0.72
Observations	198	141	57
*****,** and * indicate significance at 1%, 5% and 10% level of significance**			

The regression analysis in Table 6 delves into the dynamics of AI adoption across different demographic segments, as represented by four distinct models: Model 1 for the overall sample, Model 2 for students, Model 3 for faculty, and Model 4 for administrators. In Model 1, the results reveal that ATT (Coefficient: 0.28***, p-value < 0.01) and KW (Coefficient: 0.33***, p-value < 0.01) significantly influence AI adoption, contributing to an Adjusted R-squared of 0.68 based on 198 observations.

Model 2, focusing on students, shows that ATT (Coefficient: 0.24*, p-value < 0.05) and KW (Coefficient: 0.34**, p-value < 0.05) play key roles, resulting in a similar Adjusted R-squared of 0.68 from 88 observations.
Model 3, tailored for faculty, emphasizes the significance of ATT (Coefficient: 0.50***, p-value < 0.01) and KW (Coefficient: 0.36*, p-value < 0.05), with an exceptional Adjusted R-squared of 0.74 based on 42 observations. Lastly, Model 4 for administrators suggests that KW (Coefficient: 0.31*, p-value < 0.05) plays a pivotal role in AI adoption, contributing to an Adjusted R-squared of 0.64 from 68 observations.

These findings underscore the nuanced variations in the determinants of AI adoption across diverse demographic groups, providing valuable insights for targeted strategies in fostering technology acceptance within specific organizational segments.

Table 6. Regression Results Comparison by Overall Sample vs. Category

Dependent Variables (AI adoption)				
Independent Variables	**Model 1 (All)**	**Model 2 (Students)**	**Model 3 (Faculty)**	**Model 4 (Admin)**
Attitude	0.28*** (0.08)	0.24* (0.13)	0.50*** (0.14)	0.06 (0.17)
Perceived Behavioural Control explained by Knowledge (KW)	0.33*** (0.10)	0.34** (0.15)	0.36* (0.20)	0.31* (0.18)
Effort Expectancy	0.11 (0.08)	0.15 (0.12)	-0.05 (0.16)	0.20 (0.16)
Performance Expectancy	0.06 (0.09)	0.05 (0.13)	-0.02 (0.18)	0.21 (0.17)
Usefulness	0.22* (0.11)	0.27 (0.17)	-0.03 (0.22)	0.29 (0.22)
Ease of Use	0.08 (0.13)	0.01 (0.21)	0.40 (0.25)	-0.01 (0.29)
Adj. R square	0.68	0.68	0.74	0.64
Observations	198	88	42	68
*****,** and * indicate significance at 1%, 5% and 10% level of significance**				

The regression analysis as shown in Table 7 discerns the factors influencing AI adoption across distinct age groups, as encapsulated in five models: Model 1 for the overall population, Model 2 for individuals aged 15-20, Model 3 for those aged 21-26, Model 4 for the 27-35 age bracket, and Model 5 for individuals above 35. In Model 1, ATT (Coefficient: 0.28***, p-value < 0.01) and KW (Coefficient: 0.33***, p-value < 0.01) emerge as significant contributors to AI adoption, resulting in an Adjusted R-squared of 0.68 from 198 observations.

Examining age-specific models, Model 2 (15-20 age group) reveals ATT (Coefficient: 0.28, p-value > 0.05) as influential, while in Model 3 (21-26 age group), KW (Coefficient: 0.39, p-value < 0.05) and EE (Coefficient: 0.60***, p-value < 0.01) play key roles, contributing to an Adjusted R-squared of 0.62 based on 21 and 30 observations, respectively.

For Model 4 (27-35 age group), ATT (Coefficient: 0.33**, p-value < 0.01) and EE (Coefficient: 0.11, p-value > 0.05) are significant factors, leading to an Adjusted R-squared of 0.80 from 56 observations. In Model 5 (individuals above 35), ATT (Coefficient: 0.34***, p-value < 0.01) and KW (Coefficient: 0.22, p-value < 0.05) exhibit importance, contributing to an Adjusted R-squared of 0.62 based on 91 observations.

These findings illuminate the nuanced interplay of psychological and usability factors across age groups in shaping AI adoption, underscoring the need for targeted strategies tailored to the specific preferences and challenges of distinct demographic segments.

Table 7. Regression Results Comparison by Overall Sample vs. Age

Dependent Variables (AI adoption)					
Independent Variables	**Model 1 (All)**	**Model 2 (15-20)**	**Model 3 (21-26)**	**Model 4 (27-35)**	**Model 5 (> 35)**
Attitude	0.28*** (0.08)	0.28 (0.29)	0.08 (0.30)	0.33** (015)	0.34*** (0.11)
Perceived Behavioural Control explained by Knowledge (KW)	0.33*** (0.10)	0.56 (0.51)	0.39 (0.27)	0.26* (0.13)	0.22 (0.17)
Effort Expectancy	0.11 (0.08)	-0.02 (0.25)	0.60*** (0.21)	0.11 (0.14)	0.06 (0.13)
Performance Expectancy	0.06 (0.09)	-0.45 (0.48)	0.25 (0.20)	0.18 (0.14)	0.03 (0.14)
Usefulness	0.22* (0.11)	0.94** (0.39)	-0.23 (0.35)	0.23 (0.17)	0.12 (0.19)
Ease of Use	0.08 (0.13)	-0.34 (0.49)	-0.01 (0.39)	0.17 (0.21)	0.26 (0.21)
Adj. R square	0.68	0.62	0.73	0.80	0.62
Observations	198	21	30	56	91
*****,** and * indicate significance at 1%, 5% and 10% level of significance**					

5.3 Hypotheses Testing

The results of the regression analysis indicate that among the formulated hypotheses H3, H5, H6 and H7 have been accepted, shedding light on the critical factors influencing the behavioural intention and adoption of AI in education. Hypothesis H3 posited that knowledge significantly affects the behavioural intention to use and adopt AI in education. The acceptance of H3 suggests that individuals' knowledge, encompassing skills and contextual factors, plays a pivotal role in shaping their intention to adopt AI in an educational setting. This underscores the importance of educational initiatives and training programs to enhance users' knowledge and capabilities for successful AI integration.

Hypothesis H5 proposed that EU significantly affects ATT toward the use and adoption of AI in education. The acceptance of H5 underscores the impact of users' perceptions regarding the usefulness of AI on shaping their attitudes. It emphasizes the need for educational stakeholders to highlight the practical benefits and advantages of AI in order to foster positive attitudes and, subsequently, encourage adoption.

Hypothesis H6 asserted that ATT significantly affects the behavioural intention to use and adopt AI in education. The acceptance of H6 emphasizes the central role of individuals' attitudes in influencing their behavioural intentions. This finding underscores the importance of cultivating positive attitudes toward AI to drive intentions and, ultimately, adoption in educational contexts.

Hypothesis H7 posited that behavioural intention positively affects the use and adoption of AI in education. The acceptance of H7 suggests that individuals' strong intent, as evaluated within their specific context, plays a significant role in shaping the actual use and adoption of AI in an educational setting. This underscores the importance of understanding and cultivating positive behavioural intentions to drive successful adoption outcomes.

While some hypotheses were not supported by the regression results, the acceptance of H3, H5, and H6 provides actionable insights for educators, policymakers, and technology developers aiming to promote the effective and widespread adoption of AI in education. It highlights the significance of addressing knowledge gaps, emphasizing the usefulness of AI, and fostering positive attitudes among users to enhance the successful integration of AI technologies in educational settings.

5.4 Correlation Analysis

The correlation matrix as displayed in Table 8 provides insights into the relationships among variables. The correlations between BI and its factors, particularly ATT, KW, and EU, are notably high, indicating a significant relationship between these factors and AI adoption Behavioural intention. KW demonstrates consistent strong correlations with most factors, suggesting its influential role in shaping attitudes and perceptions related to AI adoption. EE and USFELNESS also exhibit moderate to strong correlations with other factors, indicating their relevance in understanding AI adoption behaviours. The correlation matrix highlights strong associations between AI Adoption Behavioural Intention (BI) and several factors, including ATT, KW, EE, EU, and Usefulness. These correlations signify the interdependence and influence of these factors on individuals' inclinations toward adopting AI technologies. Notably, ATT, KW, and EU demonstrate particularly robust associations with BI, suggesting their pivotal roles in influencing AI adoption behaviours among respondents.

Table 8. Correlation Analysis Result

	AI Adoption (BI)	**ATT**	**KW**	**PE**	**EE**	**EU**	**Usefulness**
AI Adoption (BI)	1						
ATT	0.74	1					
KW	0.76	0.72	1				
PE	0.69	0.72	0.72	1			
EE	0.71	0.70	0.79	0.64	1		
EU	0.76	0.75	0.82	0.75	0.81	1	
Usefulness	0.74	0.76	0.72	0.79	0.69	0.88	1

5.5 Potential AI Usage Finding

The survey findings outline distinct intentions among students, faculty, and administrators regarding AI utilization in academic and professional domains as shown in Table 9. For students, 41% aim to use AI for writing skills, 37% for assignment preparation, 30% for creating presentations, and 26% for feedback on submissions. Additionally, 19% are interested in AI-driven personalized tutoring. Faculty members show intentions: 36% for preparing lectures, 31% for presentations, and around 20% for grading, plagiarism detection, and automating administrative tasks. Administrators/employees aim: 38% for reports, 31% for meeting minutes, 25% for task automation, 20% for multimedia content creation, and 23% for documentation and scheduling automation using AI. The survey depicts diverse preferences across roles: students prioritize academic support, faculty focus on teaching aids, while administrators prioritize workflow optimization and data-driven decision-making using AI.

Table 9. Responses for Intentional Usage

If you are a student, please answer the following: **I have intention to use AI because it helps me when I…..**	**COUNT**	**%**
Improve my writing skills	81	41
Prepare my assignments	74	37
Create my presentations	59	30
Get feedback for my submissions	52	26
Have a personalized tutor	37	19
If you are a faculty/teacher, please answer the following: **I have intention to use AI because it helps me when I….**		
Prepare my lectures	71	36
Create my presentations	61	31
Grade assignments and tests	39	20
Detect plagiarism in student's submission	35	18
Automate administrative tasks	39	20
If you are an administrator/employee, please answer the following: **I have intention to use AI because it helps me when I….**		
Record meeting of minutes	61	31
Generate creative reports and dashboards	75	38
Convert my text into speech and generate videos	40	20
Automate documentation	46	23
Manage calendars and schedules	46	23
Automate repetitive tasks	50	25

5.6 AI Readiness Assessment Tool

In response to one of the identified research gaps surrounding the absence of a comprehensive AI readiness assessment tool, an innovative application designed to evaluate users' readiness for the adoption of AI in various facets of their professional or educational spheres have been developed. Our AI Assessment Tool serves as a pioneering solution, addressing the critical need for an evaluation mechanism in the realm of AI integration. This tool meticulously analyses and assesses an individual's preparedness and suitability for incorporating AI into their work or educational practices. The application offers a thorough evaluation process covering multiple dimensions of AI adoption readiness, employing the TPB, UTAUT, and TAM. The tool allows users to receive personalized feedback based on their specific strengths and areas for improvement in relation to AI adoption. The function of the tool is presented in the form of a flowchart shown in Figure 6.

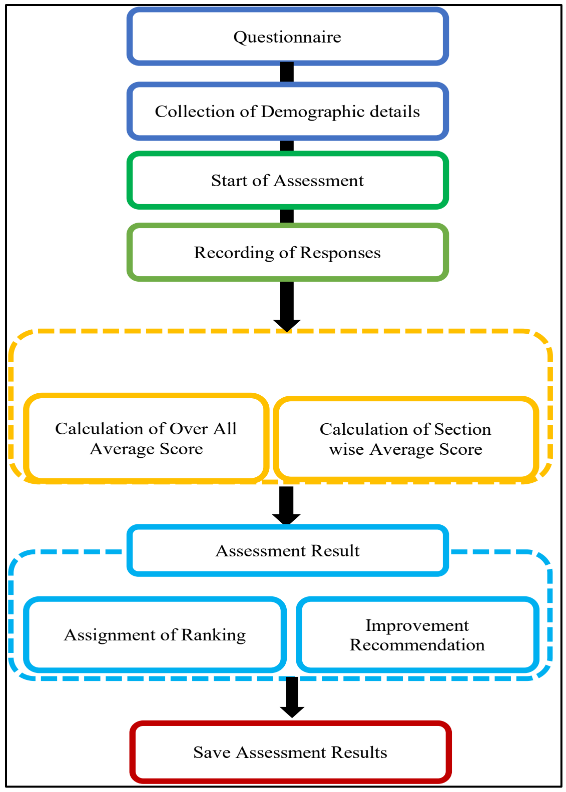

Figure 6. Functioning of AI Readiness Assessment Tool

The tool utilizes the Likert scale to assess the user's AI readiness across seven sections, aligning with previously developed hypotheses. Each question presents five possible responses ranging from 'Strongly disagree' to 'Strongly agree,' corresponding to rankings from 1 to 5, respectively. Rankings are then assigned based on the average score obtained, using a scale; 1.0-1.5: Poor, 1.51-2.5: Average, 2.51-3.5: Good, 3.51-4.5: Very good, and 4.51-5.0: Excellent (see Figure 7).

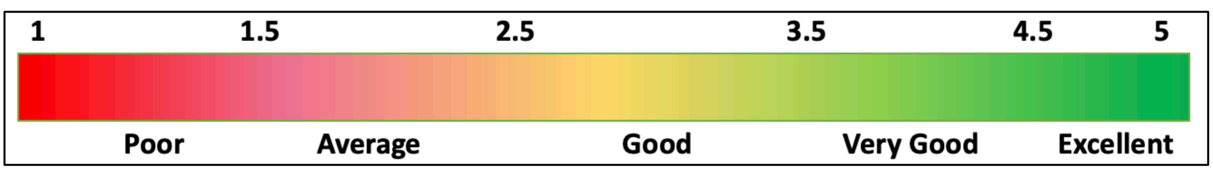

Figure 7. Ranking Scale

The tool recommends improvement based on the sections with least average score. The application has been meticulously crafted using a robust blend of HTML, CSS, and JavaScript. Leveraging the power of these languages, our team has meticulously coded and optimized the tool to ensure a smooth and responsive user experience across various platforms and devices. A short description of these languages is given in following paragraphs.

HTML (Hypertext Markup Language): At the core of our application lies HTML, the fundamental language that structures and presents content on the web. HTML forms the backbone of our tool, providing the structural framework for creating the various elements that comprise the assessment interface. It enables the creation of interactive components and ensures the compatibility of our application across different browsers and devices.

CSS (Cascading Style Sheets): CSS plays a pivotal role in the aesthetic and stylistic appeal of our assessment tool. It provides the visual styling and layout specifications, allowing for the customization and enhancement of the user interface. Through CSS, it is ensured that a visually engaging and intuitive design, optimizing the user experience by presenting information in an organized and visually appealing manner.

***JavaScript**:* JavaScript, a versatile scripting language, forms the dynamic and interactive layer of our application. Leveraging the power of JavaScript, our tool incorporates functionalities such as real-time validation, interactive prompts, and responsive elements. It enables the creation of dynamic content, facilitates user interactions, and enhances the overall responsiveness of the assessment tool.

The utilization of HTML, CSS, and JavaScript ensures the application's compatibility across various platforms, including desktops, tablets, and mobile devices. This compatibility allows users to access the assessment tool seamlessly from their preferred devices without compromising functionality or user experience.

The AI Readiness Assessment Tool stands out as a pioneering solution in the landscape of AI adoption. Its comprehensive evaluation framework, and user-friendly design make it a pivotal asset for individuals seeking to gauge their readiness for the AI-driven future. Screenshots of the assessment tool are given Annexure-D .

5.7 Validation
The validation of results assessing readiness for AI adoption in education involved a rigorous process, including consultation with an educational expert with over 20 years of experience. The expert's feedback enhanced the study's credibility by evaluating assessment tools, methodology, and alignment with objectives. This collaborative validation aimed to produce reliable and meaningful findings, refining the research design and addressing potential biases. Overall, the involvement of the educational expert strengthened the study's rigor and credibility in assessing the readiness of students, teachers, and administrators for AI integration in education.

6. Conclusion
AI stands at the lead of revolutionizing educational paradigms, especially within the dynamic landscape of the KSA. This transformative potential of AI promises to guide in innovative pedagogical methods and adapted learning experiences tailored to individual needs. However, a critical impediment to its seamless integration remains the absence of a comprehensive theoretical framework that can guide its application effectively.

This research has undertaken a meticulous exploration, aiming to construct such a fundamental theory explaining AI's role in amplifying pedagogical efficacy within KSA. By diving deep into various facets of AI's application, including its public perception, usability, benefits, and challenges, this study seeks to furnish educators, policymakers, and technologists with indispensable insights. The ultimate objective is to architect an educational framework that not only resonates with the Vision 2030 goals but also optimally harnesses AI's transformative capabilities.

Addressing the gaps identified, this research navigates the intricacies associated with AI's adoption in KSA's educational realm. Utilizing established theoretical frameworks like the TPB, UTAUT, and TAM, coupled with empirical survey methodologies, the study provides a comprehensive understanding of AI's potentials and hurdles in the educational domain. Utilizing the established theories and methodologies, the research introduces an AI assessment tool, guiding KSA towards a modern, adaptive, and effective educational future aligned with Vision 2030. The regression analyses undertaken to understand the determinants of AI adoption across diverse demographic segments have provided valuable insights into the nuanced factors influencing technology acceptance. Across gender differences, the significance of ATT and KW is evident, with variations in the impact of EE and Usefulness. Notably, females exhibit a stronger positive relationship between ATT and AI adoption.

In examining academic roles, ATT and KW consistently emerge as critical factors highlighting the unique dynamics within this segment. Further, the exploration of age groups reveals distinct patterns. The 27-35 age group demonstrates exceptional receptivity to AI adoption, emphasizing the prominent roles of ATT and EE in this demographic. These findings collectively underscore the importance of tailoring strategies for promoting AI adoption based on the unique characteristics of each demographic segment. While psychological factors such as ATT and KW consistently contribute to technology acceptance, the varying impact of other factors emphasizes the need for targeted interventions. As educational institutions strive to implement AI technologies, understanding and addressing the specific preferences and challenges within diverse user groups will be crucial for successful adoption and integration into everyday practices. This study provides systematic guidelines and strategies for students, faculty, and administration to harness AI's potential in education. Employing theoretical frameworks like TPB, UTAUT, and TAM revealed positive inclinations toward AI showing nuanced differences in perceptions across age demographics and genders. Regression analyses highlighted attitude's influence among different segments, emphasizing age-specific nuances in AI acceptance, while perceived behavioural control exhibited broader significance across ages. However, in certain models, individual variables like EE and PE did not significantly predict AI adoption intention. Additionally, systematic guidelines tailored within the TAM framework were developed. An innovative AI Readiness Assessment Tool is introduced to evaluate users' preparedness for AI integration, offering a comprehensive analysis based on TPB, UTAUT, and TAM frameworks. Based on the study's results within the TAM framework, specific systematic guidelines and operational strategies, tailored for students, faculty, and administrative staff to harness the potential of AI in education, have been developed. These are depicted in Figures 8, 9, and 10, respectively.

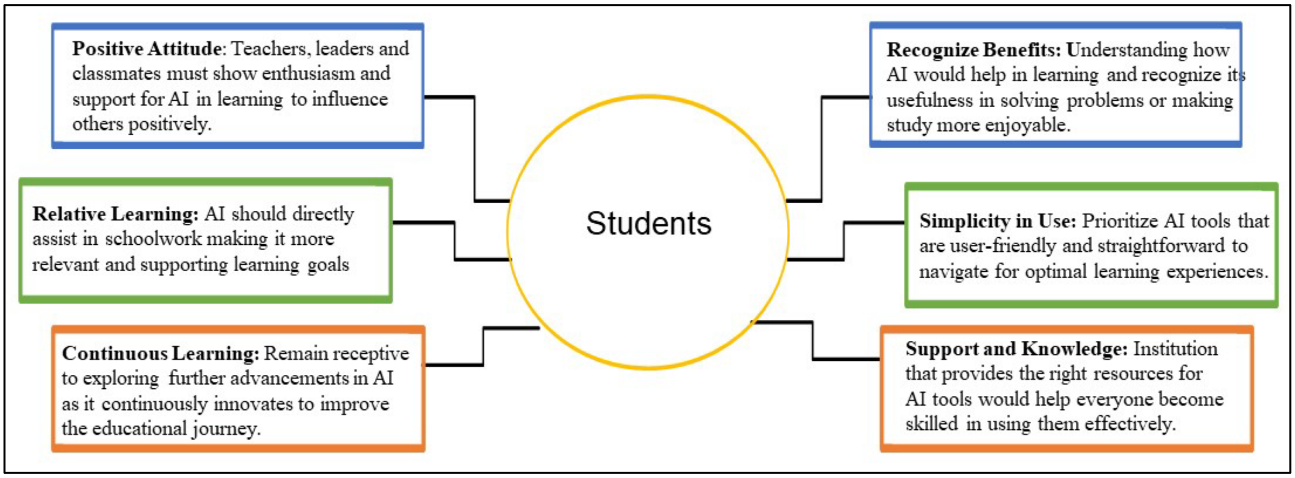

Figure 8. Operational Strategies for Students

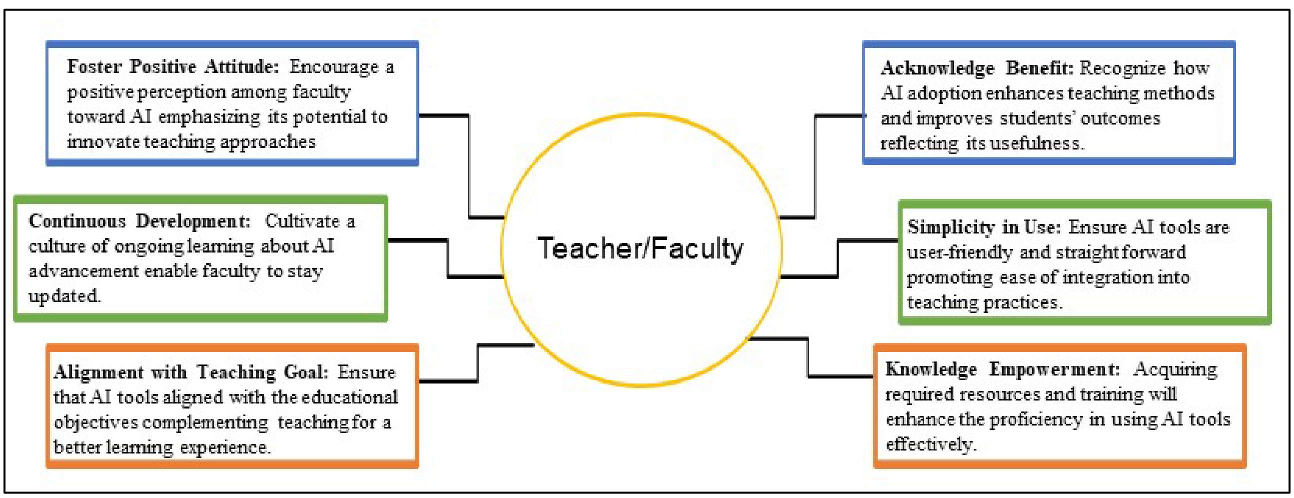

Figure 9. Operational Strategies for Faculty

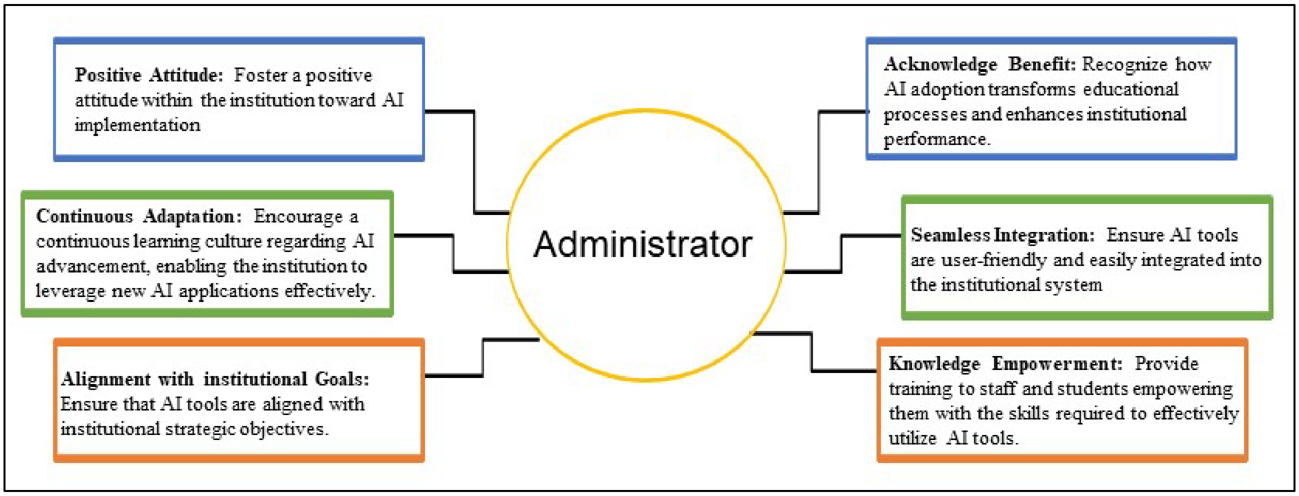

Figure 10. Operational Strategies for Administrator

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Biographies

Iman H. Musawa is a PhD student at Effat University, Saudi Arabia, specializes in the philosophy of Business Administration. She earned her Bachelor's degree in Management Information Systems and a Master in Business Administration from Dar Al-Hekma University, Jeddah. With over a decade as a technical specialist, Ms. Iman excels in managing and supporting systems. Her passion for bridging technology and business led her to pursue a PhD at Effat University, where she focuses on Artificial Intelligence topics. Ms. Iman's commitment to academic excellence, coupled with her rich professional background, positions her as a dynamic and forward-thinking scholar. With a solid foundation in both technology and business, she aspires to make meaningful contributions to the fields of Business Administration and Management Information Systems, driving innovation and fostering a deeper understanding of the evolving business landscape.

Rasha A. Almalik is currently pursuing a Ph.D., continues to embody a commitment to academic and professional excellence. As a seasoned IT professional turned doctoral candidate, Rasha's journey reflects a seamless transition from leadership roles to a pursuit of advanced knowledge. Having previously served as an experienced IT Director with a track record of successful digital strategy execution, Rasha's decision to pursue a Ph.D. in Business Administration signifies a deep dedication to continuous learning. This transition highlights Rasha's recognition of the evolving landscape and the importance of staying at the forefront of industry trends. Despite a shift to the academic realm, Rasha's background in management information systems, business administration, and a strong technological foundation enriches the scholarly pursuits. This unique blend of practical experience and academic curiosity positions Rasha as a dynamic and insightful contributor to the academic community. As a student in the Ph.D. program, Rasha is likely to bring a wealth of real-world insights to the academic environment, bridging theory and practice. Rasha's passion for technology-driven transformation remains a driving force, now channeled into rigorous research and scholarly exploration. Undoubtedly, Rasha's journey as a Ph.D. student adds a new dimension to an already impressive professional narrative, promising contributions that span both academia and the rapidly evolving field of information technology.

Rahatullah M. Khan with an extensive and diverse accomplished professional and academic background spanning more than 30 years, he has garnered substantial expertise as a senior executive and academic specializing in business and entrepreneurship/start-up development and growth, personnel management, and teaching across diverse regions such as Asia, the Middle East, and Europe. His professional journey traverses' sectors including heavy industry, process management, services, real estate, and higher education, where he has successfully nurtured and developed numerous start-ups. Adopting the philosophy of economic gardening, his approach centers on catalyzing the creation and development of start-ups, as well as fostering the growth of first and second-stage entrepreneurs. He provides robust and enriched support, offering guidance that empowers businesses to not only grow and thrive but also contribute to employment generation. In the realm of education, his teaching pedagogy is founded on principles of empowerment, personal transformation, and the practical application of theory. He is dedicated to enhancing students' knowledge, skills, and competencies by leveraging expertise, fostering reflective practices, and establishing authentic evidence. He firmly believes in an education that is dynamic, responsive to development, and adaptable to industry requirements. In addition to his professional pursuits, he has actively coached and mentored students, guiding them in strategic thinking, and inspiring innovation and creativity in their endeavors. He is the owner of www.plansane.com. It is a complete business planning and automated financial modelling website. He continues to bring his wealth of experience to the forefront, facilitating a platform that aligns with his commitment to fostering growth, innovation, and excellence in both business and education.