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Factors Influencing on Behavioral Intention to Adopt Artificial Intelligence for Startup Sustainability

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Abstract

This study investigates the factors affecting startup business owners and founders' intentions to adopt AI in the context of their business operations in Saudi Arabia. Employing a cross-sectional survey methodology, structured questionnaires were administered to startup business owners and founders, providing a snapshot of their perceptions and intentions regarding AI adoption. The data analysis was conducted utilizing the PLS-based structural equation modeling method. The study reveals that perceived usefulness, perceived ease of use, trialability, and observability positively influence attitudes toward AI adoption, underlining the importance of these factors. However, effort expectancy and facilitating conditions did not significantly impact attitudes. A positive attitude remains central in shaping the intention to adopt AI, aligning with Saudi Arabia's aspirations for technological advancement. These findings offer practical implications for entrepreneurs, emphasizing the need to prioritize user-friendly AI solutions, showcase successful AI implementations, and cultivate positive attitudes in their AI adoption journeys, aligning with Saudi Arabia's Vision 2030 goals.

Keywords: *Artificial Intelligence, Startup Business, Intention, Saudi Arabia.*

Introduction

Artificial Intelligence (AI) applications, powered by machine learning, are witnessing a significant surge across various sectors, including clinical (Busnatu et al., 2022), agricultural (Ben Ayed and Hanana, 2021), and educational research (Almaiah et al., 2022). This surge presents enticing opportunities for targeted utilization, attracting considerable attention from technology developers and entrepreneurial minds (Gupta et al., 2023). Nonetheless, the extent of AI adoption by startup founders and co-founders lacks comprehensive evidence, and outcomes vary based on research settings, resulting in inconclusive findings (Giuggioli and Pellegrini, 2023). AI has undeniably emerged as a transformative catalyst in the contemporary business landscape, offering startups a multitude of opportunities to revolutionize their operations, streamline processes, and secure a competitive advantage (Enholm et al., 2022; Bahoo et al., 2023). However, the decision to incorporate AI goes beyond technical considerations; it is intricately intertwined with the behavioral intentions of startup leaders and key stakeholders. In this intricate interplay of technology, innovation, and human dynamics, comprehending the 'why' and 'how' behind startup decisions to embrace AI is a critical endeavor (Dwivedi et al., 2021; Lévesque et al., 2022). This understanding is not only pivotal for the

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journey towards AI integration but also essential for unlocking the full transformative potential that AI holds for startups operating in today's dynamic business ecosystem.

In the era of digital disruption, startups are distinguished not only by their agility and innovation but also by their ability to leverage emerging technologies that can propel them to success (Enholm et al., 2022; Giuggioli and Pellegrini, 2023). AI, with its unparalleled ability to process vast data, discern patterns, and make intelligent predictions, has become a game-changer in this context. It equips startups with the means to extract valuable insights, automate routine tasks, and develop cutting-edge solutions at the forefront of industry innovation (Lee et al., 2019). Nonetheless, the adoption of AI is a nuanced process, influenced by a multitude of factors, primarily revolving around the behavioral intentions of those steering the startup. These intentions encompass the motivations, objectives, and aspirations that drive the startup's leadership and, consequently, the entire organization, to embrace AI technologies. This involves not only the willingness but also the readiness of decision-makers to undertake the necessary actions that usher their startup into the AI era (Schulte-Althoff et al., 2021; Santos, 2022).

In the context of Saudi Arabia, the behavioral intention to adopt Artificial Intelligence (AI) for startups takes center stage as the country undergoes a significant economic transformation through Vision 2030. The Saudi government's active promotion of AI and technology, evident in initiatives like the Saudi Data & AI Authority (SDAIA) and the National Strategy for Data & AI (NSDAI), creates a supportive ecosystem for startups eager to integrate AI into their operations (Ahmed et al., 2019; Al Anezi, 2021). The Saudi market, characterized by a large and increasingly tech-savvy population, provides a fertile ground for AI-driven startups to thrive (Al-Khalidi Al-Maliki, 2021; Al Hamli and Sobaih, 2023). Furthermore, sector-specific needs in industries like healthcare, finance, and logistics, alongside international collaborations with leading AI institutions, serve as strong motivators for startup founders and stakeholders to embrace AI. With government support in talent development and a burgeoning investment climate, Saudi startups have access to the resources and expertise needed to fuel their AI-driven aspirations. However, they must also navigate challenges related to regulations, data privacy, and cybersecurity, all of which influence the behavioral intentions of founders and stakeholders in their AI adoption decisions (Bakry and Saud, 2021; Alshahrani et al., 2022; Al-Ayed et al., 2023). Understanding these behavioral intentions is pivotal in guiding Saudi Arabia's path toward economic diversification and technological innovation.

Comprehending these behavioral intentions is a multifaceted endeavor, as they are shaped by a myriad of factors. These factors encompass the startup's ambitions, strategic goals, and recognition of the unique value proposition that AI offers. AI has emerged as a transformative force in the modern business landscape, presenting numerous opportunities for startups to innovate, streamline operations, and gain a competitive edge. However, the decision to adopt AI is not solely a technological one; it is profoundly influenced by the behavioral intentions of startup founders and key stakeholders. Understanding why and how startups choose to embrace AI is vital to unlock its transformative potential. Hence, this study delves into the concept of behavioral intention to adopt AI for startups, exploring the key factors, motivations, and challenges that shape their decisions in a rapidly evolving Saudi Arabia’s technological landscape. This research is structured into separate components. The first part addresses the research gap and provides rationale for the study's objectives. The following section presents the conceptual framework and hypotheses. The third segment elaborates on the study's methodology and data analysis techniques, while the fourth segment utilizes structural equation modeling to present the results. The final part discusses the discussion and the implications of the findings.

Theoretical Background

In the realm of digital retail business, the utilization of information and communication technology has garnered considerable attention in the field of technology adoption research. Various theoretical frameworks have been extensively employed to investigate this phenomenon. Notable theories commonly utilized in the context of technology adoption encompass the Diffusion of Innovation theory (Rogers, 2003), the Theory of Reasoned Action (Fishbein and Ajzen, 1975), the DeLone and McLean Model of Information Success (DeLone and McLean, 2003), the Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (TAM) (Davis, 1986; Davis et al., 1989), Bailey and Pearson's analysis of computer user satisfaction (Bailey and Pearson, 1983) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012).

It's important to highlight the significant role that the Technology Acceptance Model (TAM) plays in the realm of information system research (Chuah et al., 2016; Kim and Chiu, 2019; Al-Ayed and Al-Tit, 2024). TAM, originally derived from the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975) in social psychology, has gained widespread recognition. While TRA has been applied in various domains, Davis introduced TAM specifically within the context of information systems (Davis, 1986). TAM comprises three fundamental components: attitude, perceived ease of use (PEU), and perceived usefulness (PU), collectively explaining a user's motivation to adopt new technology. Additionally, Davis and colleagues introduced behavioral intention (BI) as a new construct within TAM, directly influenced by attitude and perceived usefulness. Research by Legris et al. (2003) has emphasized that TAM accounts for a significant portion of system usage, typically ranging from 30% to 40%. Furthermore, numerous studies have identified perceived usefulness as the most influential element within the model (Legris et al., 2003; McFarland and Hamilton, 2006). Therefore, this research opts to utilize the TAM model as its theoretical foundation.

In spite of the extensive utilization of TAM in the realm of information system research, certain constraints have become apparent. For example, TAM may have difficulties in addressing emerging solutions or services (Wu, 2011). Garaca (2011) has voiced reservations about its constrained ability to predict and explain outcomes, as well as its practical suitability. Furthermore, it has been noted by others that empirical investigations employing TAM might produce inconclusive or erratic findings, emphasizing the necessity to identify supplementary elements that ought to be incorporated into the model (Legris et al., 2003). Tarhini et al. (2017) have endorsed the incorporation of context-specific elements into TAM, as such augmentations have the potential to enhance its explanatory capability. This highlights the importance of extending the TAM model with domain-specific variables.

Model and Construct Development

The foundational conceptual framework of this study builds upon TAM and introduces supplementary constructs, notably effort expectancy, trialability, observability and facilitating conditions, all of which are mentioned in Figure 1. Consequently, these additional constructs are derived from external factors that exert an impact on the intention to adopt AI for startup.

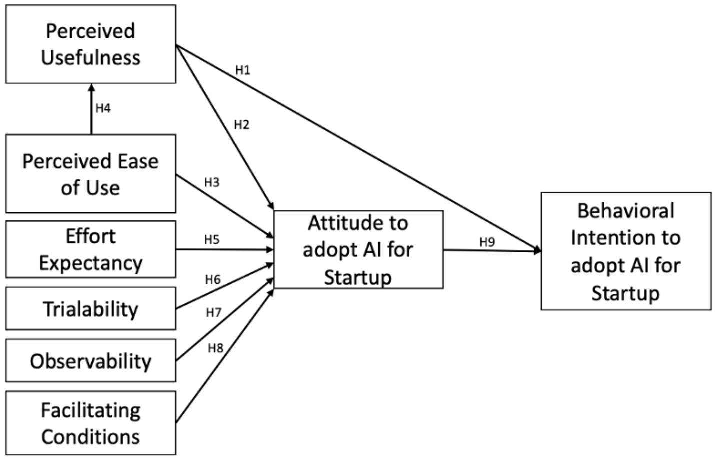

Figure 1. Research Model

Perceived Usefulness

Perceived usefulness, as defined in the TAM by Davis (1989), refers to the extent to which an entrepreneur believes that utilizing AI technology will enhance their performance and effectiveness. Substantial research has highlighted the crucial role of perceived usefulness in influencing behavioral intentions related to the adoption of various new technologies, including virtual reality (Fagan et al., 2012), mobile exergames (Broom et al., 2019), and mobile applications (Hsu and Lin, 2015). Sumak et al. (2011) have confirmed that perceived usefulness significantly and positively impacts attitude. Notably, researchers consistently identify perceived usefulness as a key predictor when explaining and forecasting users' intentions to accept and embrace information technology (Chuah et al., 2016; Dutot et al., 2019). When users believe that information technology offers benefits for their endeavors, this positive perception acts as a driving force for them to adopt the technology.

In the startup landscape of Saudi Arabia, comprehending how traditional entrepreneurs perceive the usefulness of AI is of utmost importance. Entrepreneurs need to assess whether they view AI as a tool that can enhance their startup's operations, innovation, and overall success. Entrepreneurs who perceive AI as beneficial and advantageous are more likely to exhibit a positive attitude towards its adoption and express a stronger intention to integrate it into their business operations. The following hypotheses are proposed based on these considerations.

H1: *Perceived usefulness influences on intention to adopt AI for startup*

H2: *Perceived usefulness influences on attitude to adopt AI for startup*

Perceived Ease of Use

Perceived ease of use is closely linked to how entrepreneurs perceive new services or products when considering their adoption for startups. The ease of using a new technology is a key factor that affects its adoption, especially in terms of how easy it is to incorporate into their business operations (Rogers, 2003). Various research studies consistently show that when entrepreneurs find a technology easy to use, it has a significantly positive impact on their attitudes toward it (Yulihasri et al., 2010; Lim and Ting, 2012). Additionally, users' attitudes toward technology usage are closely linked to their perception of its ease of use. When entrepreneurs view a technology as straightforward and user-friendly, they are more likely to embrace and regularly use it (Sevim et al., 2017). The ease of use of a technology is a critical factor in determining its acceptance, whereas complexity tends to reduce the intention to use it (Selamat et al., 2009).

In the realm of AI adoption for startups, perceived ease of use refers to the degree to which entrepreneurs view the use of AI tools and platforms as straightforward and user-friendly. In the Saudi context, traditional entrepreneurs may harbor concerns regarding the potential complexities and challenges associated with integrating AI into their startup operations. This hypothesis suggests that entrepreneurs' perceptions of the ease of using AI technology will play a significant role in shaping their attitudes toward AI adoption and their views on its usefulness for their startups. If traditional entrepreneurs find AI technology to be user-friendly and accessible, it is anticipated to positively influence their attitude, reinforcing their belief in the benefits and practicality of adopting AI for their startups. Consequently, the following hypotheses are proposed.

H3: *Perceived ease of use influences on attitude to adopt AI for startup*

H4: *Perceived ease of use influences on perceived usefulness*

Effort Expectancy

Effort expectancy refers to the level of ease or difficulty that consumers associate with using a particular technology (Venkatesh et al., 2012). Effort expectancy pertains to the perceived level of effort required to use AI in an organization (Cao et al., 2021). When individuals perceive AI as requiring less effort, it positively influences their overall attitude toward its adoption. In simpler terms, if they believe that implementing AI is not overly demanding or complex, they are more likely to have a positive attitude toward it. In a context where the Saudi government is investing in workforce development and skill-building programs for AI (Al Anezi, 2021; Al Hamli and Sobaih, 2023), it is expected that if individuals perceive that adopting AI for their startup requires less effort, it will lead to a more positive attitude toward AI adoption. The government's support in enhancing skills and reducing the effort required to use AI plays a role in shaping this perception. Consequently, the following hypothesis is proposed.

H5: *Effort expectancy influences on attitude to adopt AI for startup*

Trialability

Trialability refers to the ability of individuals to experiment with AI in their startup before fully committing to its adoption. Similarly, the ability to test AI's suitability and benefits in a real-world startup context can lead to a more favorable attitude (Park and Chen, 2007; Xu et al., 2023). Rogers (2003) put forth the idea that when individuals or organizations are given the opportunity to try or experiment with a new technology, it tends to facilitate a smoother and more rapid process of adoption and implementation. This trial period allows users to gain familiarity with the technology, assess its benefits, and reduce uncertainties or barriers, ultimately making the transition to adoption easier and more efficient. With the Saudi government encouraging experimentation and innovation, it is hypothesized that the opportunity to trial AI technology will have a positive impact on the overall attitude toward AI adoption for Saudi Arabian startups. The government's promotion of innovation and trialability is expected to shape a more favorable attitude. This hypothesis proposes that the opportunity to trial AI has a positive impact on their overall attitude toward AI adoption.

H6: *Trialability influences on attitude to adopt AI for startup*

Observability

Observability is related to how visible the outcomes and advantages of using AI are to others, including stakeholders and competitors (Xu et al., 2023). The idea is that the more visible the positive results, the more likely they are to have a favorable attitude (Alserr and Salepçioğlu, 2021). Increased observability enhances the likelihood of user adoption. When users can easily see and perceive an innovation, it becomes more probable that they will adopt it (Park and Chen, 2007). In the context of Saudi Arabia, where the outcomes of AI adoption are made more observable through government-backed initiatives and investments, it is expected that the visibility of positive results will have a positive influence on the general attitude toward AI adoption for startups. The government's commitment to making AI outcomes more observable plays a role in shaping this perception. This hypothesis suggests that when the outcomes of using AI are readily observable, it positively influences individuals' overall attitude toward AI adoption for their startup. Consequently, the following hypothesis is proposed.

H7: *Observability influences on attitude to adopt AI for startup*

Facilitating Conditions

Facilitating conditions encompass the presence of support, resources, and infrastructure required for successful AI adoption (Venkatesh et al., 2003; 2012). When these facilitating conditions are in place, they have a positive influence on individuals' overall attitude toward adopting AI (Brown and Venkatesh 2005). If the necessary resources and support systems are available, it contributes to a more positive attitude. In a context where the Saudi government and private sector are actively investing in infrastructure and resources for AI adoption, it is hypothesized that when these facilitating conditions are present, they will positively influence the overall attitude toward AI adoption. The government's support and investment incentives contribute to a more positive attitude among entrepreneurs. Consequently, the following hypothesis is proposed.

H8: *Facilitating conditions influence on attitude to adopt AI for startup*

Attitude

Ajzen (1991) argued that attitude plays a pivotal role in shaping behavioral intention. Yadav and Pathak (2017), in their study conducted in India, substantiated this notion by demonstrating a positive impact of attitude on behavioral intention. This alignment is in harmony with the findings of numerous other studies, indicating a robust and positive relationship between attitude and intention (Karjaluoto and Leppaniemi, 2013; Nasar et al., 2019). Attitudes are dynamic and subject to change over time as entrepreneurs accumulate experience and knowledge about AI technology for startups. If entrepreneurs hold a positive attitude toward AI adoption, they are more likely to express a strong intention to incorporate it into their startup operations. Conversely, if entrepreneurs exhibit a negative attitude, it is anticipated to diminish their intention to adopt AI, potentially leading to hesitation or even reluctance to embrace AI-driven strategies in their startup endeavors. Consequently, the following hypothesis is proposed.

H9: *Attitude influences on intention to adopt AI for startup*

Attitude With Mediating Effect

Venkatesh et al. (2003) have suggested that attitude functions as an intermediate factor in the relationship between perceived usefulness and behavioral intention. In the realm of technology acceptance research, Schaper and Pervan (2007) have also confirmed this connection, particularly in the healthcare sector. Gajanayake et al. (2014) have revealed that attitude plays a partially mediating role in linking perceived usefulness and behavioral intention. Additionally, Krishanan et al. (2016) have put forth the idea that attitude serves as a mediating factor in the relationship between perceived ease of use, perceived usefulness, and behavioral intention. Consequently, the following hypotheses are articulated.

H10: *Attitude mediates between perceived usefulness and intention*

H11: *Attitude mediates between perceived ease of use and intention*

H12: *Perceived usefulness and attitude mediate between perceived ease of use and intention*

H13: *Attitude mediates between effort expectancy and intention*

H14: *Attitude mediates between trialability and intention*

H15: *Attitude mediates between observability and intention*

H16: *Attitude mediates between facilitating conditions and intention*

Perceived Usefulness with Mediating Effect

The relationship between how easy a technology is perceived to be used and one's attitude towards it has been a central focus in technology acceptance literature (Gefen and Straub, 2000; Hussein et al., 2019). This connection is often influenced by perceived usefulness, a factor that plays a crucial role in shaping individuals' attitudes toward adopting technology (Makmor et al., 2019). When individuals find a technology easy to use, they are more likely to see it as valuable and beneficial for their specific needs. This positive perception of usefulness, in turn, contributes to the development of a favorable attitude toward the technology. As a result, the following hypotheses are put forward.

H17: *Perceived usefulness mediates between perceived ease of use and attitude*

H18: *Perceived usefulness mediates between perceived ease of use and intention*

Research Methods

Data collection

Survey data were gathered from startup business owners and founders in Saudi Arabia using a questionnaire that consisted of eight constructs and a total of 33 items. Participants were asked to share their opinions by using a five-point Likert scale, where 5 indicated strong agreement and 1 indicated strong disagreement. The data collection period extended from October to November in 2023. To ensure clarity and relevance, the questionnaire items were translated into Arabic, the native language of the respondents, following established translation guidelines, including both forward and backward translations, for linguistic consistency (Sousa and Rojjanasrirat, 2011).

Before the main study, a preliminary assessment involving 30 startup owners and founders was carried out to validate the questionnaire's reliability. This phase resulted in refinements and the removal of certain items to enhance the questionnaire's effectiveness, with the validated questionnaire being based on a previously published version. The online questionnaire was then made accessible to the target sample using a convenience sampling technique. A total of 621 responses were successfully collected from the participants. An overview of the demographic profiles of the survey participants is provided in Table 1. It shows that the majority were male (71%), with females making up the remaining 29%. The participants varied in age, with the largest group being below 25 years (34%). Most had a Bachelor's degree (73%), and their experience levels ranged from less than 3 years (39%) to more than 10 years (25%). The workplace sizes varied, with most having less than 10 employees (38%). Geographically, the "Central" region was the most common workplace location (79%).

Study Measures

The first part of the survey was allocated to clarify the research objectives and provide participants with guidance on how to fill out the questionnaire. Following that, participants were asked to supply their personal information in the subsequent section. The third section was specifically crafted to assess the constructs being studied. To assess the intention to adopt AI for startup, we incorporated three items from the works of Venkatesh et al. (2012) and Cao et al. (2021). The evaluation of attitude employed four items adapted from Dwivedi et al. (2017) and Cao et al. (2021). For the measurement of perceived usefulness and ease of use, we utilized six items for each, drawing from various sources including Davis (1989) and Park and Chen (2007). The assessment of effort expectancy consisted of four items adapted from Venkatesh et al. (2012) and Cao et al. (2021). To gauge trialability, we integrated four items from Moore and Benbasat (1991) and Park and Chen (2007). Observability was measured using two items, sourced from Moore and Benbasat (1991), Wu and Wu (2005), and Park and Chen (2007). The evaluation of facilitating conditions encompassed four items adapted from Venkatesh et al. (2012) and Cao et al. (2021). For a comprehensive overview of each construct and its associated items, refer to Table 2.

Table 1: Demographic of Participants (n=621).

	Frequency	**Percent**
Gender		
Male	443	71%
Female	178	29%
Age		
Below 25 years	211	34%
26-30 years	174	28%
31-40 years	130	21%
Above 40 years	106	17%
Education		
High school diploma	112	18%
Bachelor's degree	451	73%
Master's degree	46	7%
PhD	12	2%
Experience		
Less than 03 years	242	39%
3-5 years	131	21%
6-10 years	90	14%
Above 10 years	158	25%
Number of employees		
Less than 10	237	38%
10 to 20	112	18%
20 to 30	85	14%
30 to 40	58	9%
Above 40	129	21%
Workplace region		
Southern	14	2%
Northern	17	3%
Western	50	8%
Central	488	79%
Eastern	52	8%

Data analysis techniques

The data analysis employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, using SmartPLS 4 for this purpose. PLS-SEM is widely acknowledged and applied in the fields of management and information technology due to its reputation for producing reliable results

(Avkiran and Ringle, 2018). It is a non-parametric approach designed to capture the explained variance in latent dimensions that cannot be directly observed. PLS-SEM has the advantage of analyzing both direct and indirect effects of latent variables on a larger scale, making it suitable for evaluating strong and weak path coefficients within complex models (Hoyle, 1999; Heuer and Liñán, 2013).

PLS-SEM was selected as the analytical tool in this study because it provides a framework that integrates relevant theories and empirical data. Consequently, the use of PLS-SEM allows for the validation of theoretical concepts and simplifies the exploration of relationships among variables (Henseler et al., 2009). Following a methodological approach proposed by Leguina (2015), a two-step strategy was adopted. The first step involved examining the outer model to establish discriminant and convergent validity in line with the proposed theoretical model. Subsequently, the inner model was evaluated to test the hypotheses. This methodological approach and the use of PLS-SEM in the analysis ensure the robustness and validity of the research findings, allowing for a comprehensive exploration of the relationships and hypotheses outlined in the study.

Results

Measurement Model

The measurement model for this study includes eight key constructs, each assessed through a set of items mentioned in Table 2. Perceived Usefulness (PU) is characterized by a strong association with its items (PU1 to PU6), displaying high internal consistency with a Cronbach's alpha of 0.891, and reliable composite reliability of 0.576, along with an Average Variance Extracted (AVE) of 0.576. Perceived Ease of Use (PEU) also demonstrates strong loadings for items (PEU1 to PEU6) and boasts a high Cronbach's alpha of 0.857, along with a composite reliability of 0.501 and an AVE of 0.501. Effort Expectancy (EE), evaluated through items (EE1 to EE4), exhibits strong loadings, a high internal consistency with a Cronbach's alpha of 0.828, and a reliable composite reliability of 0.547, along with an AVE of 0.547. Trialability (TR) maintains robust loadings for items (TR1 to TR4), with high internal consistency (Cronbach's alpha of 0.839) and reliable composite reliability of 0.567, along with an AVE of 0.567. Observability (OB), represented by items OB1 and OB2, reveals strong loadings, high internal consistency (Cronbach's alpha of 0.822), and reliable composite reliability of 0.822 along with AVE value of 0.698. Facilitating Conditions (FC) displays strong loadings for items (FC1 to FC4), with moderate internal consistency (Cronbach's alpha of 0.732) and composite reliability of 0.509, along with an AVE of 0.509. Attitude to adopt AI for Startup (ATT) showcases strong loadings for items (ATT1 to ATT4), high internal consistency (Cronbach's alpha of 0.845), and a reliable composite reliability, along with an AVE. Intention to adopt AI for Startup (IU) is characterized by strong loadings for items (IU1 to IU3), high internal consistency (Cronbach's alpha of 0.854), a reliable composite reliability of 0.663, and an AVE of 0.663, signifying its substantial role in explaining variance within its items. These findings collectively affirm the robustness and reliability of the measurement model, reinforcing its suitability for exploring the study's relationships and hypotheses.

Table 3 displays the results of the Fornell-Larcker criterion, which is employed to assess the discriminant validity of the constructs in the study. The criterion helps determine whether each construct is distinct from the others by comparing the square root of the Average Variance Extracted (AVE) for each construct to the correlations between constructs. The square root of AVE for a given construct should be greater than the correlations involving that construct with other constructs to demonstrate discriminant validity. These results indicate that the constructs in the study are indeed separate and do not overlap, which is a crucial prerequisite for further analysis and interpretation of their relationships.

Structural Model

Table 4 presents the path coefficients representing the direct effects of various factors on users' attitudes and intentions regarding AI adoption in startup settings, along with associated statistical measures and results. The study's first hypothesis posited that perceived usefulness positively influences users' intentions to adopt AI in startup contexts. The analysis revealed a significant path coefficient of 0.425 (T statistic = 4.254, p-value = 0.000), supporting H1. This implies that when users perceive AI as useful for their startup operations, they are more likely to have the intention to adopt it. H2 suggested that perceived usefulness positively influences users' attitudes towards AI adoption in startups. The findings indicate a strong positive relationship, with a path coefficient of 0.48 (T statistic = 6.009, p-value = 0.000), thus supporting H2. This means that users who perceive AI as useful have a more positive attitude towards its adoption. H3 proposed that perceived ease of use positively affects users' attitudes towards AI adoption. The results show a positive relationship, with a path coefficient of 0.326 (T statistic = 3.239, p-value = 0.021), supporting H3. Users who find AI easy to use tend to have a more positive attitude towards its adoption. H4 suggested that perceived ease of use positively influences perceived usefulness of AI. The data supports this hypothesis, with a path coefficient of 0.532 (T statistic = 6.300, p-value = 0.000), affirming the positive impact of ease of use on the perceived usefulness of AI. H5 posited that effort expectancy positively influences users' attitudes towards AI adoption. However, the results indicate no significant relationship, with a path coefficient of 0.134 (T statistic = 1.580, p-value = 0.114). Thus, H5 is not supported. H6 proposed that trialability positively affects users' attitudes towards AI adoption. The findings support this hypothesis, with a path coefficient of 0.182 (T statistic = 2.121, p-value = 0.034). Users who have the opportunity to trial AI tend to have a more positive attitude towards its adoption. H7 suggested that observability positively influences users' attitudes towards AI adoption. The results confirm this hypothesis, with a path coefficient of 0.298 (T statistic = 3.565, p-value = 0.000), indicating that when users can readily observe AI in use, it positively influences their attitudes. H8 posited that facilitating conditions positively influence users' attitudes towards AI adoption. However, the findings reveal no significant relationship, with a path coefficient of -0.043 (T statistic = 0.453, p-value = 0.651). Hence, H8 is not supported, suggesting that the availability of resources and support does not strongly influence users' attitudes. The final hypothesis, H9, suggested that a positive attitude positively influences users' intentions to adopt AI in startup settings. The results support this hypothesis, with a path coefficient of 0.31 (T statistic = 2.403, p-value = 0.016). This indicates that a positive attitude towards AI adoption positively influences users' intentions.

Table 5 provides insights into the indirect effects of various factors. H10 posited that the relationship between perceived usefulness and intention is mediated by users' attitudes. The findings reveal a significant indirect effect ($\beta = 0.149$, $p = 0.017$), supporting H10. This underscores that users' positive attitudes towards AI adoption in startups partially mediate the impact of perceived usefulness on their intention to adopt AI. H11 proposed that users' attitudes mediate the relationship between perceived ease of use and intention. The results substantiate this hypothesis, showing a significant positive indirect effect ($\beta = 0.208$, $p = 0.025$). Therefore, users' attitudes play a mediating role in translating their perceived ease of use into the intention to adopt AI in startup settings. H12 suggested that the dual mediation between perceived ease of use and intention is mediated by perceived usefulness and attitudes. The data supports this hypothesis with a significant indirect effect ($\beta = 0.079$, $p = 0.033$), emphasizing that users' perceived usefulness and attitudes act as mediators in the relationship between these constructs, collectively influencing their intention. H13 proposed that the relationship between effort expectancy and intention is mediated by users' attitudes. However, the results indicate no significant mediating effect ($\beta = 0.041$, $p = 0.191$), not supporting H13. It suggests that users' attitudes may not significantly mediate the relationship between perceived effort expectancy and their intention to adopt AI in startups. H14 suggested that trialability influences users' intention through their attitudes. The findings reveal no significant indirect effect ($\beta = 0.056$, $p = 0.171$), not supporting H14. It implies that users' attitudes may not serve as a strong mediator in the relationship between trialability and their intention to adopt AI in startup environments. H15 postulated that observability affects intention via users' attitudes. However, the results show no significant indirect effect (β = 0.092, p = 0.086), not supporting H15. It suggests that users' attitudes may not significantly mediate the relationship between observability and their intention to adopt AI in startup contexts. H16 proposed that facilitating conditions influence users' intention through their attitudes. The findings indicate no significant mediating effect (β = -0.013, p = 0.681), not supporting H16. It implies that users' attitudes may not significantly mediate the relationship between facilitating conditions and their intention to adopt AI in startups. H17 posited that perceived ease of use influences attitudes through perceived usefulness. The results support this hypothesis with a significant indirect effect (β = 0.256, p = 0.000), emphasizing the mediating role of perceived usefulness in the relationship between perceived ease of use and attitudes towards AI adoption in startups. H18 suggested that the interplay of perceived ease of use, perceived usefulness, and intention is mediated by perceived usefulness. The data supports this hypothesis with a significant indirect effect (β = 0.226, p = 0.001), underlining that perceived usefulness acts as a mediator in the relationship between perceived ease of use and users' intention to adopt AI in startup environments.

Figure 2 serves as a valuable resource for assessing the goodness of fit in regression models pertaining to three key variables. The R-squared (R^2) and adjusted R-squared (R^2 adjusted) values provide insights into the model's explanatory power. For attitude, the model explains 60.3% of the variance ($R^2 = 0.603$), with a robust adjusted R-squared of 0.576. Intention is explained at 45.2% ($R^2 = 0.452$), and perceived usefulness at 28.3% ($R^2 = 0.283$), both retaining reliability with adjusted R-squared values of 0.44 and 0.275, respectively. These results demonstrate the model's effectiveness in capturing users' perceived usefulness, attitudes, and intentions, and in the context of AI adoption in startups.

Table 2: Measurement Model.

Items with constructs	Loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Perceived Usefulness		0.852	0.891	0.576
PU1: "Using the AI in my startup would enable me to accomplish tasks more quickly"	0.787			
PU2: "Using the AI would improve my performance"	0.784			
PU3: "Using the AI in my startup would increase my productivity"	0.825			
PU4: "Using the AI would enhance my effectiveness in the startup"	0.756			
PU5: "Using the AI would make it easier to do my routine startup work"	0.74			
PU6: "I would find the AI useful in my startup"	0.754			
Perceived Ease of Use		0.8	0.857	0.501
PEU1: "Learning to operate the AI would be easy for me"	0.696			
PEU2: "I would find it easy to get the AI to do what I want it to do"	0.707			
PEU3: "My interaction with the AI would be clear and understandable"	0.697			
PEU4: "I would find the AI to be flexible to interact with"	0.741			
PEU5: "It would be easy for me to become skillful at using the AI"	0.676			
PEU6: "I would find the AI easy to use"	0.727			
Effort Expectancy		0.727	0.828	0.547
EE1: "Learning how to use AI is easy for me"	0.71			
EE2: "My interaction with AI is clear and understandable"	0.739			
EE3: "I find AI easy to use"	0.77			
EE4: "It is easy for me to become skillful at using AI"	0.739			
Trialability		0.75	0.839	0.567

TR1: "Before deciding on whether or not to adopt the AI for my startup, I would need to use it on a trial basis"	0.781			
TR2: "Before deciding on whether or not to adopt the AI for my startup, I would need to properly try it out"	0.7			
TR3: "I would be permitted to use the AI for my startup on a trial basis long enough to see what it can do"	0.759			
TR4: "I know where I can go to satisfactorily try out various uses of the AI for my startup"	0.77			
Observability		0.767	0.822	0.698
OB1: "It is easy for me to observe others using the AI for startup"	0.831			
OB2: "I have had a lot of opportunity to see the AI for startup being used"	0.84			
Facilitating Conditions		0.718	0.732	0.509
FC1: "I have the resources necessary to use AI"	0.793			
FC2: "I have the knowledge necessary to understand AI"	0.75			
FC3: "AI is compatible with other technologies I use"	0.756			
FC4: "I can get help from others when I have difficulties using AI"	0.691			
Attitude to adopt AI for Startup		0.754	0.845	0.576
ATT1: "Using AI is a good idea"	0.766			
ATT2: "Using AI is a foolish idea"	0.737			
ATT3: "I like the idea of using AI"	0.794			
ATT4: "Using AI would be pleasant"	0.737			
Intention to adopt AI for Startup		0.742	0.854	0.663
IU1: "I intend to use AI in the future"	0.72			
IU2: "I will always try to use AI in my workplace"	0.877			
IU3: "I plan to use AI frequently"	0.837			

Table 3: Discriminant Validity (Fornell-Larcker Criterion).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Attitude	0.759							
(2) Effort Expectancy	0.51	0.74						
(3) Facilitating Conditions	0.582	0.587	0.639					
(4) Intention	0.592	0.67	0.621	0.814				
(5) Observability	0.655	0.528	0.68	0.697	0.835			
(6) Perceived Ease of Use	0.553	0.641	0.572	0.503	0.701	0.708		
(7) Perceived Usefulness	0.663	0.64	0.57	0.631	0.616	0.532	0.759	
(8) Trialability	0.68	0.578	0.512	0.606	0.673	0.666	0.661	0.753

Table 4: Path Coefficients (Direct Effect).

Paths	Beta	Standard deviation	T statistics	P values	Results
Perceived Usefulness -> Intention	0.425	0.1	4.254	0.000	H1 supported
Perceived Usefulness -> Attitude	0.48	0.08	6.009	0.000	H2 supported
Perceived Ease of Use -> Attitude	0.326	0.109	3.239	0.021	H3 supported
Perceived Ease of Use -> Perceived Usefulness	0.532	0.084	6.300	0.000	H4 supported
Effort Expectancy -> Attitude	0.134	0.085	1.580	0.114	H5 not supported
Trialability -> Attitude	0.182	0.086	2.121	0.034	H6 supported
Observability -> Attitude	0.298	0.084	3.565	0.000	H7 supported
Facilitating Conditions -> Attitude	-0.043	0.094	0.453	0.651	H8 not supported

Attitude -> Intention	0.31	0.129	2.403	0.016	H9 supported

Table 5. Path Coefficients (Indirect Effect).

Paths	Beta	Standard deviation	T statistics	P values	Results
Perceived Usefulness -> Attitude -> Intention	0.149	0.062	2.387	0.017	H10 supported
Perceived Ease of Use -> Attitude -> Intention	0.208	0.036	2.221	0.025	H11 supported
Perceived Ease of Use -> Perceived Usefulness -> Attitude -> Intention	0.079	0.037	2.133	0.033	H12 supported
Effort Expectancy -> Attitude -> Intention	0.041	0.032	1.309	0.191	H13 not supported
Trialability -> Attitude -> Intention	0.056	0.041	1.37	0.171	H14 not supported
Observability -> Attitude -> Intention	0.092	0.054	1.717	0.086	H15 not supported
Facilitating Conditions -> Attitude -> Intention	-0.013	0.032	0.411	0.681	H16 not supported
Perceived Ease of Use -> Perceived Usefulness -> Attitude	0.256	0.066	3.891	0.000	H17 supported
Perceived Ease of Use -> Perceived Usefulness -> Intention	0.226	0.07	3.227	0.001	H18 supported

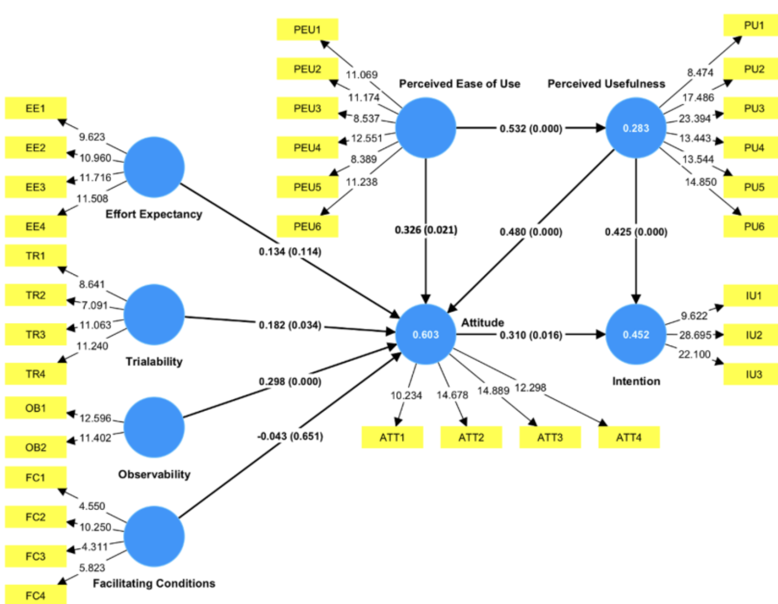

Figure 2. Model for Behavioral Intention to Adopt AI for Startup

Discussion

The research findings yield valuable insights into the adoption of AI within Saudi Arabian startup landscapes. Perceived usefulness emerges as a linchpin factor, reflecting the acknowledgment of AI's potential to augment performance and operational efficiency. In the Saudi context, where the Vision 2030 plan underscores the importance of technological innovation, this perception of usefulness becomes pivotal in driving the intention to adopt AI among entrepreneurs and startups. Hence, similar findings reported in other studies by Sumak et al., (2011) and Dutot et al. (2019). The significant influence of perceived ease of use resonates strongly in a region characterized by a diverse population. The findings emphasize the necessity of user-friendly AI design to cater to a broad spectrum of users, including those with varying levels of technical proficiency (Selamat et al., 2009; Sevim et al., 2017; Al-Ayed, 2024). As Saudi Arabia steers towards a digitally empowered future, ensuring that AI solutions are accessible and intuitive remains paramount. Effort expectancy, while not showing a substantial impact on attitudes, underlines the significance of offering trial opportunities. This aligns with the broader trend of innovation and experimentation within the Saudi entrepreneurial ecosystem. Allowing users to familiarize themselves with AI technologies before full-scale adoption can reduce resistance and bolster positive attitudes (Cao et al., 2021; Xu et al., 2023; Alateeg and Alhammadi, 2023). Observability's positive influence on attitudes is particularly relevant in the Saudi context. As the nation strives for digital transformation, the visibility of successful AI implementations in local startups bolsters trust in the utility and benefits of these technologies. It is a testament to the power of showcasing AI applications in driving positive attitudes, which are vital for successful adoption (Alserr and Salepçioğlu, 2021; Venkatesh et al., 2012; Alateeg and Alhammadi, 2024). The findings regarding facilitating conditions raise intriguing questions. While not strongly influencing attitudes, this could reflect the inherent resilience and self-reliance of Saudi entrepreneurs. Further exploration is warranted to understand how these entrepreneurs navigate the challenges and leverage the opportunities presented by AI technologies. The study unequivocally establishes the central role of attitude in shaping intentions to adopt AI in Saudi Arabian startups. A positive attitude proves to be a catalyst for embracing and leveraging AI technologies (Karjaluoto and Leppaniemi, 2013; Yadav and Pathak, 2017), which is in alignment with Saudi Arabia's ambitions of economic diversification and technological advancement.

These research findings offer critical guidance for Saudi Arabian startups looking to embark on their AI adoption journeys. As the nation strides towards the realization of its Vision 2030 goals, leveraging the insights on perceived usefulness, ease of use, trialability, observability, and attitude is essential. Moreover, a deeper examination of the unique cultural, economic, and policy aspects within Saudi Arabia's AI adoption landscape is necessary to ensure the seamless integration of these technologies and the achievement of national objectives.

The research findings present several pivotal implications that hold significant relevance for the adoption of AI within the Saudi Arabian startup ecosystem. Firstly, startups must focus on accentuating the concrete and practical advantages that AI can bring to their operations. This entails a proactive effort to showcase the tangible benefits of AI, such as improved efficiency, enhanced performance, and increased productivity. By highlighting these advantages, startups can foster a more favorable perception of AI among their stakeholders, including founders, employees, and investors. Secondly, it is imperative for startups to invest in user-friendly design when implementing AI solutions. Saudi Arabia's diverse population encompasses individuals with varying levels of technical proficiency. Hence, the importance of making AI technology accessible and intuitive cannot be overstated. User-friendly design not only encourages broader adoption but also ensures a smoother and more seamless integration of AI into startup processes. Moreover, providing trial opportunities is a strategy that can significantly influence startup stakeholders' attitudes and intentions regarding AI adoption. By offering trial experiences, startups can effectively bridge the gap between skepticism and enthusiastic adoption. Startup founders and teams must remain open to ongoing education and skill development, staying abreast of the latest AI advancements and best practices. By embracing these recommendations, startups can play a crucial role in driving the nation's digital transformation and achieving its ambitious objectives.

Conclusion

The study sought to uncover the determinants impacting the intention to adopt AI for startup among traditional entrepreneurs in Saudi Arabia. It formulated and empirically examined a model based on the TAM, customized to the Saudi Arabian setting. It has provided valuable insights into the adoption of AI for both startup founders and policymakers. First and foremost, the research emphasizes the significance of perceived usefulness in driving the intention to adopt AI. The study also underscores the importance of perceived ease of use in a region with a diverse population. Designing AI solutions that are user-friendly and accessible to individuals with varying technical proficiencies is essential for successful adoption. Furthermore, offering trial opportunities for AI technologies can significantly reduce resistance and foster positive attitudes among users. The Saudi entrepreneurial ecosystem, known for its innovative spirit, can benefit greatly from experimenting with AI before full-scale adoption. Observability, or the visibility of AI implementations in local startups, is crucial for building trust and encouraging positive attitudes toward AI. While facilitating conditions may not be a strong driver of attitudes, this finding suggests that Saudi entrepreneurs are resilient and self-reliant, navigating AI challenges independently. Further exploration of how they leverage opportunities and overcome obstacles in the AI landscape is warranted. Overall, the central role of attitude in shaping AI adoption intentions is remarkable. A positive attitude serves as a catalyst for embracing and leveraging AI technologies, aligning perfectly with Saudi Arabia's ambitions for economic diversification and technological advancement. As AI continues to reshape the entrepreneurial landscape, the study serves as a valuable resource for startup founders, policymakers, and stakeholders seeking to navigate the dynamic field of AI adoption in Saudi Arabia. Saudi entrepreneurs need to recognize AI's potential to enhance performance and operational efficiency. As the nation pursues its Vision 2030 goals, understanding the usefulness of AI becomes paramount.

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