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Measuring gender disparities in the intentions of startups to adopt artificial intelligence technology: A comprehensive multigroup comparative analysis

Sura I. Al-Ayed[a*] and Ahmad Adnan Al-Tit[b]

[a]*Associate Professor of Business Administration, College of Business Studies, Arab Open University, Riyadh, Saudi Arabia*
[b]*Department of Business Administration, College of Business & Economics, Qassim University, Qassim 52571, Saudi Arabia*

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This study examines gender differences in attitudes and intentions to adopt artificial intelligence among startup professionals. Utilizing a survey methodology encompassing responses from male and female participants, key constructs including attitude, perceived ease of use, perceived usefulness, and intention to use were analyzed through a comparative lens. The results reveal nuanced disparities between male and female perspectives on AI adoption. While minor differences were observed in the influence of attitude and perceived ease of use on adoption intentions, a significant gender gap emerged in the perception of how ease of use impacts perceived usefulness. These findings underscore the importance of recognizing gender dynamics in shaping attitudes and intentions towards AI adoption, highlighting the need for gender-inclusive strategies in fostering technology adoption among startups. This study contributes to the understanding of gender-specific considerations in AI adoption processes and offers insights for policymakers and industry stakeholders seeking to promote equitable and inclusive technological advancement.

1. Introduction

Artificial Intelligence (AI), powered by machine learning, is revolutionizing various sectors such as healthcare, agriculture, and education. This rise in AI's use brings exciting opportunities for its targeted application, catching the interest of technology developers and entrepreneurs (Ben Ayed and Hanana, 2021; Almaiah et al., 2022). However, how much AI is being used by startup founders and co-founders is unclear because research results vary, leaving without a definite answer (Lee et al., 2019; Enholm et al., 2022). In recent years, AI has emerged as a transformative force, revolutionizing industries and reshaping business landscapes worldwide (Busnatu et al., 2022; Giuggioli & Pellegrini, 2023). As startups navigate the rapidly evolving technological landscape, the adoption of AI technologies holds immense promise for driving innovation, enhancing competitiveness, and unlocking new growth opportunities (Schulte-Althoff et al., 2021; Giuggioli and Pellegrini, 2023). However, the extent to which professionals within startup environments, particularly across different genders, embrace AI remains a subject of inquiry and exploration (Santos, 2022; Gupta et al., 2023). In Saudi Arabia, amid significant economic transformation through Vision 2030, the behavioral intention to adopt AI for startups takes center stage. The government's active promotion of AI and technology, alongside a tech-savvy population and sector-specific needs, provides a conducive environment for AI-driven startups to thrive (Ahmed, 2019; Al Anezi, 2021; Al-Khalidi Al-Maliki, 2021). Gender dynamics play a crucial role in shaping attitudes and behaviors towards technology adoption, reflecting broader societal norms, expectations, and experiences. Despite progress towards gender equality in various domains, disparities persist in the realm of technology adoption and utilization. Understanding these gender differences is essential for developing inclusive strategies that promote equitable access and participation in the digital economy.

* Corresponding author
E-mail address s.alayed@arabou.edu.sa (S. I. Al-Ayed)

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This study seeks to examine gender differences in attitudes and intentions to adopt artificial intelligence among professionals within startup environments. By employing a survey methodology encompassing responses from male and female participants, key constructs including attitude, perceived ease of use, perceived usefulness, and intention to use AI are analyzed through a comparative lens. The findings shed light on nuanced disparities between male and female perspectives on AI adoption, offering valuable insights for policymakers, industry stakeholders, and startup communities. The exploration of gender-specific considerations in AI adoption processes not only advances our understanding of technology adoption dynamics but also informs the development of gender-inclusive strategies aimed at fostering technological advancement within startup ecosystems. By recognizing and addressing gender dynamics, stakeholders can promote diversity, inclusion, and innovation, ultimately driving more equitable and sustainable technological development. The research aims to address this gap and provide insights into the factors driving AI adoption decisions among startups. It presents a conceptual framework, hypotheses, methodology, data analysis techniques, results from structural equation modeling, and discussion of implications, thereby contributing to the understanding of AI adoption dynamics in the startup ecosystem.

2. Theoretical Background

Technology Acceptance Model by Davis (1986) and Davis et al. (1989) plays a vital role in information technology research. TAM comprises three core components: attitude, perceived ease of use, and perceived usefulness, collectively elucidating a user's motivation to adopt new technology. Additionally, behavioral intention was introduced as a new construct that was directly influenced by attitude and perceived usefulness. Despite its extensive utilization, TAM has certain limitations. For instance, it may struggle to address emerging solutions or services (Wu, 2011), and its ability to predict and explain outcomes has been questioned (Garaca, 2011). Additionally, empirical investigations using TAM may provide robust findings, underscoring the need to identify supplementary elements for inclusion in the model (Legris et al., 2003). Hence, this study employs the TAM model as its theoretical foundation.

3. Model Development

The primary conceptual framework of this study is rooted in the Technology Acceptance Model (TAM), which serves as the foundation for understanding the adoption of AI among startup entrepreneurs.

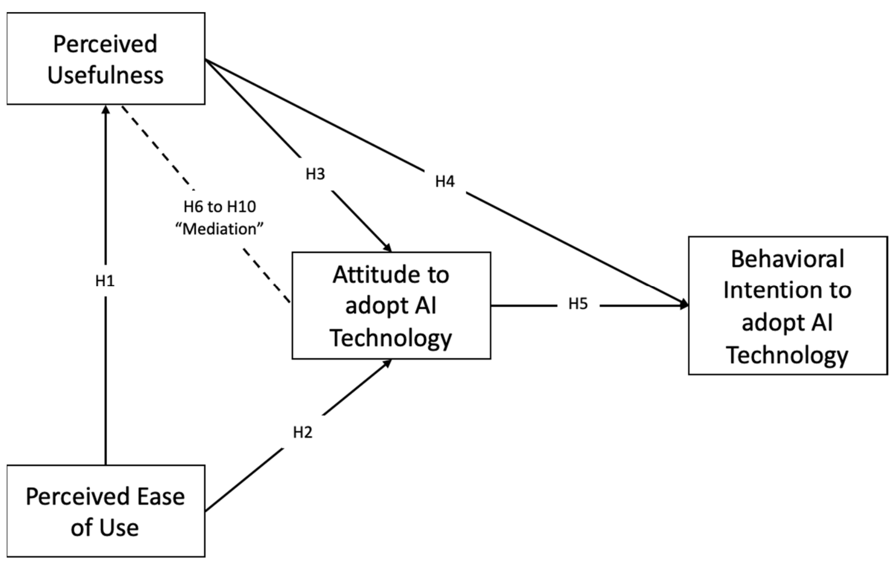

Fig. 1. Research Model

3.1. Perceived Ease of Use

Perceived ease of use (PEU) refers to how easy people think it is to use a new technology. In simpler terms, it's about how simple or difficult something seems to be to use (Rogers, 2003). This concept is important because it affects whether people are willing to adopt and use a new technology (Lim and Ting, 2012). If something is perceived as easy to use, people are more likely to try it out and use it regularly. Conversely, if something seems too complicated or difficult to use, people may be hesitant to adopt it, even if they see its potential benefits. Easy-to-use AI tools empower startups to experiment with different AI applications and explore innovative use cases without fear of complexity or failure. By selecting user-friendly AI tools and platforms, startups can accelerate learning curves, promote user engagement, minimize resistance to change, facilitate experimentation and innovation, and enable agile adaptation to drive sustainable growth and success in today's competitive landscape. Consequently, the following hypotheses are proposed.

H1: *PEU influences on PU.*

H2: *PEU influences on ATT.*

3.2. Perceived Usefulness

Perceived usefulness (PU), from an entrepreneurial standpoint, holds immense significance in the context of integrating AI into startup operations. Entrepreneurs view AI as a tool that can significantly enhance the efficiency of their startup operations. PU lies in AI's ability to automate mundane tasks, streamline processes, and accelerate decision-making. By leveraging AI technologies, entrepreneurs can optimize resource allocation, minimize manual errors, and free up valuable time to focus on strategic aspects of their ventures. It extends to AI's role in facilitating scalability and fostering growth for startups. By implementing AI-driven solutions, entrepreneurs can build scalable systems that can adapt and expand as their ventures grow. Studies have shown that people's belief in how helpful a new technology can be plays a big role in whether they want to use it or not. For example, researchers found this to be true for things like virtual reality, mobile exercise games, and mobile apps (Fagan et al., 2012; Hsu and Lin, 2015; Broom et al., 2019). Another study showed that when people think technology is useful, they tend to have a more positive attitude towards it (Sumak et al., 2011). As such, the subsequent hypotheses are postulated.

H3: *PU influences on ATT.*

H4: *PU influences on IU.*

3.3. Attitude

Attitude (ATT), in psychology and social sciences, refers to a learned tendency to evaluate things in a certain way (Ajzen, 1991). It involves feelings, beliefs, and behaviors directed towards a particular object, person, group, or event. Attitudes can be positive, negative, or neutral and can vary in intensity (Yadav and Pathak, 2017). Most of the studies indicated a positive significant relation between ATT and IU (Nasar et al., 2019; Saputra et al., 2024; Ismatullaev & Kim, 2024). In essence, the attitude toward AI among entrepreneurs is characterized by a blend of optimism, pragmatism, and purpose. By harnessing the power of AI thoughtfully and strategically, the aim is to drive innovation, create value, and shape the future of startup ventures. Consequently, the following hypothesis is presented.

H5: *ATT influence on IU.*

3.4. Mediating effect of PU and ATT

The mediating effect of PU and ATT often comes into play in the context of technology acceptance and adoption models, particularly in the field of information systems and consumer behavior research. In the TAM and similar models, the relationship between external variables (e.g., system characteristics, social influence) and actual usage behavior is often mediated by PU and ATT. This means that the influence of these external factors on technology acceptance and usage is partially or fully explained by their effects on PU and ATT. Thus, the subsequent hypotheses are formulated.

H6: *ATT mediates between PEU and IU.*

H7: *ATT mediates between PU and IU.*

H8: *PU and ATT mediate between PEU and IU.*

H9: *PU mediates between PEU and ATT.*

H10: *PU mediates between PEU and IU.*

4. Methodology

4.1. Data collection

Data for the survey were collected from startup founders and owners in Saudi Arabia with four constructs and 19 items. Respondents rated their views on a five-point Likert scale (1-diagree to 5-agree).

Table 1
Participants Demographic (n=419)

	Frequency	Percent		Frequency	Percent
Gender					
Male	263	63%			
Female	156	37%			
Age			Experience		
Below 25 years	149	36%	Less than 03 years	135	32%
26 to 30	113	27%	3 to 5	104	25%
31 to 40	92	22%	6 to 10	70	17%
Above 40 years	65	16%	Above 10 years	110	26%
Workplace region			Education		
Southern	12	3%	Diploma High School	103	25%
Northern	15	4%	Bachelor's degree	281	67%
Western	30	7%	Master's degree	27	6%
Central	320	76%	PhD	8	2%
Eastern	42	10%			

The survey was conducted in October and November 2023, with questionnaire items translated into Arabic for clarity. The online questionnaire was distributed using convenience sampling. The demographic characteristics of the participants in the study, outlined in Table 1 with a total sample size of 419 individuals, offer valuable insights into the composition of the sample. In terms of gender distribution, the majority of participants were male, comprising 63% of the sample, while females accounted for 37%. Regarding age distribution of below 25 years, constituting 36%. Educational attainment varied among participants, with the majority holding a bachelor's degree (67%), followed by those with a high school diploma (25%). Experience levels varied as well, with a significant portion of participants having less than 3 years of experience (32%). Geographically, the majority of participants were from the central region (76%), followed by the eastern region (10%).

4.2. Measurement

To gauge the intention to adopt AI for startup purposes, three items were incorporated, drawing from Cao et al. (2021) and Venkatesh et al. (2012). Attitude assessment utilized four items adapted from Cao et al. (2021) and Dwivedi et al. (2017). Perceived usefulness and ease of use were measured using six items each, sourced from Park and Chen (2007). Refer to Table 2 for items related to constructs.

4.3. Data analysis procedures

The analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4, a widely utilized method in management and information technology (IT) known for its reliability. PLS-SEM, a non-parametric approach, captures latent dimensions' variance, making it suitable for analyzing both direct and indirect effects within complex models (Hoyle, 1999). Its selection was based on its ability to integrate theories and empirical data, facilitating validation and exploration of variable relationships (Henseler et al., 2009). Following Leguina's (2015) methodology, the analysis proceeded in two steps: first, assessing discriminant and convergent validity in the outer model, then testing hypotheses in the inner model.

5. Analysis

5.1. Measurement Model

Table 2 shows measurement model results, which evaluates the reliability and validity of constructs pertinent to the adoption of AI among startup professionals.

Table 2
Measurement Model

Items and constructs	Loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Perceived Usefulness (PU)		0.901	0.924	0.67
PU1: "Using the AI in my startup would enable me to accomplish tasks more quickly"	0.836			
PU2: "Using the AI would improve my performance"	0.821			
PU3: "Using the AI in my startup would increase my productivity"	0.848			
PU4: "Using the AI would enhance my effectiveness in the startup"	0.842			
PU5: "Using the AI would make it easier to do my routine startup work"	0.725			
PU6: "I would find the AI useful in my startup"	0.831			
Perceived Ease of Use (PEU)		0.878	0.907	0.62
PEU1: "Learning to operate the AI would be easy for me"	0.754			
PEU2: "I would find it easy to get the AI to do what I want it to do"	0.768			
PEU3: "My interaction with the AI would be clear and understandable"	0.804			
PEU4: "I would find the AI to be flexible to interact with"	0.787			
PEU5: "It would be easy for me to become skillful at using the AI"	0.807			
PEU6: "I would find the AI easy to use"	0.802			
Attitude (ATT)		0.825	0.884	0.66
ATT1: "Using AI is a good idea"	0.869			
ATT2: "Using AI is a foolish idea"	0.725			
ATT3: "I like the idea of using AI"	0.881			
ATT4: "Using AI would be pleasant"	0.847			
Intention to Use (IU)		0.804	0.884	0.718
IU1: "I intend to use AI in the future"	0.843			
IU2: "I will always try to use AI in my workplace"	0.865			
IU3: "I plan to use AI frequently"	0.834			

The assessment encompasses four key constructs: PU, PEU, Attitude, and IU. The item loadings for all the constructs above 0.7 met the threshold. For Perceived Usefulness, the analysis reveals high levels of internal consistency (Cronbach's alpha = 0.901) along with strong composite reliability (0.924) and convergent validity (AVE = 0.67), indicating that the items reliably measure the perceived usefulness of AI among respondents. Similarly, the assessment indicates robust reliability and validity for the Perceived Ease of Use construct, with Cronbach's alpha of 0.878, composite reliability of 0.907, and AVE of 0.62, affirming the accuracy and consistency of measurements related to the perceived ease of using AI. Furthermore, the Attitude construct demonstrates strong internal consistency (Cronbach's alpha = 0.825), reliability (composite reliability = 0.884), and convergent validity (AVE = 0.66), underscoring the reliability of measurements capturing respondents' attitudes towards AI adoption. Lastly, the assessment of Intention to Use reveals high levels of reliability and validity, with Cronbach's alpha of 0.804, composite reliability of 0.884, and AVE of 0.718, indicating the precision and consistency of measurements related to respondents' intentions to adopt AI. The Fornell-Larcker criterion results, as presented in the Table 3, validate the discriminant validity among the key constructs.

Table 3
Discriminant validity (Fornell-Larcker criterion)

	ATT	IU	PEU	PU
ATT	0.812			
IU	0.658	0.848		
PEU	0.587	0.57	0.787	
PU	0.775	0.745	0.65	0.818

5.2. Structural Model

Table 4 structured around a series of hypotheses, delves into the intricacies of AI adoption among startup professionals, with a particular focus on gender disparities. Firstly, Hypothesis 1 posits that PEU is positively associated with PU. The analysis supports this hypothesis (β = 0.65***), indicating that when AI is perceived as easy to use, it is also perceived as more useful, a trend observed consistently across both male and female respondents. Building upon this, Hypothesis 2 suggests that PEU influences ATT. The findings affirm this hypothesis (β = 0.144***), indicating that when AI is perceived as easy to use, individuals, regardless of gender, tend to harbor a more positive attitude towards its adoption. Moving forward, Hypothesis 3 suggests that PU influences ATT. The results confirm this hypothesis (β = 0.681***), highlighting that perceived usefulness significantly contributes to fostering positive attitudes towards AI, irrespective of gender differences. Furthermore, Hypothesis 4 proposes that PU is positively linked to IU. The analysis provides strong support for this hypothesis (β = 0.587***), revealing that when AI is perceived as useful, individuals are more inclined to express intentions to adopt it, a trend consistent across both male and female respondents. Lastly, Hypothesis 5 posits that a positive attitude towards AI correlates with a stronger intention to use it. The results support this hypothesis (β = 0.203***), revealing a significant positive relationship between ATT and IU across both male and female respondents.

Table 4
Path Coefficients (direct effect)

Paths	β (Full Sample)	β (Male Sample)	β (Female Sample)	Results
PEU → PU	0.65***	0.611***	0.74***	H1 - supported
PEU → ATT	0.144***	0.13***	0.193***	H2 - supported
PU → ATT	0.681***	0.678***	0.671***	H3 - supported
PU → IU	0.587***	0.575***	0.608***	H4 - supported
ATT → IU	0.203***	0.198***	0.222***	H5 - supported

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.

Table 5 encapsulates the outcomes of a sequential path analysis, investigating the sequential relationships among key constructs—PEU, PU, Attitude, and IU—in the context of AI adoption within startup environments. The analysis is meticulously structured around a series of hypotheses aimed at unraveling the intricate dynamics of AI adoption pathways, while also considering potential gender variations among respondents. Hence, the results for H6 to H10 are supported for full sample, male sample and female sample.

Table 5
Path Coefficients (Indirect effect)

Paths	β (Full Sample)	β (Male Sample)	β (Female Sample)	Results
PEU → ATT → IU	0.029***	0.026***	0.043***	H6 - supported
PU → ATT → IU	0.138***	0.135***	0.149***	H7 - supported
PEU → PU → ATT → IU	0.09***	0.082***	0.11***	H8 - supported
PEU → PU → ATT	0.443***	0.414***	0.496***	H9 - supported
PEU → PU → IU	0.382***	0.351***	0.45***	H10 - supported

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.

Fig. 2, Fig. 3 and Fig. 4 outline the coefficients of determination (R^2) for key constructs—ATT, IU, and PU—pertaining to AI adoption among startup professionals. These values elucidate the proportion of variance in each construct explained by the predictor variables within the regression model, offering valuable insights into the predictive power of the model and potential differences across gender groups. For attitude towards AI adoption, the R-squared value stands at 0.612 for the full sample, indicating that approximately 61.2% of the variability in attitude is accounted for by the predictor variables. Upon gender disaggregation, a slightly lower R-squared value of 0.584 is observed for males, while females exhibit a higher value of 0.679, suggesting that the predictor variables explain 58.4% and 67.9% of the variability in attitude for males and females, respectively. Similarly, for Intention to Use AI, the R-squared value is 0.571 for the full sample, denoting that approximately 57.1% of the variance in intention to use AI is explained by the predictor variables. Upon gender stratification, males exhibit an R-squared value of 0.543, while females demonstrate a higher value of 0.64, indicating that the predictor variables explain 54.3% and 64.0% of the variance in intention to use for males and females, respectively. Regarding PU, the R-squared value is 0.423 for the full sample, signifying that approximately 42.3% of the variance in PU is explained by the predictor variables. Upon gender disaggregation, males exhibit an R-squared value of 0.373, while females display a higher value of 0.547, suggesting that the predictor variables account for 37.3% and 54.7% of the variance in PU for males and females, respectively.

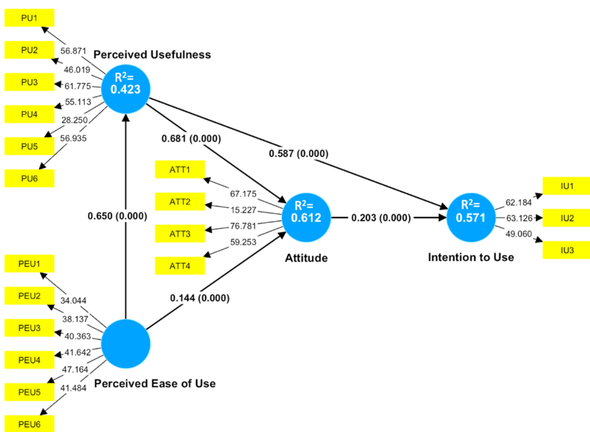

Fig. 2. Full Sample Evaluation of Structural Model

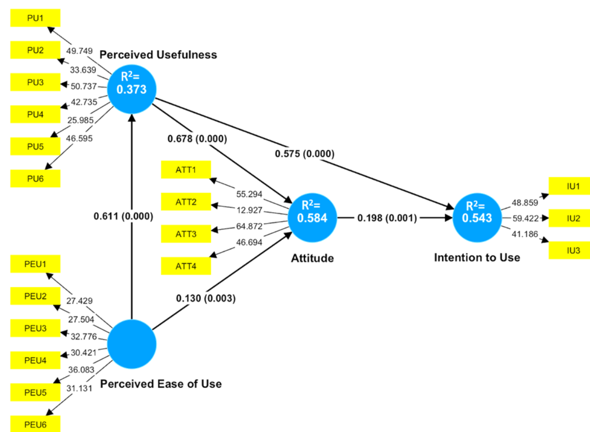

Fig. 3. Male Sample Evaluation of Structural Model

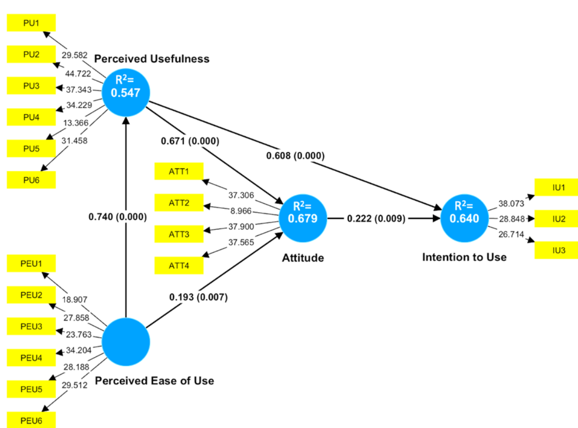

Fig. 4. Female Sample Evaluation of Structural Model

Table 6 presents findings from a multigroup analysis investigating potential gender differences in the relationships between key constructs—ATT, PEU, PU, and IU—regarding AI adoption among startup professionals. Results indicate no significant gender disparity in the relationship between ATT and IU (H1), as evidenced by a minimal difference of -0.024 and non-significant p-values (0.591 for 1-tailed, 0.817 for 2-tailed). Similarly, the relationship between PEU and ATT (H2) shows no substantial gender difference, with a minor difference of -0.063 and non-significant p-values (0.776 for 1-tailed, 0.449 for 2-tailed). However, a notable gender difference emerges in the relationship between PEU and PU (H3), with a difference of -0.129 and a significant 2-tailed p-value (0.017). This suggests that gender influences how individuals perceive the usefulness of AI based on its PEU. Conversely, no significant gender disparities are observed in the relationships between PU and ATT (H4), as well as PU and IU (H5), with negligible differences and non-significant p-values in both cases. These findings offer insights into the nuanced gender dynamics shaping attitudes and intentions towards AI adoption among startup professionals. The identification of a significant gender difference in the perceived usefulness of AI highlights the importance of considering gender-specific perspectives in designing strategies to promote inclusive AI adoption in startup ecosystems.

Table 6
Multigroup Analysis

Paths	Difference (Male - Female)	1-tailed (Male vs Female) p value	2-tailed (Male vs Female) p value	Results
ATT → IU	-0.024	0.591	0.817	H1 no difference
PEU → ATT	-0.063	0.776	0.449	H2 no difference
PEU → PU	-0.129	0.992	0.017	H3 difference
PU → ATT	0.007	0.46	0.92	H4 no difference
PU → IU	-0.033	0.635	0.729	H5 no difference

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

6. Discussion

The discussion section explores the implications of the study's findings regarding the factors influencing the behavioral intention to adopt AI among startups in Saudi Arabia. The results underscore the significance of attitudes towards AI adoption, as evidenced by the strong positive impact on the IU. This highlights the importance of cultivating favorable attitudes among startup founders and stakeholders towards AI technologies (Xu et al., 2023). Moreover, the study reveals the critical role of PEU and PU in shaping attitudes towards AI adoption. Simplifying the user experience and emphasizing the practical benefits of AI technologies are essential in fostering positive attitudes and driving adoption intentions among startups (Sevim et al., 2017; Dutot et al., 2019). Additionally, the findings highlight the mediating role of attitudes in the relationship between PEU, PU, and IU. This underscores the complex interplay between cognitive perceptions, attitudes, and behavioral intentions in the context of AI adoption among startups. Furthermore, the study provides insights into potential gender differences in the pathways influencing AI adoption intentions. While no significant differences were observed in certain paths, a notable gender difference was detected in the transition from PEU to PU. These findings contribute to a deeper understanding of the factors influencing AI adoption among startups in Saudi Arabia and have implications for policymakers, industry practitioners, and researchers seeking to facilitate AI adoption and innovation in the startup ecosystem. By leveraging these insights, stakeholders can develop targeted strategies to foster a conducive environment for AI adoption and drive sustainable growth in the startup sector (Selamat et al., 2009; Sumak et al., 2011).

The findings of this study carry significant implications for the Saudi Arabian context, particularly within the dynamic landscape of startup ecosystems and technological innovation (Alserr and Salepçioğlu, 2021; Cao et al., 2021). Firstly, policymakers can leverage these insights to craft policies and initiatives that support and incentivize the adoption of AI among startups. By understanding the factors influencing behavioral intentions towards AI, policymakers can design targeted programs to facilitate access to resources, funding, and specialized training programs tailored to the unique needs of startups (Alateeg & Alhammadi, 2024). Secondly, nurturing a supportive entrepreneurial ecosystem is paramount. Initiatives such as startup accelerators, incubators, and collaborative platforms can provide startups with essential resources, networking opportunities and mentorship crucial for navigating the complexities of AI adoption (Venkatesh et al., 2012; Yadav and Pathak, 2017). Thirdly, investors and venture capitalists can use these findings to inform their investment strategies, favoring startups that exhibit positive attitudes towards AI adoption and clear intentions to integrate AI into their operations. Moreover, investing in education and training programs focused on AI literacy and skills development will equip entrepreneurs with the knowledge and skills needed to leverage AI effectively. Addressing gender disparities in the startup ecosystem is also essential, promoting inclusivity and diversity to foster a more vibrant and innovative environment (Karjaluoto and Leppaniemi, 2013). Finally, fostering international collaboration and partnerships in AI research and entrepreneurship can facilitate technology transfer, knowledge exchange and access to global markets, further positioning Saudi Arabia as a regional leader in AI innovation and entrepreneurship. Overall, embracing these implications can catalyze the growth of the startup ecosystem in Saudi Arabia and propel the nation towards a future driven by AI innovation.

7. Conclusion

This study delved into the behavioral intentions of startup founders and co-founders in Saudi Arabia regarding the adoption of AI. Through an analysis of various factors influencing attitudes and intentions towards AI adoption, several key findings emerged. The research revealed significant support for the hypotheses posited, indicating a positive relationship between PU, PU, attitude, and IU among startups. Furthermore, the study highlighted gender differences in certain pathways, shedding light on the importance of addressing gender disparities in the startup ecosystem. These findings carry important implications for policymakers, industry stakeholders, investors, and educational institutions in Saudi Arabia. By leveraging these insights, policymakers can formulate policies and initiatives to support AI adoption among startups, while fostering a supportive entrepreneurial ecosystem. Investors can make informed decisions based on startups' attitudes towards AI, while educational institutions can develop programs to equip entrepreneurs with the necessary skills and knowledge. Moreover, promoting gender inclusivity and fostering international collaboration in AI research and entrepreneurship are essential steps towards building a vibrant and innovative startup ecosystem. By embracing these implications and taking proactive measures, Saudi

Arabia can position itself as a regional leader in AI innovation and entrepreneurship, driving economic growth and technological advancement in the years to come.

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