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Empowering Women Entrepreneurs: Navigating the Adoption of Generative AI Tools Through Innovation Diffusion Theory

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Abstract

The role of women entrepreneurs in driving economic growth and instigating social change is crucial, yet they encounter distinctive obstacles when embracing innovative technologies, particularly Generative Artificial Intelligence (GenAI) tools. These tools have the potential to revolutionize business operations through task automation and data-driven insights. The present study aims to investigate the factors that influence the adoption of GenAI tools among women entrepreneurs, addressing gaps in existing literature concerning the specific challenges and barriers they face. Drawing on Rogers' innovation diffusion theory, the research utilizes Structural Equation Modeling (SEM) to examine the motivating factors (observability and trialability) and barriers (privacy concerns and biases in GenAI algorithms) that affect the adoption of GenAI tools by women entrepreneurs. The findings indicate that trialability and observability have a positive influence on GenAI adoption, while privacy concerns and algorithmic bias represent significant barriers. When taken together, these factors account for 53% of the variance in adoption rates, underscoring the pivotal role of privacy and security in the technology adoption process. The study recommends an expansion of the Diffusion of Innovations (DOI) model to encompass privacy concerns and algorithmic bias as significant barriers, particularly in gendered contexts. It underscores the necessity for robust data protection policies and strategies to mitigate bias in AI outputs, advocating for increased trialability and observability to empower women entrepreneurs in utilizing GenAI technologies.

Keywords: Women Entrepreneurs, GenAI Bias, GenAI Adoption, Small and Medium-Sized Enterprises.

Women entrepreneurs are crucial in driving economic growth and effecting social change (Moral et al., 2024). Their involvement in entrepreneurship is increasingly acknowledged as vital for achieving sustainable development (Siddiqua & Chan, 2024). In developing areas, women entrepreneurs have been instrumental in stimulating local economies, although they often encounter obstacles hindering their advancement (Jain, 2021). Their involvement in entrepreneurship not only boosts economic growth but also fosters social inclusion and empowerment (Emon & Nipa, 2024; Silva et al., 2023).

In addition, the rise of Generative Artificial Intelligence (GenAI), which are algorithms such as ChatGPT capable of generating new content (Kalota, 2024), has sparked a revolution across various industries, delivering groundbreaking solutions and elevating operational effectiveness (Kanbach et al., 2024). These tools have great potential for women entrepreneurs. It can automate repetitive tasks and provide data-driven insights to help make important business decisions (Abdul-Azeez et al., 2024). Notably, innovative AI tools like ChatGPT can improve customer interaction and streamline business procedures, empowering women entrepreneurs to focus on driving growth and creativity rather than getting bogged down by administrative tasks (Townsend, 2023).

The adoption of GenAI tools among women entrepreneurs is a critical area of study due to its significant implications for gender equality (Orser et al., 2019), economic growth, and technological advancement (Cooke & Xiao, 2021). Understanding the factors that influence women's entrepreneurial adoption of GenAI tools is essential for fostering an inclusive digital economy (Abdelwahed et al., 2024). Addressing the challenges faced by women entrepreneurs in embracing AI is crucial for reducing the gender gap in entrepreneurship and ensuring equitable access to technological progress (Akpuokwe et al., 2024; Ezeugwa et al., 2024; Roopaei et al., 2021).

Despite the potential benefits of GenAI tools, several barriers hinder their widespread adoption by women entrepreneurs. Privacy concerns are a major issue, as the risk of unauthorized data access and surveillance can discourage the use of these technologies (Gupta et al., 2023; Isser et al., 2024). In addition, the inherent biases in GenAI algorithms, which often reflect and perpetuate societal inequalities, present significant challenges (Leavy, 2018; Nadeem et al., 2021; Wellner, 2020).

Moreover, there is a noticeable void in the literature concerning the adoption of GenAI technology by women entrepreneurs. Existing research predominantly concentrates on the overall adoption of digital technologies by women entrepreneurs and lacks specific insights into the adoption of AI (Altarawneh & Albloush, 2023; Feranita et al., 2023; Imdad, 2022). The scarce studies that do reference AI adoption lack a comprehensive understanding of the subject (Bhatt, 2023; Feranita et al., 2024; Gupta, 2024).

The study seeks to fill previous knowledge voids by examining the factors influencing the adoption of GenAI tools among women entrepreneurs. The research will analyze motivating factors (observability and trialability) and barriers (privacy concerns and biases in GenAI algorithms) to provide insight into integrating these tools into women-led businesses. The objective is to contribute to a better thorough understanding of AI adoption and propose strategies to overcome challenges, supporting economic empowerment and technological advancement for women entrepreneurs.

To enhance the understanding of adoption, Rogers' innovation diffusion theory is applied, which suggests five factors impacting diffusion rate: relative advantage, complexity, compatibility, observability, and trialability (Miller, 2015). Considering GenAI, women entrepreneurs are also concerned with privacy and GenAI bias (Golda et al., 2024; Gumusel et al., 2024; Rahaman, 2023; Sadok & Assadi, 2024), so the study extends DOI with these constructs.

This article adheres to a specific structure. It commences with an overview of the use of GenAI by women in entrepreneurial endeavors, offering background for our research. We then conduct a review of existing literature on this subject, emphasizing the fundamental theoretical frameworks. Based on this review, we put forward our research model. After discussing the results, we highlight theoretical and practical implications, along with prospective avenues for future research.

Literature review

Women entrepreneurs are vital for the advancement and expansion of small and medium-sized enterprises (SMEs) on a global scale (Hasan & Almubarak, 2016). These enterprises, which are the cornerstone of many economies, not only contribute to job creation but also encourage innovation and competitiveness (Gherghina et al., 2020). However, women entrepreneurs often encounter distinct obstacles such as limited access to funding, networks, and resources, which can hinder their ability to adopt new technologies (Khawaldah & Alzboun, 2022; Panda, 2018). The incorporation of generative artificial intelligence (GenAI) into business operations represents a significant opportunity for SMEs led by women to enhance efficiency, improve decision-making, and ultimately drive growth (Basir, 2023; Sadok & Assadi, 2024).

The integration of GenAI tools technologies in small and medium-sized enterprises (SMEs) has the potential to empower women entrepreneurs by simplifying processes and providing data-driven insights (Shahbazi et al., 2024). AI can support various facets of business operations, such as marketing, customer service, inventory management, and financial planning refer to figure 1 (Javaid et al., 2022; Shahbazi et al., 2024). By leveraging GenAI tools, women entrepreneurs can surmount traditional barriers and bolster their competitiveness in the marketplace (Sicat et al., 2020). Furthermore, AI technologies can aid in identifying fresh market opportunities and understanding customer preferences, enabling women-led businesses to tailor their offerings more effectively and adapt to shifting market dynamics (Ubfal, 2024).

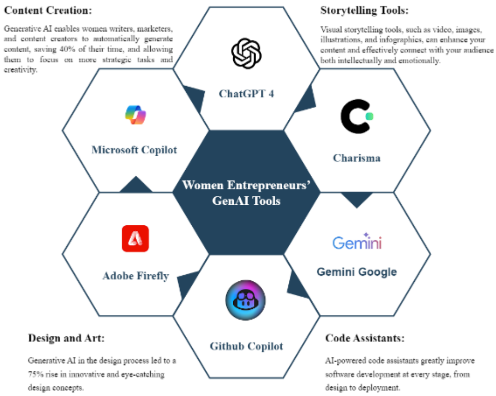

Figure 1. Key categories of Generative AI tools used by women entrepreneurs.

Recent studies highlight the importance of digital technologies, particularly Artificial Intelligence, for women entrepreneurs in navigating today's intricate business landscapes, particularly in developing regions with traditional barriers (Kaningini et al., 2023). Embracing GenAI enables women not only to streamline business processes but also to take advantage of new growth opportunities in a rapidly evolving digital environment (Joel & Oguanobi, 2024). Research also shows how the adoption of IT can boost the performance and competitiveness of women-led SMEs in Jordan (Al-Zagheer et al., 2022). Despite the recognition of AI's significance for future economic success in Germany, its integration into SMEs remains slow (Anggraini et al., 2023). Furthermore, the adoption of GenAI tools among women entrepreneurs remains a critical area of study due to its significant implications for gender equality (Orser et al., 2019), economic growth, and technological advancement (Cooke & Xiao, 2021). Understanding the factors that influence women's entrepreneurial adoption of GenAI tools is crucial for nurturing an inclusive digital economy (Abdelwahed et al., 2024).

Additionally, addressing the challenges faced by women entrepreneurs in embracing GenAI is essential for reducing the gender gap in entrepreneurship and ensuring equitable access to technological progress(Akpuokwe et al., 2024; Ezeugwa et al., 2024; Roopaei et al., 2021).

The Diffusion of Innovations (DOI) model, created by Everett Rogers (Yu, 2022), is a valuable theoretical framework for studying the uptake of AI technologies among female entrepreneurs (Chatterjee et al., 2020; Soon et al., 2016). This model focuses on how innovations are communicated over time within a social system (Khan et al., 2020). In the realm of female entrepreneurs, the DOI model illustrates how factors like social networks, cultural norms, and access to resources can significantly impact the adoption of AI technologies (Mittal & Bhandari, 2021). Female entrepreneurs often encounter distinct challenges such as limited access to funding and mentorship, which can influence their ability to integrate AI into their businesses (Khan et al., 2020). Applying the DOI model allows researchers to gain insights into the specific obstacles and enablers that female entrepreneurs face in the adoption process, leading to more tailored support strategies (Alghaith, 2016).

Hypothesis development and theoretical model

The Diffusion of Innovations (DoI) theory was introduced by Rogers in 1962 and has been widely applied in fields such as Artificial Intelligence, Information Science, Information Systems, and healthcare (Alonso & Calderón, 2014; Lampo, 2022; Minishi-Majanja, 2013; Nemutanzhela & Iyamu, 2015). This theory provides a comprehensive framework for understanding how new ideas and technologies spread within social systems, focusing on factors such as complexity, trialability, and observability (Salazar et al., 2020). Unlike models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which focus on perceived ease of use, usefulness, and performance expectancy, the DOI model considers socio-environmental factors and innovation characteristics alongside individual perceptions (Lampo, 2022; Nascimento & Meirelles, 2022). This holistic approach allows for a more comprehensive understanding of how women entrepreneurs navigate the adoption of GenAI tools technologies in their unique business environments.

Even though the DOI provides a solid theoretical foundation for technology adoption research, it has not been as widely used as the TAM and the UTAUT (Acikgoz et al., 2023). The AI adoption technologies depends not only on user acceptance, commonly assessed through TAM or UTAUT but also on the speed and factors driving its incorporation into society (Acikgoz et al., 2023; Ismatullaev & Kim, 2022; Kelly et al., 2022). Furthermore, Rogers (1983) suggests that researchers examining diffusion should be receptive to considering other relevant characteristics that might be critical in specific circumstances for distinct groups of people adopting a unique array of innovations.

In the realm of GenAI tools, women entrepreneurs must prioritize the security and protection of their data to prevent unauthorized surveillance(M. Gupta et al., 2023; Isser et al., 2024). Amini & Jahanbakhsh Javid (2023) and Parthasarathy et al. (2021) have extended the DOI model to include privacy concerns. Another important factor to consider in GenAI tools is the presence of gender bias in their algorithms, which can have a disproportionate impact on women and contribute to societal inequalities (Nadeem et al., 2021; Wellner, 2020). This bias, which originates from the data used to train GenAI apps, is evident in various AI applications (Leavy, 2018). Therefore, it is crucial to expand the DOI model to encompass the concept of GenAI bias when examining the adoption of GenAI apps by women entrepreneurs.

Furthermore, the concept of complexity, defined as the perceived difficulty in understanding and using an innovation should be excluded (Lyytinen & Damsgaard, 2001). With the current focus on simplicity in the development and design of GenAI apps, complexity is not as relevant in the realm of

GenAI tools, as these tools streamline the complexity and time needed for customizing messaging (Feng et al., 2024; Harjamäki et al., 2024; Huang & Rust, 2024). As a result, we argue that, for the sake of simplicity, complexity can be omitted from the research model.

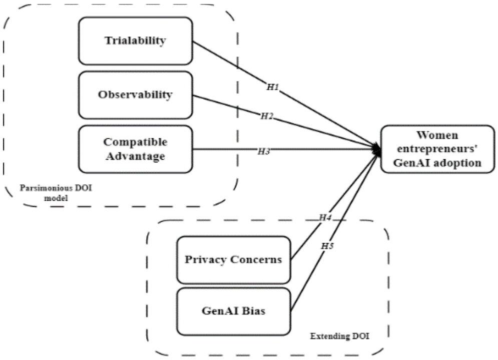

Figure 2. Study Model

Trialability

The concept of trialability, a crucial aspect of the Diffusion of Innovation theory, significantly influences the adoption of new technologies like GenAI (Ghimire & Edwards, 2024). Trialability refers to the extent to which an innovation can be tested on a limited basis. Innovations that can be trialed in parts create less uncertainty for individuals, allowing them to learn by experimenting with new ideas (Rogers, 2001). Research on outcome valence and confidence judgments demonstrates that trialability plays a pivotal role in influencing women's confidence in using GenAI technologies (Pethig & Kroenung, 2023; Zhong & Gou, 2023). The opportunity to engage in trial-and-error learning processes with GenAI technologies affects women's confidence levels in their decision-making about these technologies (Ren & Olechowski, 2020; Sandoval-Martin & Martínez-Sanzo, 2024). Allowing women to experiment and gain experience with GenAI technologies through trials enables them to develop a deeper understanding of the outcomes and functionalities, leading to increased confidence in using these tools for entrepreneurial endeavors (Kotturi et al., 2024). Thus, integrating trialability features into the design and implementation of GenAI technologies can positively impact women's confidence levels. This can empower them to make well-informed decisions about adopting GenAI.

H1: Trialability positively impacts on women entrepreneurs' GenAI adoption.

Observability

Observability, as defined by Rogers (2001), refers to the degree to which an individual can observe the results or effects of an innovation. In the context of women entrepreneurs adopting Generative AI (GenAI), observability plays a pivotal role in promoting a culture of learning and innovation (Jin et al., 2024). When women entrepreneurs have the opportunity to witness their peers successfully implementing GenAI tools, it helps demystify the technology and demonstrate its practical advantages (Chouksey & Bedarkar, 2022; Feranita et al., 2024). This visibility alleviates concerns about adopting new technology, as potential users can see concrete examples of how GenAI can streamline operations, foster creativity, and enhance decision-making processes (Dobrin, 2024; Gursoy & Cai, 2024; Minguez Orozco & Welin, 2024).

Additionally, the shared experiences of other women entrepreneurs can serve as compelling endorsements, motivating others to embrace GenAI as a viable solution for their business challenges (Imdad, 2022; M.Suresh & Senthilkumar, 2024). Women entrepreneurs who witness their peers benefiting from GenAI are more likely to perceive it as a valuable tool for their ventures. Consequently, this collective visibility and shared learning experience empowers women to adopt GenAI, thereby driving their businesses forward and contributing to broader economic growth and empowerment. In recap, the evidence suggests that H2: observability has a positive impact on women entrepreneurs' GenAI adoption

H2: Observability positively impacts women entrepreneurs' GenAI adoption.

Compatible advantage

The adoption of innovations is influenced by several key factors, including compatibility, relative advantage, and complexity, all of which have consistently shown significant relationships to adoption (Almaiah et al., 2022). However, there is an ongoing debate concerning the conceptual overlap between relative advantage and compatibility (Eschenbrenner & Shaw, 2023). Some researchers argue that these constructs display both theoretical and empirical overlap, leading to inconsistent treatment across studies (Van Slyke et al., 2008). Furthermore, some researchers suggest that compatibility is a sub-dimension of relative advantage, resulting in its exclusion from models like UTAUT (Kiwanuka, 2015). Shaw et al. (2022) support these arguments and propose that relative advantage and compatibility should be modeled as one construct, 'compatible advantage'. According to their argument, the compatibility of GenAI tools hinges on meeting the specific needs and challenges of potential women entrepreneurs. If these tools fail to address these unique requirements, they will not be considered compatible, regardless of their other features. The relative advantage of an innovation is only realized when it aligns with the needs of the adopters. If the GenAI tools do not meet their needs, potential advantages such as efficiency or cost savings will not be perceived or valued. Therefore, the perceived relative advantage is inherently tied to the compatibility of the GenAI tools with the needs of women entrepreneurs.

H3: Compatible advantage positively impacts women entrepreneurs' GenAI adoption

Privacy concerns

AI-driven strategies present promising opportunities for entrepreneurial success, encompassing market analysis, product development, and customer engagement (Usman et al., 2024). However, recent studies have emphasized privacy concerns as significant obstacles to adopting digital technologies, including generative AI (GenAI), especially among women entrepreneurs (Huy et al., 2024; Isguzar et al., 2024; Alhur et al 2022; Michota, 2013). Research indicates that women are more apprehensive about sharing personal information online than men (Michota, 2013). These apprehensions can dampen their willingness to embrace new technologies and online business platforms (Batool & Ullah, 2020). The swift advancements in GenAI models like ChatGPT have also brought forth additional cybersecurity and privacy implications, including the potential for exploitation by malicious users (M. Gupta et al., 2023).

In the realm of entrepreneurship, women entrepreneurs commonly voice heightened privacy concerns when integrating new technologies. Xu et al. (2024) revealed that integrating generative AI with the Internet of Things (IoT) introduces various security risks, such as data breaches and the misuse of AI technologies. These risks can undermine trust and safety in AI-driven environments, posing specific concerns for women who may feel more susceptible to privacy violations in such scenarios (Xu et al., 2024).

H4: Privacy concerns negatively impacts women entrepreneurs' GenAI adoption.

GenAI Bias

Generative AI models like Midjourney, Stable Diffusion, and DALL-E 2 have been shown to exhibit troubling biases against women in several studies (Bhandari, 2023; Latif et al., 2023; Zhou et al., 2024). These AI generators not only reflect systematic gender biases by depicting women as younger, happier, and more submissive than men but also showcase the underrepresentation of women in male-dominated fields and overrepresentation in female-dominated occupations (Sandoval-Martin & Martínez-Sanzo, 2024). Additionally, the OpenAI text-embedding-ada-002 language model is found to be partially gender-biased due to underlying biases in training data, highlighting the critical importance of addressing and mitigating gender biases in AI models during design and training processes (Wodziński et al., 2024).

The biases recognized in AI-generated images raise significant concerns about inclusivity and the potential reinforcement of harmful stereotypes, underscoring the urgency of rectifying biases in generative AI technologies for a more equitable and unbiased future (Shin et al., 2024). These biases can have broad implications, particularly for women entrepreneurs who may feel cautious about adopting generative AI tools due to worries about gender discrimination and the perpetuation of negative stereotypes(Bhandari, 2023; Sandoval-Martin & Martínez-Sanzo, 2024).

H5: GenAI Bias negatively impacts women entrepreneurs' GenAI adoption.

Methodology

This study used a cross-sectional analysis to investigate 224 women entrepreneurs from small and medium enterprises located in Amman, the capital city of Jordan. Amman was selected due to its status as the most populous and economically significant city in the country, making it ideal for generalizing the study's findings (Sharaf, 2023).

Jordan accounts for 3% of the MENA region's population, and 23% of tech entrepreneurs in the MENA region come from Jordan (Ministry of Digital Economy and Entrepreneurship, 2024). Participants were selected with the assistance of the Microfund for Women, Jordan's first and largest private not-for-profit shareholding microfinance company. The MFW is dedicated to empowering entrepreneurs, especially women, and offers a range of financial and non-financial services tailored to support businesses and livelihoods, promoting financial inclusion (Microfund for Women, 2024). The research team randomly selected 234 women entrepreneurs from Microfund for Women reports using a random number generator software. The inclusion criteria required participants to be women running small and medium enterprises.

The questionnaire was originally in English and later translated into Arabic and adapted from previous studies such as (Chor et al., 2015; Eschenbrenner & Shaw, 2023; Islam et al., 2021; Shaw et al., 2022; Vorisek et al., 2023). Pilot testing with 50 women entrepreneurs showed satisfactory reliability (Cronbach's alpha: 0.75–0.91). Between February 2nd and April 6th, 2024, survey questionnaires and informed consent were distributed via a Google Forms link, resulting in a 96% response rate after excluding ten surveys (4%). The final sample size for the current study is 224, sufficient for SEM refer to Figure3.

The researchers utilized Soper's (2023) approach to determine the required sample size for Structural Equation Modeling (SEM) by assessing the effect size. Mizutani et al. (2015) outlined the different categories for effect sizes, which include small (0.1 to 0.3), moderate (0.3 to 0.5), and large (greater than 0.5). A moderate effect size of 0.30 was considered appropriate for this study.

Assessing statistical power is crucial for distinguishing between strong and weak models in SEM, as emphasized by Hermida et al. (2015); McQuitty (2004). In the field of business research, a minimum statistical power of 0.80 is generally necessary (Franck & Damperat, 2022). Given the presence of 6 latent variables and 24 observed items, a sample size of at least 161 participants is needed to validate the model structure.

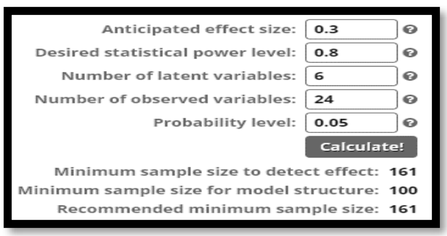

Fig.3 Calculate the required sample size for SEM.

Participants Profile

The data outlined in Table 1 offers a comprehensive overview of the demographic characteristics of the study participants. Notably, the age distribution indicates that the largest age group falls within the 31-40 years' bracket, accounting for 38.8% of the sample. This is closely followed by the 40 years and over age group at 32.6% and the 20-30 years' age group at 28.6%, demonstrating a well-distributed age range among the participants. In terms of educational qualifications, the majority of the participants hold an undergraduate degree, constituting 70.5%, while 23.7% possess a postgraduate degree, and a smaller segment, 5.8%, have a high school education.

Marital status and employment sector further supplement the demographic profile. A sizable proportion of the participants are single, making up 63.4%, in comparison to 36.6% (n=82) who are married. Regarding employment sectors, the services sector emerges as the most prevalent, with 53.1% of participants employed in this field, followed by the agriculture sector at 23.2%, the technology sector at 16.1%, and other sectors accounting for the remaining 7.6%.

Table 1. Participants profile

Personal Data	Categories	Count	Percent
Age group	20-30 years	64	28.6%
	31-40 years	87	38.8%
	40 yrs. and over	73	32.6%
	Total	224	100.0%
Highest qualification	Undergraduate	158	70.5%
	Postgraduate	53	23.7%
	High school	13	5.8%
	Total	224	100.0%
Marital status	Married	82	36.6%
	Single	142	63.4%
	Total	224	100.0%
Sector	Technology sector	36	16.1%
	Services sector	119	53.1%
	Agriculture sector	52	23.2%
	Others	17	7.6%
	Total	224	100.0%

Study results

Confirmatory Factor analysis

An initial assessment of the model used in the study involved 24 items that were analyzed using IBM-SPSS v26. The results showed satisfactory correlations among all the items. The Kaiser-Meyer-Olkin measure of sampling sufficiency was computed at 0.921, surpassing the recommended threshold of 0.6 (Hair et al., 2019). Furthermore, Bartlett's test of sphericity produced a significant outcome, $\chi^2(276) = 5158.128$, $p < .001$, confirming the suitability of the correlation structure for factor analysis (Hair et al., 2006, 2019).

Consequently, the 24 items were found suitable for exploratory factor analysis. After applying a cutoff of 0.40 and Kaiser's criterion of eigenvalues greater than 1, a six-factor solution was produced. This solution explained 77.34% of the variance, aligning well with the theoretical framework (Hooper, 2012). Stabilization of eigenvalues on the scree plot occurred after the sixth factor, supporting the preference for the six-factor solution.

The process of conducting structural equation modeling (SEM) as described by Hair and colleagues was carried out in two stages using AMOS 26 (Hair et al., 2019). During the initial stage, the measurement model was assessed, and all goodness-of-fit indices met the recommended criteria: $\chi^2(236) = 403.972$, (χ^2/df) = 1.712, comparative fit index (CFI) = 0.962, standardized root mean square residual (SRMR)

= 0.056, and root mean square error of approximation (RMSEA) = 0.056, with a p-value of 0.126 (Crawford & Kelder, 2019; Hooper et al., 2007). The second stage involved the examination of the structural model, with the findings provided in a dedicated section.

During the confirmatory factor analysis (CFA) phase, descriptive statistics for the six constructs were summarized in Table 3. The skewness and kurtosis values were found to be within an acceptable range for assuming a normal distribution (Hair et al., 2006). The Trialability construct had the highest average value at 3.95. Additionally, we conducted a CFA to evaluate the reliability and validity of the constructs (refer to Tables 3 and 4). All factor loadings exceeded the threshold of 0.50, ranging from 0.732 to 0.937 (Hair et al., 2021). We assessed the constructs' reliability using Cronbach's alpha, which showed internal consistency above the recommended threshold of 0.70 (Hayes & Coutts, 2020).

Table 2. CFA model result

Items	Factor Loadings	α	M(SD)	Skewness	Kurtosis
TR1	0.781	0.867	3.95 (0.786)	-.742	.666
TR3	0.857				
TR2	0.848				
OB1	0.892	0.908	3.77 (1.010)	-.811	.234
OB2	0.884				
OB3	0.862				
CA3	0.904	0.938	3.62 (1.017)	-.628	-.432
CA2	0.937				
CA5	0.883				
CA4	0.893				
CA1	0.732				
PC3	0.889	0.934	3.83 (0.847)	-.524	-.185
PC4	0.845				
PC1	0.912				
PC2	0.882				
GenAI5	0.866	0.948	3.75 (0.906)	-.662	-.525
GenAI3	0.873				
GenAI4	0.934				
GenAI2	0.888				
GenAI1	0.923				
WEA3	0.851	0.932	3.80 (1.059)	-.500	-.609
WEA2	0.898				
WEA1	0.867				
WEA4	0.918				

Note: TR: Trialability; OB: Observability; CA: Compatible Advantage; PC: Privacy Concerns; GenAI: GenAI Bias; WEA: Women Entrepreneurs' GenAI Adoption; α= Cronbach's Alpha coefficient; M(SD)= Mean & Standard deviation.

The instrument's validity and reliability were thoroughly assessed, and the results are summarized in Tables 2 and 3. To determine the convergent validity of the confirmatory factor analysis, we utilized composite reliability (CR) and average variance extracted (AVE) following the guidelines of Hair et al. (2019). Convergent validity is indicated when composite reliability values exceed 0.70 and AVE values are higher than 0.50, while also ensuring that AVE values surpass both the average shared variance (ASV) and the maximum shared variance (MSV). Our findings revealed that all composite reliability values were above 0.70 and all AVE values exceeded 0.50, confirming the model's convergent validity, as detailed in Table 3 (Almén et al., 2018).

In assessing discriminant validity, we used Fornell and Larcker's approach and Henseler et al.'s criteria (Fornell & Larcker, 1981; Henseler et al., 2015). Regarding Fornell and Larcker's approach, discriminant validity is achieved if the square roots of the AVE values in Table 3 exceed the corresponding inter-construct correlation coefficients. Our analysis indicated that the minimum square root of AVE was 0.829, which surpassed the highest correlation coefficient of 0.647, thus confirming the discriminant validity of our model. Additionally, all HTMT values in Table 4 were below the 0.80 threshold, further supporting the discriminant validity of the measures based on Henseler et al.'s (2015) criteria. Consequently, our research model demonstrated both convergent and discriminant validity, providing confidence in the appropriate construct validity of the measurement items utilized in this study.

Table 3. Discriminant validity

Factors	CR	AVE	MSV	MaxR(H)	CA	GenAI	WEA	PC	OB	TR
CA	0.941	0.762	0.355	0.953	**0.873**					
GenAI	0.954	0.805	0.382	0.958	-0.476	**0.897**				
WEA	0.935	0.781	0.395	0.938	0.570	-0.564	**0.884**			
PC	0.933	0.778	0.419	0.936	-0.596	0.548	-0.614	**0.882**		
OB	0.911	0.773	0.419	0.912	0.589	0.618	0.628	-0.647	**0.879**	
TR	0.868	0.688	0.212	0.873	0.393	-0.396	0.461	-0.410	0.434	**0.829**

Note: TR: Trialability; OB: Observability; CA: Compatible Advantage; PC: Privacy Concerns; GenAI: GenAI Bias; WEA: Women Entrepreneurs' GenAI Adoption; Average Variance Extracted = AVE > 0.50, Composite Reliability = (CR) > 0.70, Maximum Shared Variance = AVE > MSV and McDonald Construct Reliability = MaxR(H) > 0.7. The square roots of the AVE are presented as bold values along the diagonal.

Table 4. Heterotrait-Monotrait validity result

Factors	CA	GenAI	WEA	PC	OB	TR
CA	-----					
GenAI	0.504	-----				
WEA	0.596	0.571	-----			
PC	0.613	0.559	0.614	-----		
OB	0.614	0.629	0.630	0.645	-----	
TR	0.383	0.401	0.450	0.397	0.425	-----

Note: TR: Trialability; OB: Observability; CA: Compatible Advantage; PC: Privacy Concerns; GenAI: GenAI Bias; WEA: Women Entrepreneurs' GenAI Adoption

Structural Model

In the concluding phase of our Structural Equation Modeling (SEM) analysis, we transitioned from the measurement model to a structural model. Our findings aligned with the benchmarks established by Crawford & Kelder (2019). Notably, the chi-square statistic ($\chi2$) was 403.852, with a ratio of $\chi2$ to degrees of freedom ($\chi2/df$) at 1.779. The model demonstrated a CFI of 0.965, SRMR of 0.043, RMSEA of 0.059, and p-value of 0.057.

The analysis provided evidence supporting hypotheses H1 ($\beta = 0.141$, $p < 0.05$) and H2 ($\beta = 0.214$, $p < 0.05$), indicating that both Trialability and Observability significantly and positively affect the adoption of GenAI among Women Entrepreneurs. Additionally, hypothesis H3 ($\beta = 0.177$, $p < 0.05$) was also confirmed, highlighting the important role of Compatible Advantage in this context.

Conversely, hypotheses H4 (β = -0.219, p < 0.05) and H5 (β = -0.172, p < 0.01) were validated, demonstrating a significant negative influence of Privacy Concerns and GenAI Bias on the adoption of GenAI by Women Entrepreneurs (refer to Table 5). Moreover, the structural model explained 53% of the variance in Women Entrepreneurs' GenAI Adoption (see Appendix 2).

Table 5. Hypotheses testing

Hypothesis path				Standardized Beta	Unstandardized Beta	S.E.*	t-value	P
H1	Trialability	→	Women Entrepreneurs' GenAI Adoption	0.141	0.164	0.072	2.277	0.023*
H2	Observability	→	Women Entrepreneurs' GenAI Adoption	0.214	0.194	0.075	2.586	0.01*
H3	Compatible Advantage	→	Women Entrepreneurs' GenAI Adoption	0.177	0.152	0.06	2.551	0.011*
H4	Privacy Concerns	→	Women Entrepreneurs' GenAI Adoption	-0.219	-0.235	0.082	2.847	0.004**
H5	GenAI Bias	→	Women Entrepreneurs' GenAI Adoption	-0.172	-0.151	0.059	2.541	0.011*

Note: S.E. = Standard Error, P<0.05*, P<0.01**

Discussion

The study employed Structural Equation Modeling (SEM) to analyze the utilization of GenAI tools by female entrepreneurs. The findings indicate that Trialability and Observability positively influence adoption, whereas Privacy Concerns and GenAI Bias have a negative impact. Specifically, Trialability significantly increases the likelihood of adoption, while Privacy Concerns and GenAI Bias act as significant barriers. These factors collectively account for 53% of the variance in GenAI adoption, underscoring their importance.

These results are consistent with prior literature that underscores the critical role of privacy and security in technology adoption among women entrepreneurs. Gupta et al. (2023) and Isser et al. (2024) emphasize the need for robust data protection against unauthorized surveillance, aligning with the negative impact of Privacy Concerns revealed in this research. Additionally, the study's findings support the integration of privacy concerns into the Diffusion of Innovations (DOI) model, as discussed by Amini & Jahanbakhsh Javid (2023) and Parthasarathy et al. (2021), emphasizing the importance of addressing privacy within the adoption framework.

The existence of gender bias in Generative AI tools, highlighted by Zhou et al. (2024) and Danaher (2024), is evident in the outcomes. The outputs of Generative AI still demonstrate a significant amount of bias based on gender and sexuality, linking feminine names with conventional gender roles, propagating detrimental stereotypes, and showing inadequate representation (Hacker et al., 2024). This suggests that biases in AI algorithms can impede women's entrepreneurial endeavors (M. Gupta et al., 2022; Lévesque et al., 2020).

While previous research has often focused on the complexity of technology adoption (Lyytinen & Damsgaard, 2001), this study suggests that complexity may be less relevant in the context of GenAI tools. The current trend towards user-friendly designs in GenAI applications indicates a shift that simplifies the adoption process, contrasting with earlier studies that identified complexity as a significant barrier. This finding calls for reevaluating the DOI model, particularly in light of the evolving landscape of AI tools designed for ease of use (Feng et al., 2024; Harjamäki et al., 2024; Huang & Rust, 2024).

In outline, the study highlights the dual impact of factors influencing the adoption of GenAI among women entrepreneurs. The positive effects of trialability and observability suggest that experimenting with and observing the benefits can increase adoption rates. Conversely, the notable adverse effects of privacy concerns and GenAI bias underscore crucial obstacles that need to be overcome to ensure fair access to these technologies.

Theoretical and practical implications

The findings of the study have several noteworthy implications for understanding the adoption of technology by women entrepreneurs. Firstly, they suggest that the Diffusion of Innovations (DOI) model should be expanded to include privacy concerns and algorithmic bias as significant barriers to adoption, particularly in gendered contexts. Secondly, the results challenge the traditional view that complexity hinders adoption, indicating that the user-friendly design of GenAI tools diminishes its impact on the adoption process, prompting a reevaluation of existing frameworks to prioritize usability and accessibility. Lastly, the research underscores the importance of considering gender-specific factors in technology adoption theories. The negative effects of privacy concern and algorithmic bias emphasize the unique challenges faced by women in embracing technology.

At a practical level, the findings emphasize the need for strong data protection policies to address privacy concerns specific to women entrepreneurs. This requires policymakers to implement regulations that enhance data security. Organizations developing GenAI tools should prioritize strategies to mitigate bias and ensure fair representation in AI outputs, thereby promoting increased adoption among women. Moreover, stakeholders should encourage trialability and observability by creating opportunities for women entrepreneurs to experiment with GenAI tools through workshops and pilot programs. By emphasizing user-centric design, these technologies can become more accessible, and educational initiatives should equip women with the knowledge to navigate potential risks associated with GenAI tools. Together, these strategies can empower women entrepreneurs to effectively leverage technology in their businesses.

Limitation and further work

The study has limitations that need consideration. Firstly, it focused on a specific demographic—women entrepreneurs—potentially limiting the findings' generalizability. Also, relying on self-reported data may introduce bias, as participants could overstate their experiences or perceptions of GenAI tool adoption. Additionally, the study's cross-sectional design captures a snapshot in time and may not reflect the dynamic nature of technology adoption processes. The factors influencing GenAI adoption could evolve as technology advances and as women entrepreneurs gain more experience, suggesting that longitudinal studies would provide deeper insights.

It is essential for future research to encompass a broader spectrum of demographics and sectors to enhance the relevance of the findings. Employing mixed-methods approaches could provide more profound insights, and conducting longitudinal studies is advisable to monitor changes in attitudes and behaviors over time. Furthermore, it is important to delve into the various factors influencing the adoption of GenAI tools, particularly among women entrepreneurs, to promote equitable technology adoption.

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