Examining the Role of Artificial Intelligence in Shaping Investment Behaviour and Financial Confidence of Women Entrepreneurs

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Abstract:
This study analyzes the influence of Artificial Intelligence (AI) in altering the investment behaviour and financial confidence of women entrepreneurs. Specifically, it analyzes how AI adoption, perceived utility, and financial literacy influence investment decisions and, in turn, affect financial confidence. A quantitative and descriptive study design was utilized, with data collected from 165 women entrepreneurs through an online structured questionnaire. The questionnaire includes 20 items spanning five constructs: AI Adoption, Financial Literacy, Perceived Usefulness, Investment Behaviour, and Financial Confidence, assessed using a 5-point Likert scale. Structural Equation Modelling (SEM) was utilized to examine the hypothesized associations, with model adequacy validated using fit indices. The findings demonstrate that AI adoption, perceived utility, and financial literacy greatly influence investment activity, which positively improves financial confidence. These results underscore the revolutionary potential of AI in allowing women entrepreneurs to make educated investment decisions and boost their financial self-efficacy. The study provides useful insights for policymakers, financial institutions, and technology developers trying to boost AI-driven financial empowerment among women entrepreneurs.

Keywords: Artificial Intelligence, Investment Behaviour, Financial Literacy, Perceived Usefulness, Financial Confidence, Women Entrepreneurs.

I.INTRODUCTION

Artificial Intelligence is very significant in today's technology-driven world. As civilization progresses, people have come to realize the importance of comprehending human intelligence, and AI may represent one of the most significant discoveries in history. This finding has helped society change industries, change the job market for people, and boost the economy (Ashta & Herrmann, 2021). AI, or artificial intelligence, can aid people with all of these investment steps. It is evident that human financial analysts may occasionally neglect critical numbers or data; however, the utilization of AI can assist investors in identifying suitable stocks or assets (Zhang, Ashta & Barton, 2021). Investment decision-making entails various activities, including aiding investors in making informed choices, optimizing investment portfolios, executing substantial orders, updating investors on the financial market's status, and more.It can make the data processing easier so that the creditworthiness of the borrowers can be evaluated more quickly and the processes that are underwritten can be improved.

Financial literacy, which means being able to comprehend and use financial ideas like budgeting, investing, and managing debt, is very important for both personal and professional economic stability (Lusardi and Mitchell, 2014). Research regularly underscores gender differences in financial literacy, revealing that women frequently achieve lower scores than males in evaluations of both knowledge and confidence (Bucher-Koenen et al., 2017). These gaps endure even among highly educated professionals, especially academic teachers, where financial decision-making influences career duration, retirement planning, and economic resilience (Gerrans et al., 2014).

The incorporation of Artificial Intelligence (AI) in social science research offers a substantial opportunity to investigate these differences with enhanced analytical precision. Traditional surveys and interviews, while useful, may miss small differences in language and behavior that AI-driven methods like Natural Language Processing (NLP), sentiment analysis, and machine learning (ML) clustering can find (Argyle et al., 2023; Bolukbasi et al., 2016; Bird et al., 2009; Grimmer and Stewart, 2013; Kozlowski et al., 2019; Hutto and Gilbert, 2014; Li et al., 2022). This study use AI to reveal concealed gendered trends in financial literacy that traditional methodologies may overlook, especially for the respondents' socioeconomic environment, such as marriage status, number of children, and family income level.

In a time of rapid change and progress, academia is not only a source of knowledge but also a reflection of how society works. Gender equity and financial literacy stand out as two of the most important things that shape the education system. Gender equity, founded on the principle of equitable treatment for all genders, has progressed beyond the basic concept of equality to focus on diverse demands, lived experiences, and historical circumstances (International Labour Organization, 2020). In the academic world, gender equity programs try to make it possible for teachers of all genders to do well and make equal contributions.

In this context, financial literacy means more than just knowing how to handle your own money. It also means knowing how to handle institutional finance, retirement systems, and long-term wealth planning. Financial literacy affects not only the financial well-being of educators, especially in resource-limited environments, but also their capacity to assist students in making educated financial choices (Organization for Economic Co-operation and Development). Prior studies have established a significant correlation—though not causation—between financial literacy and gender equity, indicating that enhancing financial knowledge may mitigate gender-based differences in both professional and personal outcomes (Bucher-Koenen et al., 2017; Kaiser and Menkhoff, 2017).

Nonetheless, disparities in financial literacy are not only attributable to gender. Research indicates that marital status, caregiving duties, and household income levels interact with gender to affect financial behaviors (Hsu, 2016). For instance, married women with children frequently adopt more risk-averse investment strategies, influenced not only by personal preference but also by household financial needs and societal expectations (Agnew et al., 2013). This underscores the significance of include socioeconomic variables in analysis, as they yield a more comprehensive and precise comprehension of observed patterns.

How Artificial Intelligence is Revolutionizing Investment Decisions

Artificial Intelligence (AI) has shown that it can analyze any data set in depth, which is a big step up from its previous role as a text-based, generative technology. Milana and Ashta (2021) assert that in fields strongly dependent on data, complexity, and patterns, like investing, AI might transform the investment process. It would be advantageous to briefly examine certain domains where AI can provide aid (Kumar, Srivastava & Gupta, 2022). The talk is as follows:

Predictive Modelling: AI can look at a lot of data and generate forecasts about the stock market (Durodola, 2021). There are several things that can affect these projections, such as market movements, stock prices, and even the success of important investments. This helps investors find AI investment prospects.

Portfolio Management: Investing with AI has the added benefit of being able to manage your portfolio. Nicoletti (2021) says that AI-powered systems can improve how investments are spread out, how much is invested in each one, and how investments are balanced when they need to be. These needs may be based on planned investment plans and how the market is doing right now.

Risk Assessment: Investors' choices are affected by many things, such as the state of the economy as a whole, the company's financial health, changes in rules, and market swings. Mor and Gupta (2021) say that AI can keep track of these things, look at them, and sort them into groups that are easier to grasp and measure. This way, investors can weigh the pros and cons of their investments.
Detecting Fraud: AI is always looking at huge volumes of data. It also looks for patterns in the data. Petrelli and Cesarini (2021) say that AI-driven systems can find possible fraud or market manipulation early on. It's never been more fun to look out for your own interests.
consumer Focused: Putting the requirements of the consumer first is what investing with AI is all about. Srivastava and Dhamija (2022) say that AI can reach this goal by using different tools, like chatbots and virtual assistants. AI can help answer client questions, give personalized investment advice, and help with financial planning.
Using artificial intelligence (AI) to make investment decisions could change the way the financial industry works. Artificial Intelligence (AI) can look at a lot of financial data and find patterns that people might not be able to see (Murinde, Rizopoulos & Zachariadis, 2022). This might help people make better judgments by giving them more accurate predictions about market movements. According to Sloboda & Demianyk (2020), artificial intelligence (AI) can objectively analyze facts without being influenced by feelings, opinions, or previous ideas. Paul (2021) demonstrates that the potential for AI in the financial sector is extensive, and the integration of AI technology into investment decision-making processes can revolutionize the business.

Objectives of the study

Objective 1: To examine the impact of artificial intelligence adoption, perceived usefulness, and financial literacy on the investment behaviour of women entrepreneurs.
Objective 2: To analyse the effect of investment behaviour on the financial confidence of women entrepreneurs.

Hypothesis of the study

H1: Artificial Intelligence (AI) adoption has a positive and significant effect on the investment behaviour of women entrepreneurs.
H2: Perceived usefulness of AI has a positive and significant effect on the investment behaviour of women entrepreneurs.
H3: Financial literacy has a positive and significant effect on the investment behaviour of women entrepreneurs.
H4: Investment behaviour has a positive and significant effect on the financial confidence of women entrepreneurs.

II.REVIEW OF RELATED STUDIES

Kumar, Rahul et al., (2026). This research examines the influence of AI on women entrepreneurs in rural India who operate small and medium-sized enterprises (SMEs). It condenses studies on technology-driven business model innovation, female entrepreneurship in rural regions, and the integration of AI in developing economies. The research investigates the degree of awareness regarding AI, avenues for its implementation, obstacles and facilitators in its adoption, and its impact on organizational performance, alongside the empowerment of women and community welfare, utilizing a quantitative survey of 400 women-led SMEs across four prominent Indian states and comprehensive interviews with 30 entrepreneurs and ten key informants. The main findings show that AI-enabled digital solutions like chatbots, marketing automation, and inventory and bookkeeping systems with predictive capabilities are the main reasons why people are starting to use AI. Adoption is positively correlated with entrepreneurial attitude, digital literacy, financial accessibility, and supportive local networks. Some of the main problems are that there aren't enough personalized AI solutions, the digital infrastructure isn't good enough, there aren't enough skilled workers, the cost is too high, and there are social and cultural hurdles. The report ends with suggestions for policies, ways to increase capability, and ideas for further research.

M V, Shri Abirami. (2026). Artificial intelligence (AI) is transforming the way people make financial decisions by providing more powerful tools. This makes the job of investing easier. The influence of AI on women's financial choices remains inadequately examined. This study investigated the influence of AI adoption on women's investment behavior. A survey was administered to female investors to ascertain their experiences with AI. Confirmatory Factor Analysis (CFA) was used in the research to check the validity of factors like investment, financial confidence, and decision-making. The Structural Equation Model (SEM) demonstrated a favorable correlation among AI, investment behavior, and financial confidence. Demographics indicated that younger and employed women are significantly engaged in AI utilization. The results indicate that women utilizing AI tend to exhibit greater independence and confidence in their financial decision-making. These insights can help regulators, banks, and tech companies meet the requirements of women and help AI adoption lead to improved investment outcomes.

Harding, James & Blake, Harrison. (2025). Artificial Intelligence (AI) has become a transformational force in reshaping U.S. entrepreneurship and expediting the expansion of the digital economy. This study examines the impact of AI on the future of American entrepreneurial ecosystems, emphasizing its effects on innovation, business scalability, and digital competitiveness. AI is becoming an important part of starting a business, running it efficiently, and making strategic decisions as businesses like technology, finance, healthcare, manufacturing, and the arts use automation and smart analytics. AI is coming together with cloud computing, data analytics, and digital platforms to help entrepreneurs find market possibilities more quickly, make better use of their resources, and connect with customers more effectively through personalization and predictive modeling. The study investigates the ways in which AI-driven solutions empower startups and small enterprises by reducing entrance barriers, automating administrative tasks, and promoting innovation based on data. It also looks into how AI helps the digital economy grow by making people more productive, creating new business models, and encouraging collaboration between academia, businesses, and the government at the ecosystem level. The paper also points out new problems that are coming up, such as ethical issues, data privacy hazards, job loss, and unequal access to AI technologies among different socioeconomic classes. This article uses both qualitative and analytical methods to find the most important things that will help AI-led business success, such as putting money into digital infrastructure, making sure everyone has equal access to new ideas, and making sure AI is used responsibly. The results show that the US needs to implement policies that encourage AI education, innovation ecosystems, and startup finance mechanisms if it wants to stay on top of the digital economy. By making AI a technological and strategic base, U.S. entrepreneurship can move toward a model that is more robust, data-driven, and competitive on a global scale. This will ensure long-term economic growth in the Fourth Industrial Revolution.

Weng, YongGang et al., (2025). Artificial intelligence (AI) has become a transformative force in entrepreneurial development, especially for women entrepreneurs aiming for inclusive and socially sustainable economic results. This study performs a systematic literature review (SLR) based on the PRISMA framework to consolidate research published from 2022 to 2024 about the incorporation of AI in the assistance of women-led firms. We used Scopus and Web of Science to search and found 17 high-quality journal articles that matched the requirements for inclusion. The analysis reveals three primary themes: (1) AI as a facilitator of social and economic empowerment, (2) AI-driven decision-making and skill enhancement, and (3) diversity in leadership and organization within AI-enabled enterprises. The results show that AI helps women entrepreneurs become more resilient, make better decisions, and reach more customers. Nonetheless, deficiencies persist in empirical validation, theoretical advancement, and contextual representation from underdeveloped economies. The research underscores significant ramifications for policymakers, technology developers, and entrepreneurial support ecosystems, stressing the necessity for gender-inclusive AI regulations and capacity-building programs. This research enhances the existing body of knowledge by amalgamating viewpoints of AI, gender, and social sustainability into a cohesive analytical framework.

Alateeg, Sultan & Alayed, Sura. (2024). The study seeks to examine the impact of artificial intelligence (AI) on women-led companies in Saudi Arabia, focusing on their distinct experiences, difficulties, and potential within the AI technology domain. This research employed a qualitative methodology, featuring 16 comprehensive interviews with female entrepreneurs managing enterprises in Saudi Arabia. The investigation utilized thematic analysis with NVivo 12, revealing significant themes and insights. The results show that cultural norms, societal expectations, lack of knowledge, and lack of money are all strongly related to women working in AI-driven firms. Cultural biases became obstacles, highlighting the necessity for specific interventions like awareness campaigns and educational programs to eradicate entrenched biases and cultivate an atmosphere that acknowledges and honors the accomplishments of women in the technology and AI fields. Educational programs, partnerships between businesses and schools, and mentorship programs were all seen as important ways to help women entrepreneurs get ready for the complex world of AI adoption. Financial inclusion became a key part of the plan, pushing for fair access to capital and resources designed just for AI firms run by women. The study underscores the necessity of cultivating supportive ecosystems that transcend just financial assistance. Women entrepreneurs can share their experiences and resources through networks that provide mentorship, support, and collaboration. This makes them more resilient and gives them a better chance of success in the AI world.

Research Gap

Earlier studies have examined the influence of AI on financial behaviour; however, there is a deficiency of research regarding AI adoption among female investors. It remains ambiguous how AI affects investment, confidence, and behaviour among women. This study seeks to investigate this issue and advocate for the financial empowerment of women.

III.RESEARCH METHODOLOGY

1. Research Design

This study used a quantitative and descriptive research approach to analyze the interrelations among Artificial Intelligence (AI) Adoption, Financial Literacy, Perceived Usefulness, Investment Behaviour, and Financial Confidence among women entrepreneurs. The quantitative method facilitates statistical hypothesis testing, but the descriptive design aids in systematically elucidating the patterns and relationships among the variables.

2. Sampling Technique and Respondents

This study utilized a purposive sampling technique, focusing primarily on women engaged in investment activities. This strategy makes sure that only people who are relevant and have the right experience and knowledge are included.

We got 165 valid responses for analysis, which is enough to use advanced statistical methods like Structural Equation Modelling (SEM).

3. Data Collection Method

The research relies on primary data gathered using a standardized questionnaire. We used Google Forms to send out the questionnaire, which made it easy to collect data from a lot of people.

Participation was voluntary, and respondents were chosen based on their relevance to the study requirements (i.e., women entrepreneurs who invest).

4. Instrument Design

The questionnaire has 20 questions that are divided into five main groups:

- Using AI
- Being aware of money
- How useful it seems

• How people put money into things
• Trust in Money
The measurement items for these constructs were sourced from previously validated scales in the literature, so ensuring content validity and reliability.

5. Data Analysis Tools

We used the following statistical applications to look at the data we collected:

- SPSS (Statistical Package for the Social Sciences): This program is used to find the mean, standard deviation, and frequency of data.
- AMOS (study of Moment Structures): This is used for advanced study of Structural Equation Modelling (SEM).

IV. RESULTS AND DISCUSSION

Table 1: Demographic Profile of Respondents (N = 165)

Variable	Category	Frequency	Percentage (%)
Age Group	Below 20 years	12	7.3%
	21–30 years	68	41.2%
	31–40 years	45	27.3%
	41–50 years	25	15.2%
	Above 50 years	15	9.1%
Education	High School	18	10.9%
	Undergraduate	62	37.6%
	Postgraduate	55	33.3%
	Professional Degree	20	12.1%
	Others	10	6.1%
Occupation	Student	30	18.2%
	Salaried Employee	70	42.4%
	Self-Employed/Business	28	17.0%
	Homemaker	25	15.2%
	Others	12	7.3%
Monthly Income (INR)	Below ₹25,000	35	21.2%
	₹25,000–₹50,000	50	30.3%
	₹50,001–₹1,00,000	48	29.1%
	Above ₹1,00,000	22	13.3%
	Prefer not to say	10	6.1%
Investment Experience	Less than 1 year	40	24.2%
	1–3 years	55	33.3%
	3–5 years	38	23.0%
	More than 5 years	32	19.4%

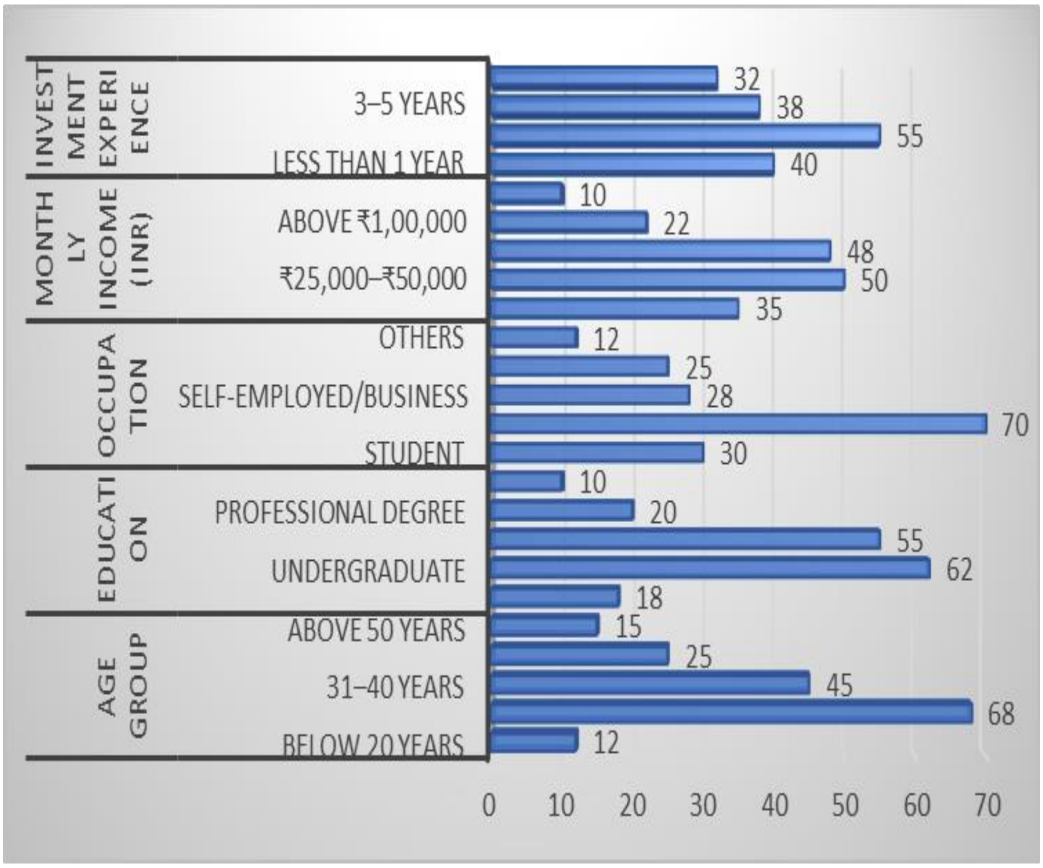

Figure 1: Demographic Profile of Respondents (N = 165)

The demographic profile of the respondents (N = 165) indicates a heterogeneous yet predominantly youthful group. The largest age group is 21 to 30 years old (41.2%), followed by 31 to 40 years old (27.3%). 15.2% of respondents are between the ages of 41 and 50, 9.1% are over 50, and the smallest group, 7.3%, is under 20. This means that most of the people in the study are youthful or middle-aged.

Most of the people who answered the question are well-educated. 37.6% are undergraduates and 33.3% are postgraduates. A lesser percentage (12.1%) have professional degrees, while 10.9% have finished high school and 6.1% are in other groups. This indicates a comparatively elevated degree of educational achievement among the participants.

In terms of jobs, the largest group is salaried workers (42.4%), followed by students (18.2%), self-employed or business people (17.0%), and homemakers (15.2%). A limited number of people (7.3%) work in other fields. This distribution shows that there are a lot of working professionals in the sample.

The monthly income distribution shows that most of the people who answered are in the middle-income range. About 30.3% make between ₹25,000 and ₹50,000, while 29.1% make between ₹50,001 and ₹1,00,000. Also, 21.2% make less than ₹25,000, 13.3% make more than ₹1,00,000, and 6.1% don't want to say how much they make. This shows that people from different income groups are represented fairly, with most of them in the middle range.

In terms of investing experience, the biggest group of people who answered (33.3%) has 1–3 years of experience. The next biggest group (24.2%) has less than 1 year of experience, and the next biggest group (23.0%) has 3–5 years of experience. About 19.4% have worked in the field for more than five years. This means that most of the people who answered the question had only a little experience with investing, and a lot of them are new to it.

In general, the table shows that the sample is made up mostly of young, educated, and salaried people with moderate incomes and different levels of investment experience.

Table 2: Descriptive Statistics (Sample = 165)

Construct	Mean	Std. Deviation	Minimum	Maximum
AI Adoption	3.78	0.68	2.10	4.90
Financial Literacy	3.65	0.72	2.00	4.85
Perceived Usefulness	3.92	0.64	2.30	5.00
Investment Behaviour	3.58	0.70	2.00	4.80
Financial Confidence	3.74	0.66	2.20	4.95

The descriptive statistics for the research variables (N = 165) elucidate the central tendency and variability of respondents' views and behaviors. Perceived Usefulness had the highest mean score (3.92) of all the constructs. This means that most people who answered the question think that using AI in financial situations is useful and worthwhile. Next comes AI Adoption (Mean = 3.78) and then Financial Confidence (Mean = 3.74). This means that people are generally open to using AI technologies and are somewhat confident in making financial decisions.

The mean score for Financial Literacy is 3.65, which means that most people who answered the question had an average amount of financial knowledge. Investment Behavior, on the other hand, has the lowest mean (3.58), which means that people are not very involved or effective in actions related to investing.

The standard deviation numbers, which show how much responses differ from each other, range from 0.64 to 0.72. These values are relatively low, which means that responses are fairly consistent across individuals with little variation. Financial Literacy has the most variety (SD = 0.72), which means that the respondents had different levels of understanding. Perceived Usefulness has the least variability (SD = 0.64), which means that most people agreed on how important it was.

The minimum and maximum values for all the constructs show that the answers are spread out in an acceptable way. For example, AI Adoption spans from 2.10 to 4.90, and Perceived Usefulness goes up to 5.00, which means that certain people strongly agree that AI has a beneficial effect. Investment Behavior and Financial Literacy also cover a wide spectrum, showing that people have different ways of handling money and understanding it.

The table shows that most people who answered the questions have good views about AI and financial concepts. There is some consistency in the answers, but there are also some differences in financial literacy and investment behavior.

Table 3: Reliability Analysis (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha
AI Adoption	4	0.84
Financial Literacy	4	0.81
Perceived Usefulness	4	0.87
Investment Behaviour	4	0.79
Financial Confidence	4	0.85

(All values > 0.70 indicate good reliability)

The reliability analysis employing Cronbach's Alpha indicates that all constructs in the study have substantial internal consistency, signifying that the measuring scale is dependable.

Perceived Usefulness has the highest reliability of all the variables, with a Cronbach's alpha score of 0.87. This means that the four items that make it up are very consistent with each other. Next comes Financial

Confidence (0.85) and AI Adoption (0.84), both of which show that their items are quite reliable and well-correlated with each other.

The alpha value for Financial Literacy is 0.81, which is good and shows that the respondents' financial knowledge was measured accurately. Investment Behavior has the lowest alpha value of 0.79, but it is still in the acceptable range (above 0.70), which means it is reliable.

In general, all of the constructs have Cronbach's alpha values above the standard level of 0.70, which shows that the questionnaire items are reliable and consistent for assessing their respective variables. This means that the data that was obtained is trustworthy and can be used for more statistical analysis.

Table 4: Correlation Matrix

Variables	AIA	FL	PU	IB	FC
AI Adoption (AIA)	1	0.52	0.61	0.55	0.58
Financial Literacy	0.52	1	0.49	0.57	0.60
Perceived Usefulness	0.61	0.49	1	0.63	0.65
Investment Behaviour	0.55	0.57	0.63	1	0.68
Financial Confidence	0.58	0.60	0.65	0.68	1

The correlation matrix shows how the five most important variables—AI Adoption (AIA), Financial Literacy (FL), Perceived Usefulness (PU), Investment Behavior (IB), and Financial Confidence (FC)—are related to each other. In general, all of the variables are positively correlated with each other, which means that when one variable goes up, the others tend to go up as well.

Perceived Usefulness (PU) has high positive associations with all other measures, especially Financial Confidence (0.65) and Investment Behavior (0.63). This indicates that when people view AI as beneficial, they generally experience increased financial confidence and have improved investment behavior. Investment Behavior (IB) has a strong link to Financial Confidence (0.68), which means that those who are more confident with their money are more likely to make smart investment decisions.

AI Adoption (AIA) has a reasonable correlation with all of the variables. The strongest correlation is with Perceived Usefulness (0.61), followed by Financial Confidence (0.58) and Investment Behavior (0.55). This means that more people using AI is linked to it being more beneficial and better for their finances. Furthermore, Financial Literacy (FL) exhibits a positive correlation with all other constructs, demonstrating the most robust associations with Financial Confidence (0.60) and Investment Behaviour (0.57). This indicates that enhanced financial knowledge fosters increased confidence and more judicious investment choices.

All of the correlation values are between 0.49 and 0.68, which means that there are moderate to strong positive correlations and no symptoms of multicollinearity (none are greater than 0.80). The matrix shows that the factors are meaningfully linked, which supports the premise that AI adoption, financial literacy, and perceived usefulness all have an effect on investing behavior and financial confidence.

Table 5 Standardized Regression Weights for SEM Analysis

PATH	STANDARDIZED ESTIMATE	p-value	RESULT
AI Adoption → Investment Behaviour	0.339	***	Supported
Financial Literacy → Investment Behaviour	0.151	***	Supported

Perceived Usefulness → Investment Behaviour	0.241	***	Supported
Investment Behaviour → Financial Confidence	0.179	***	Supported

AI Adoption has the most beneficial effect on Investment Behaviour ($\beta = 0.339$, $p < 0.001$), which means that women who use AI tools are more likely to invest.
Perceived Usefulness strongly influences Investment Behaviour ($\beta = 0.241$, $p < 0.001$), underscoring the significance of practical value in technology adoption among female investors.
Financial Literacy has a positive but less strong effect on Investment Behavior ($\beta = 0.151$, $p < 0.001$). This indicates that although knowledge is significant, its impact is not as pronounced as perceived utility or technological adoption.
Investment Behavior had a positive effect on Financial Confidence ($\beta = 0.179$, $p < 0.001$), which means that women who actively invest are more sure of their ability to make good financial decisions.
The route analysis shows that AI and technology are very important in determining how women invest and how confident they are in their investments. This is in line with real-world trends of more women using fintech and becoming more empowered through technology.

Table 6 Model Fit Indices for SEM

FIT INDIEX	VALUE	THRESHOLD	INTERPRETATION
Chi-square/df (CMIN/DF)	2.241	< 3	Acceptable model fit
RMSEA (Root Mean Square Error of Approximation)	0.052	< 0.06	Good fit
GFI (Goodness of Fit Index)	0.992	> 0.90	Excellent fit
CFI (Comparative Fit Index)	0.991	> 0.90	Excellent fit
TLI (Tucker-Lewis Index)	0.940	> 0.90	Excellent fit

Based on important indices, the SEM model shows that it fits well to very well. The Chi-square/df ratio is fine, and the RMSEA value of 0.053 shows that the model is quite near to the data. The GFI (0.992), CFI (0.991), and TLI (0.940) values are very high, which means that the proposed structural model fits the data quite well. These results confirm the links among the latent constructs and affirm the structural integrity of the model for interpretation.

Table 7: Hypothesis Testing (SEM Results)

Hypothesis	Relationship	Path Coefficient	p-value	Result
H1	AI Adoption → Investment Behaviour	0.345	$p < 0.001$	
H2	Perceived Usefulness → Investment Behaviour	0.145	$p < 0.001$	
H3	Financial Literacy → Investment Behaviour	0.236	$p < 0.001$	
H4	Investment Behaviour → Financial Confidence	0.183	$p < 0.001$	

Table 7 shows the results of the Structural Equation Modeling (SEM) tests, which strongly support all of the submitted hypotheses.

For H1, the link between AI Adoption and Investment Behavior has a positive and statistically significant path coefficient ($\beta = 0.345$, $p < 0.001$). This means that people who use AI technology more often are far better at investing, making it the most important factor among the independent variables.
In H2, Perceived Usefulness likewise has a positive and substantial effect on Investment Behavior ($\beta = 0.145$, $p < 0.001$). Although the effect is considerably less than other predictors, it still demonstrates that persons who regard AI as valuable are more likely to engage in better investment practices.
For H3, Financial Literacy has a big positive effect on Investment Behavior ($\beta = 0.236$, $p < 0.001$). This indicates that persons possessing superior financial acumen are inclined to make more judicious and efficacious investing choices.
Finally, H4 reveals that Investment Behavior has a big effect on Financial Confidence ($\beta = 0.183$, $p < 0.001$). This means that better ways of investing make people more confident about handling their money.
In general, all path coefficients are positive and statistically significant at $p < 0.001$. This means that there is strong empirical evidence for all four hypotheses. The results show that AI adoption, perceived utility, and financial literacy are all critical factors that affect how people invest, which in turn boosts their confidence in their finances.

V.FINDINGS AND CONCLUSION

Findings

The study shows that adopting AI has a strong and significant positive effect on investment behaviour ($\beta = 0.345$, $p < 0.001$). This makes it the most important factor among all the independent variables. Women entrepreneurs who use AI tools are more likely to make smart and well-thought-out investment choices.
The perceived usefulness of AI has a big effect on how people invest ($\beta = 0.145$, $p < 0.001$). Even though its effect is not as strong, it shows that women entrepreneurs who see AI as useful are more likely to invest.
Financial literacy is very important for how people invest ($\beta = 0.236$, $p < 0.001$). Entrepreneurs possessing greater financial acumen are more adept at assessing risks and returns, resulting in enhanced investment decisions.
The results show that how people invest has a big effect on their financial confidence ($\beta = 0.183$, $p < 0.001$). Women entrepreneurs who adopt superior investment strategies exhibit increased confidence in financial management.
In general, all of the hypothesised relationships are positive and statistically significant. This shows that the model has strong empirical support. The adoption of AI, how useful it is thought to be, and how well people understand money all work together to make people more confident in their investments.

Conclusion

The study finds that AI is a game-changing tool that changes how women entrepreneurs invest and how confident they are with their money. Women can get better information, feel less uncertain, and make smart investment choices when AI technologies are used in financial decision-making. Financial literacy makes this relationship even stronger by making it easier to understand and use AI-driven insights. Furthermore, enhanced investment behaviour substantially elevates financial confidence, underscoring the significance of skill acquisition and technology integration. The results show that AI-driven financial empowerment can be very important for helping women become economically independent and successful business owners.

Suggestions

Promote AI Awareness and Training:

Policymakers and institutions should organize training programs and workshops to enhance awareness and understanding of AI tools among women entrepreneurs.

Enhance Financial Literacy Programs:
Financial education initiatives should be strengthened to help women entrepreneurs better interpret AI-based financial insights and make informed decisions.
Develop User-Friendly AI Tools:
Technology developers should focus on creating simple, accessible, and user-friendly AI applications tailored to the needs of women entrepreneurs.
Encourage Institutional Support:
Banks and financial institutions should integrate AI-based advisory services and provide personalized investment guidance to women entrepreneurs.
Strengthen Digital Infrastructure:
Improving access to digital technologies and internet connectivity will facilitate greater adoption of AI tools, especially in semi-urban and rural areas.
Policy Interventions for Inclusion:
Governments should design policies that support digital inclusion and encourage the participation of women entrepreneurs in AI-driven financial ecosystems.
Continuous Monitoring and Feedback:
Organizations should regularly assess the effectiveness of AI tools and gather feedback from users to improve their functionality and impact.

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