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The role of AI in financial analysis on investment intentions among economics students: Mediating effect of analytical self-efficacy

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Abstract

This research deals with the influence of artificial intelligence (AI) technologies in financial analysis on the investment decision intention, highlighting the mediating role of analytical self-efficacy. Drawing upon the theory of planned behavior (TPB), the technology acceptance model (TAM), and self-efficacy theory, a conceptual framework was developed and put to test based on information gathered from 300 economics students chosen through a process of stratified random sampling. A structured questionnaire captured dimensions of AI usage, analytical self-efficacy, and investment intention, and the data were analyzed using structural equation modeling (SEM) and the Bootstrap method. Results indicated that AI usage has a significant and positive influence on both analytical self-efficacy and investment decision intention. Further, analytical self-efficacy was a partial mediator of the relationship between AI usage and investment intention. The research adds to the body of knowledge by fusing behavioral intention models with AI adoption within higher educational settings and suggesting workable solutions for curriculum construction and technology-oriented training to enhance the readiness of students to invest.

Keywords: Artificial intelligence, Financial analysis, Investment decision intention, Analytical self-efficacy, Technology acceptance, Jordanian universities

1. Introduction

In the last couple of years, there has been a great wave of the take-up of artificial intelligence (AI) tech across different business fields, especially in financial analysis. These techs have created a quick way to handle sets of data and give very good money advice that helps choose where to invest well [1]. This step helped to make the market work better and improve how well investors can see chances as well as risks.

The increased use of AI tools like robot advisors and machine learning-based predictive models has led scholars and experts to research how these technologies influence investor behavior and decision-making intentions [2]. Especially in the context of economics students, who will be part of a future generation highly capable of interacting with digital tools and understanding intelligent analytics in different financial and investment settings, this becomes an important issue to discuss.

Recent literature has it that the use of technology does not solely determine the intention of making an investment decision, but rather, it is also a part of several psychological and behavioral factors, where analytical self-efficacy, or simply the confidence one has in their abilities to analyze, takes center stage [3]. Students' confidence in their ability to comprehend and analyze financial data in a classroom positively relates to the likelihood of using the outputs of intelligent systems and converting them into real investment decisions.

This research examines the influence of AI technology used in financial analysis on the investment decision intention of economics students. An attempt is made to explore the mediating effect of analytical self-efficacy. Thus, the research will contribute to understanding in a more efficient way the behaviors of technology adoption among university students and offer insight into the type of educational strategies that can foster the desired analytical and investment-oriented thinking.

2. Problem statement

The financial sector is one of the largest in rapid transformation, driven by the adoption of artificial intelligence in financial analysis, forecasting markets, and investment choices. AI tools are now made possible for use by learners in universities. However, as scarce tools, their availability does not ensure adoption either, hence not changing much the behavior of the users positively [4]. This is especially true for university students, as they are still in the process of building their confidence and analytical skills.

Recent studies like [4] and [5] indicate that the use of AI in financial analysis may influence individuals' intentions to make investment decisions. However, this influence is not always direct, as investment intentions are mediated by psychological and behavioral factors, the most important of which is analytical self-efficacy. A good number of studies have addressed the impact of AI in the financial sector at large. However, a visible research gap is still left within the background of university students, particularly in Arab or local settings such as Jordanian public universities. Insufficient research has been conducted on how much the use of AI by students at the level of analysis of finance impacts their investment intentions, or whether there is analytical self-efficacy to work as a mediating variable in this relationship.

Thus, this study aims to answer the following question: What is the impact of using AI technologies in financial analysis on the investment decision intention of economics students in Jordanian public universities, and what is the mediating role of analytical self-efficacy in this relationship?

3. Significance of research

This research is significant because it deals with a modern issue concerning financial technology and investment behavior at an academic institution. It examines the influence of AI-based financial analysis on economics students' investment intention decisions while analytically considering the mediator at play, which is self-efficacy. It addresses a notable gap in Arabic-language research, especially in the Jordanian academic context, taking a forward-looking student population seen as the future pulse of the digital investment market.

Theoretically, this research enriches existing models of behavioral intention: the theory of planned behavior and the technology acceptance model by including the individual-level factor of analytical competence. In practice, it means that the results of the research provide actionable insights for universities to improve their curricula and training programs; for developers to understand user behavior toward AI tools; and for students to engage more efficiently with intelligent systems so that they can make informed and effective financial decisions.

4. Conceptual model

The conceptual model of this research meets at the intersection of the theories of technology adoption and psychological constructs of decision-making. It combines the technology acceptance model (TAM) [6], the theory of planned behavior (TPB) [7], and self-efficacy theory [8] to describe how using tools for artificial

intelligence in financial analysis affects the investment decision intentions of students. These intentions are further assumed to be mediated by their analytical self-efficacy.

Recent studies have shown that there is a substantial effect of AI-based financial analytics tools on the processing of financial data and the formulation of investment preferences [9] [10]. Analytical self-efficacy, as to whether a person believes in the ability of one's own analysis, has been found to predict confidence in acting on recommendations that were generated by AI [11]. Therefore, the model posits that frequent users of AI in financial tasks among students are more likely to possess high analytical confidence, which subsequently leads to high readiness for decisions related to investments.

This model positions AI usage as the independent variable, analytical self-efficacy as the mediator, and investment decision intention as the outcome. It thus seeks to reveal both the direct and the indirect mechanisms through which enabled investment behavior takes place in the setting of a university. The conceptual framework for this research is shown in the figure below.

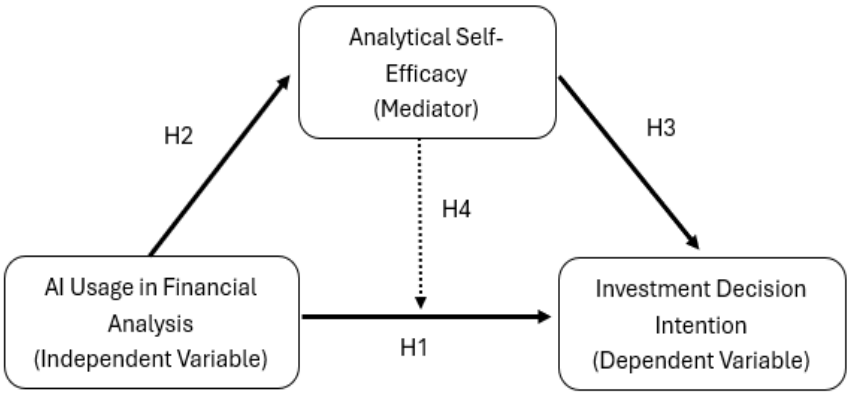

Figure 1. Research model

From Figure 1, we can see that the research variables are:

Independent variable (IV): AI Usage in Financial analysis

Represents the degree to which students utilize AI tools (e.g., robo-advisors, predictive models, AI-driven platforms) in analyzing financial data.

Mediating variable: Analytical self-efficacy

Reflects the student's confidence in their own analytical capabilities to interpret AI-generated financial insights and use them in investment-related judgments.

Dependent variable (DV): Investment decision intention

Refers to the students' cognitive intention to make investment-related decisions based on data analysis and AI-generated recommendations.

From the above, we can formulate the following hypotheses:

- **Hypothesis 1 (H1):** There is a statistically significant effect of AI usage in financial analysis on students' investment decision intention.
- **Hypothesis 2 (H2):** There is a statistically significant effect of AI usage in financial analysis on students' analytical self-efficacy.
- **Hypothesis 3 (H3):** There is a statistically significant effect of analytical self-efficacy on students' investment decision intentions.
- **Hypothesis 4 (H4):** Analytical self-efficacy mediates the relationship between AI usage in financial analysis and investment decision intention among economics students.

5. Theoretical framework

The theoretical framework is the conception of the present research that seeks to explain the relationship between the use of artificial intelligence (AI) technologies in financial analysis and economics students' investment decisions, with particular attention to the mediating role of analytical self-efficacy. These three closely related theories provide the basis for understanding the nature of the complex interaction that the present research seeks to explain: the theory of planned behavior (TPB), the technology acceptance model (TAM), and the self-efficacy theory.

5.1. Theory of planned behavior (TPB)

Proposed by Ajzen [7], the TPB explains an individual's intention to perform a specific behavior based on three components: attitude toward the behavior, subjective norm, and perceived behavioral control. According to this theory, the intention to make an investment decision does not arise solely from the availability of information or technology; it is also shaped by the individual's confidence in their ability to perform the behavior [7]. In the context of this research, AI usage serves as an external cognitive stimulus, while analytical self-efficacy contributes directly to the formation of perceived behavioral control, which in turn influences investment intention.

5.2. Technology acceptance model (TAM)

The TAM was developed by Venkatesh and Davis [6], posits that the acceptance of technology by individuals is mainly influenced by two essential factors: perceived usefulness and perceived ease of use. The model further explains that usage is not synonymous with adopting or changing behavior; an individual will adopt the best tool if he or she feels that the tool is useful and must be easy to use. This just forms the first level of accepting the tools in this investment decision through their application by students in financial analysis and investment. The investment decision, or the second level, depends on other internal psychological factors, particularly confidence in the ability to interpret the output created by the investment in AI.

5.3. Analytical self-efficacy

This idea comes from Bandura's self-efficacy theory, which says that the belief a person has in their capacity to do cognitive or analytical work has a direct impact on their willingness to take up new behaviors. We have defined analytical self-efficacy in this paper as the variable through which mediation is done through between AI use and investment decision intention. Studies done recently indicate that people who have more confidence in understanding the analysis of financial data done by AI are more likely to convert that information into real investment decisions [3].

6. Methodology

This research used a quantitative correlational method based on a descriptive-analytical framework. It intends to measure the relationship between the usage of AI in financial analysis (independent variable) and investment decision intention (dependent variable), with a view to exploring the mediating role of analytical self-efficacy. Data will be collected at one point in time using a cross-sectional design to gather the opinions of the respondents.

The population of the research consists of all economics students enrolled in public Jordanian universities officially accredited by the Jordanian Ministry of Higher Education, including the University of Jordan, Yarmouk University, the Hashemite University, Mutah University, Jordan University of Science and Technology, and Al-Balqa Applied University, during the academic year 2024–2025. Ethical approval for this study was obtained, ensuring compliance with international research ethics standards. Participation was voluntary, and informed consent was secured from all respondents prior to data collection. Participants were assured of anonymity and confidentiality, and the collected data were used solely for academic purposes.

Regarding the research sample, a stratified random sampling technique was utilized to ensure balanced representation across universities. Stratification was based on two key variables:

1. University affiliation (the six named universities).
2. Academic level (first year, second year, third year, and fourth year students) to ensure variability in academic exposure and analytical maturity.

The sample size was determined using Krejcie and Morgan's formula, resulting in a total of 300 economics students. This sample size was selected to ensure sufficient statistical power, particularly for mediation analysis using structural equation modeling (SEM). A closed-ended questionnaire was developed, comprising four main sections. The items in each section were constructed based on validated instruments from prior literature [5] [7] [9].

Table 1. Questionnaires

Section	Variable	Number of Items	Scale Type
Section 1	AI Usage in Financial Analysis (IV)	6 items	5-point Likert Scale
Section 2	Analytical Self-Efficacy (Mediator)	5 items	5-point Likert Scale
Section 3	Investment Decision Intention (DV)	5 items	5-point Likert Scale
Section 4	Demographics (age, gender, university, academic level)	4 items	Multiple choice

7. Statistical analysis

7.1. Data analysis

The data collected were analyzed using both SPSS and SmartPLS statistical software, in alignment with the mediational nature of the research. Initially, a descriptive analysis was conducted for the demographic variables using frequencies and percentages. The internal consistency of the measurement scales was then assessed using Cronbach's alpha to ensure their reliability, followed by an exploratory factor analysis (EFA) to evaluate the construct validity of the questionnaire dimensions. Upon confirming the psychometric properties of the instrument, both simple and multiple linear regression analyses were conducted to examine the direct relationships among the research variables. To assess the effect of the mediating variable, analytical self-efficacy, a path analysis was performed within the structural equation modeling (SEM) framework. In addition, the bootstrap method was employed to estimate the indirect effect and determine its statistical significance. The Sobel test was also used to verify the presence of a statistically significant mediation effect. All analyses were conducted using a significance level of 0.05, while model fit was assessed using standard indices such as the comparative fit index (CFI), goodness of fit index (GFI), and root mean square error of approximation (RMSEA) to ensure that the proposed model aligns well with the observed data. And to ensure the absence of common method bias (CMB), Harman's single-factor test was applied.

7.2. Descriptive statistics

The purpose of descriptive statistics is to provide an overall view of the respondents' levels of agreement regarding the research's three key variables. This analysis includes mean scores and standard deviations to assess the general trends and internal consistency among participants. According to Field [12], a mean score greater than 3.5 on a five-point Likert scale reflects a strong positive orientation toward the measured construct. A 5-point Likert scale was employed for all measurement items. This scale was selected over alternatives (such as 7-point or 10-point formats) because it strikes a balance between reliability and respondent clarity. Also, a 5-point scale minimizes cognitive load for participants, reduces survey fatigue, and is particularly effective in contexts involving students. It also facilitates comparability with earlier studies in the fields of technology adoption and behavioral intention, many of which have utilized 5-point scales.

Table 2. Descriptive statistics

Variable	Mean	Standard Deviation
AI Usage in Financial Analysis	4.12	0.56
Analytical Self-Efficacy	4.25	0.51
Investment Decision Intention	4.05	0.62

These relatively high means (>4.00) indicate that the students report high levels of AI usage in financial analysis, high confidence in their analytical abilities, and a strong intention to make future investment decisions.

7.3. Common method bias (CMB) test

To examine the potential threat of common method bias (CMB), Harman's single-factor test was conducted using exploratory factor analysis (EFA) with all measurement items entered simultaneously. The results indicated that the first unrotated factor accounted for 34.7% of the total variance, which is below the recommended threshold of 50% [12]. This suggests that common method bias is not a significant concern in this study.

Table 3. Harman's single-factor test results

Factor	Eigenvalue	% of Variance Explained	Cumulative %
1	8.52	34.7%	34.7%
2	4.10	16.7%	51.4%
3	2.25	9.2%	60.6%
4	1.45	5.8%	66.4%

As shown in Table 3, no single factor accounted for the majority of variance; the first factor explained only 34.7%, which is below the critical threshold of 50%. Therefore, common method bias is unlikely to distort the study results, supporting the validity and robustness of the findings.

7.4. Model fit

Fit of the model was assessed by several standard indices, such as the comparative fit index (CFI), goodness of fit index (GFI), and root mean square error of approximation (RMSEA). Results indicated that the proposed model had an acceptable to excellent fit with data since all the indices were equal to or above the most commonly recommended thresholds.

Table 4. Model fit indices

Fit Index	Recommended Threshold	Obtained Value	Interpretation
CFI	≥ 0.90 (acceptable), ≥ 0.95 (excellent)	0.962	Excellent fit
GFI	≥ 0.90	0.943	Good fit
RMSEA	≤ 0.08 (acceptable), ≤ 0.05 (close fit)	0.041	Close fit

Table 4 indicates that CFI came out to be 0.962 and GFI turned out to be 0.943, both over the recommended minimum of 0.90; this speaks volumes regarding strong model fit. In addition, the value for RMSEA was 0.041, below the threshold of less than 0.05 to indicate a very close fit of the model with observed data. Thus, these indices collectively support that the structural model gives an excellent representation of the underlying relationships among study constructs.

7.5. Internal consistency (reliability – Cronbach's alpha)

Cronbach's alpha is used to evaluate the internal consistency of each scale. According to Nunnally and Bernstein (1994), values of $\alpha \geq 0.70$ are acceptable, $\alpha \geq 0.80$ are good, and $\alpha \geq 0.90$ indicate excellent reliability [13].

Table 5. Reliability test

Scale	Cronbach's alpha (α)
AI Usage in Financial Analysis	0.89
Analytical Self-Efficacy	0.87
Investment Decision Intention	0.91

All alpha values suggest high internal reliability, indicating that the items within each scale are strongly interrelated and effectively measure their respective constructs.

7.6. Pearson correlation analysis

Pearson's correlation coefficient (r) is used to assess the strength and direction of linear relationships between variables. According to Nunnally [14] and Cohen [15]:

- r = 0.10 to 0.29 → weak correlation
- r = 0.30 to 0.49 → moderate correlation
- r ≥ 0.50 → strong correlation

Table 6. Reliability test

Relationship	Pearson's r	Significance (p)
AI Usage ↔ Analytical Self-Efficacy	0.61	$p < 0.001$
AI Usage ↔ Investment Decision Intention	0.57	$p < 0.001$
Analytical Self-Efficacy ↔ Investment Intention	0.65	$p < 0.001$

All relationships are statistically significant at the $p < 0.001$ level and demonstrate strong positive correlations, supporting Hypotheses H1, H2, and H3.

7.7. Multiple regression analysis

Multiple regression analysis was used to assess direct effects and evaluate potential mediation. According to Baron and Kenny [16], if the coefficient (β) for the independent variable decreases after the inclusion of a mediator, mediation is suggested.

Table 7. Multiple regression analysis

Pathway	Beta (β)	Significance (p)
AI Usage → Investment Intention	0.57	$p < 0.001$
AI Usage → Analytical Self-Efficacy	0.61	$p < 0.001$
Analytical Self-Efficacy → Investment Intention	0.54	$p < 0.001$
AI Usage (with mediator) → Investment Intention	0.23	$p = 0.02$

After introducing analytical self-efficacy as a mediating variable, the effect of AI usage on investment intention dropped from $\beta = 0.57$ to $\beta = 0.23$. This declines because of the presence of partial mediation, the result in the table above supporting Hypothesis H4.

7.8. Mediation analysis (bootstrap and Sobel Test)

To confirm the mediating role of analytical self-efficacy, a bootstrapping procedure with 5,000 resamples was employed. The indirect effect was evaluated using the confidence interval method. In addition, the Sobel test was applied as a complementary method [17].

Table 8. Bootstrap and Sobel test (mediation analysis)

Pathway	Indirect Effect (β)	95% Confidence Interval	Sobel z	p-value
AI Usage → Analytical SE → Investment Intention	0.33	[0.25, 0.43]	4.75	$p < 0.001$

Since the confidence interval does not include zero, the indirect effect is statistically significant. The Sobel test also confirms the mediation effect significance. This gives very strong support for Hypothesis H4.

8. Discussion of results

This study was set to determine the effects that the application of AI technologies in financial analysis would have on the intention of making investment decisions by economics students in public universities within Jordan. In specific terms, it sought to establish the role that analytical self-efficacy may play. Since all proposed hypotheses were accepted, strong proof has been obtained regarding the interaction between technological adoption and psychological confidence with behavioral intentions within an academic investment context. The discussion below is based on individual hypotheses about their relevant literature and theoretical bases.

8.1. Discussion of hypothesis (H1)

H1: There is a statistically significant effect of AI usage in financial analysis on investment decision intention.

Results of the analysis confirmed a positive, direct effect of AI use on investment decision intentions by students. This is in line with findings by Hesami [10] that the availability of intelligent platforms increases the willingness of students to participate in investment activities. It is also supported by insights provided by Bin-Nashwan and Li [18] on how AI-based financial tools heighten awareness and facilitate evidence-driven decision-making.

These results theoretically go along with the theory of planned behavior (TPB), which postulates that when individuals have access to enabling resources- such as AI technologies- perceived behavioral control becomes more robust, thereby strengthening intention. This, therefore, implies that in contexts like Jordan, where financial literacy is just taking off its feet, AI-driven platforms could be seen surfacing as enabling resources, reducing entry barriers for youth investors. The finding also delivers practice by demonstrating to policymakers and universities how injecting AI-based tools meant for education may directly raise students' financial engagement.

8.2. Discussion of hypothesis (H2)

H2: There is a statistically significant effect of AI usage on analytical self-efficacy.

Results yielded a positive and strong relationship between AI usage and students' analytical self-efficacy. This finding falls within the theoretical construct articulated by Bandura [8] in his self-efficacy theory, which postulated that mastery experiences and exposure to new tools would heighten the efficacy beliefs of individuals. Practically speaking, it seems that using AI systems creates cognitive confidence in students' minds. This finding is consistent with the work of Sajjadi et al. [4], who found that AI-based learning systems raise users' analytical reasoning abilities.

This finding also extends current knowledge in the aspect of educational technology. Whereas previous studies have highlighted general digital literacy, it is in this study that it is specified that AI technologies, rather than traditional ICT tools, profoundly inculcate domain-related specific self-efficacy. Therefore, universities implementing analytics platforms based on artificial intelligence may modernize pedagogy and, at the same time, heighten students' psychological readiness concerning investment decision-making.

8.3. Discussion of hypothesis (H3)

H3: There is a statistically significant effect of analytical self-efficacy on investment decision intentions.

Higher analytical self-efficacy in students manifests a stronger intention toward investment behavior. It is, therefore, coherent with Venkatesh and Davis [6] that in TAM, self-efficacy improves the perceived ease of use as well as improves behavioral intention. Other empirical pieces conducted by Kaur et al. [5] and Al-Omoush et al. [9] also assert that students having more analytical confidence are better and more likely to transform financial literacy into real investment behavior.

Essentially, this study provides practical evidence from Jordan, a market with low student investment activity when compared to developed economies. By stressing the mediating role of confidence, it suggests that investment education should include activities not only centered on conveying information but also on inculcating students' beliefs in their analytical skills. In simple terms, confidence-building is equally important as financial knowledge delivery.

8.4. Discussion of hypothesis (H4)

H4: Analytical self-efficacy mediates the relationship between AI usage and investment decision intention.

The bootstrap and Sobel test results confirmed a statistically significant partial mediation effect. That is to say, AI technologies not only exert a direct influence on investment decision intentions but also an indirect influence through improved self-efficacy. These results fully support the integrated framework of TPB, TAM, and self-efficacy theory, as well as, particularly, the suggestions made by Preacher and Hayes [17] regarding the explanatory power of psychological mediation in the relationship between technology and behavior. The implications are twofold. First, AI tools empower students and users with real-time analyses, simulations, and feedback, resulting in an upsurge of confidence. Second, this confidence translates into a higher behavioral intention to invest. Thus, while technological infrastructure is important, psychological enablers constitute the nexus that makes the adoption of technology worthwhile.

9. Recommendations and future research

The research results indicate that it is proposed to integrate advanced AI tools for financial analysis into university curricula and develop training modules that will enhance students' analytical skills using investment simulations and interactive platforms available. Universities should therefore adopt educational strategies that build students' confidence in their ability to analyze analytically, going further to recommend assigning faculty members the necessary projects to use AI technologies in teaching and learning to improve academic outcomes and prepare students professionally for careers in economics and finance. For future research, the researchers propose that the model be tested in other academic settings, particularly private universities or institutions in other Arab countries. Another suggestion is to apply the model to other disciplines, such as business administration and accounting. Longitudinal studies should be an improved methodology to track changes in investment intentions as the use of AI technologies grows over the years. Other possibilities include new mediating variables, like institutional support or analytical thinking style, which could enhance the explanatory power of models related to youth financial behavior in the digital age.

10. Conclusions

The findings of this research show a statistically significant and positive link between the adoption of AI technology for financial analysis and the investment decision intentions of economics students. Students using smart analytical tools for reading financial data will be more willing to take real investment choices. Further research shows that in this relationship, the critical psychological mediator is found to be analytical self-efficacy, underlining the importance of the development of both technical and cognitive skills in parallel. These findings provide empirical support for the proposed theoretical integration of TPB, TAM, and self-efficacy theory.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Mr. Maher Sharrab prepared the initial draft of this study, while Dr. Zaid Dannoun prepared the methodology, collected the data, and conducted the statistical analysis. Professor Majdi Ghaith reviewed and revised it and prepared the abstract, recommendations, and conclusion.

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