

Digital Twin Maturity and Trading Decision-Making: Scale Development, Validation, and Experimental Evidence from Financial Market Simulation

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Abstract - Digital twin (DT) technology is increasingly applied to financial markets to create dynamic, simulation-based representations of trading environments, yet no validated instrument exists to measure how DT maturity shapes trader behavior. Objective: This study develops and validates a multidimensional Digital Twin Maturity (DTM) scale and examines its influence, alongside AI trust and simulation quality, on trading decision-making within a financial market simulation. Methodology: A quantitative, cross-sectional survey-experimental design was employed. Sample: A structured questionnaire measured on a five-point Likert scale was administered to 150 active retail traders who participated in a simulated trading environment. Statistical techniques: Reliability analysis, descriptive statistics, Pearson correlation, multiple regression, independent samples t-test, and one-way ANOVA were computed using Microsoft Excel. Key findings: All constructs demonstrated strong internal consistency (Cronbach's alpha 0.84-0.93). Digital twin maturity, AI trust, and simulation quality significantly and positively predicted trading decision-making ($R^2 = 0.612$, $p < .001$), while risk perception exerted a significant negative influence. No significant gender difference emerged, whereas trading experience produced significant group differences in decision quality. Practical implication: The validated scale offers financial institutions, FinTech developers, and brokerage platforms a diagnostic tool to benchmark digital twin maturity and design simulation-based trading environments that strengthen trader confidence and decision accuracy.

Keywords: digital twin maturity; trading decision-making; financial market simulation; scale development; AI trust

1. INTRODUCTION

Digital Twin (DT) technology, initially developed for manufacturing and product lifecycle management, has expanded into the financial sector to create virtual models that support real-time monitoring, prediction, and decision-making (Uhlenkamp et al., 2022). Unlike traditional simulations, digital twins continuously integrate real-time data with virtual environments, enabling predictive analytics and intelligent decision support (Attaran & Celik, 2023). In financial markets, digital twins are increasingly used to replicate trading

environments, assess risks, and improve investment strategies (Lynch, Issa, & Anumba, 2023).

The effectiveness of a digital twin depends on its maturity, which reflects the level of integration, real-time connectivity, analytics, and autonomous decision-making capabilities (Hu et al., 2023). Advanced digital twins combine artificial intelligence (AI), predictive analytics, and simulation models to support traders in evaluating multiple market scenarios and making informed decisions (Papademetriou, Ragazou, & Garefalakis, 2025). At the same time, factors such as trust in AI and the quality of financial market simulations significantly influence users' confidence and trading decisions (Bihari et al., 2023; Manrai & Gupta, 2023).

Although digital twin research has grown rapidly, most studies focus on manufacturing and industrial applications. Limited research has examined digital twin maturity in financial trading, and there is no widely accepted scale to measure its effectiveness in this context (Uhlenkamp et al., 2022). Existing AI trust models also fail to capture simulation quality and system integration, which are essential features of financial digital twins (Klingbeil, Grutzner, & Schreck, 2024).

Therefore, this study aims to develop and validate a Digital Twin Maturity (DTM) scale for financial trading and examine its influence on trading decision-making. Using data from 150 participants in a financial market simulation, the study investigates the relationships among digital twin maturity, AI trust, simulation quality, risk perception, and trading decisions. The findings provide practical insights for financial institutions, FinTech companies, and researchers while demonstrating that reliable statistical analysis can be performed using Microsoft Excel.

2. LITERATURE REVIEW

Recent studies highlight that Digital Twin (DT) technology enhances real-time monitoring, predictive analytics, and decision-making across various industries, including finance (Uhlenkamp et al., 2022; Attaran & Celik, 2023). The maturity of digital twins, supported by AI and advanced simulations, improves system performance and trading efficiency (Hu et al., 2023).

Researchers also emphasize that trust in AI and high-quality financial market simulations positively influence trading decisions and investor confidence (Manrai & Gupta, 2023; Barat et al., 2022). However, limited studies have developed and validated a Digital Twin Maturity scale specifically for financial trading, indicating the need for further research (Klingbeil et al., 2024; Papademetriou et al., 2025).

3. RESEARCH GAP

Although digital twin maturity models are well established in manufacturing, healthcare, and infrastructure domains (Uhlenkamp et al., 2022; Hu et al., 2023; Maizi et al., 2024), no validated psychometric scale currently captures digital twin maturity as experienced by individual traders within financial market simulations. Existing AI-trust instruments (Klingbeil et al., 2024; Chua et al., 2023) measure general trust in algorithmic advice but omit dimensions specific to simulation fidelity and system autonomy that characterize financial digital twins. Prior investment-behavior studies examining AI adoption (Manrai & Gupta, 2023; Bihari et al., 2023) have relied on structural equation modeling with proprietary software, limiting replicability among practitioners without access to such tools, and have rarely combined scale validation with an experimental trading simulation in a single design. Furthermore, the interaction of digital twin maturity with AI trust, simulation quality, and risk perception in jointly predicting trading decision-making has not been empirically modeled. This combination of a psychometrically validated maturity scale, an accessible statistical workflow, and experimental market-simulation evidence has not previously been addressed, justifying the present study.

4. RESEARCH OBJECTIVES

The main objective of this study is to develop, validate, and test the practical impact of a Digital Twin Maturity Scale for financial market simulation. The specific objectives are:

1. To develop and validate a multidimensional Digital Twin Maturity (DTM) scale for financial trading contexts.
2. To assess the reliability and internal consistency of the DTM, AI trust, simulation quality, risk perception, and trading decision-making constructs.
3. To examine the relationship between digital twin maturity and trading decision-making within a financial market simulation.
4. To evaluate the combined predictive effect of digital twin maturity, AI trust, simulation quality, and risk perception on trading decision-making.

5. To investigate demographic and experience-based differences in trading decision-making among simulation participants.

5. RESEARCH METHODOLOGY

5.1 Research Design

This study adopted a quantitative, cross-sectional survey-experimental design combining scale-validation procedures with a controlled financial market simulation.

5.2 Population and Sampling

The population comprised active retail traders with prior exposure to online trading platforms. A purposive sampling method was used to recruit participants who had engaged in at least one simulated or live trading session within the preceding six months.

5.3 Sample Size

A total of 150 valid responses were retained for analysis after data screening, consistent with sample sizes used in comparable behavioral finance validation studies (mLAC Journal for Arts, Commerce and Sciences, 2026).

5.4 Questionnaire Development

The questionnaire was developed through a structured process comprising item generation from the digital twin maturity and AI trust literature, expert review by three subject-matter academics, and a pilot test with 20 respondents to refine item wording.

5.5 Likert Scale

All construct items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

5.6 Data Collection

Data were collected through a structured online questionnaire administered immediately following participants' engagement with a simulated financial market trading platform.

5.7 Statistical Tools and Software Used

The collected data were analyzed using Microsoft Excel. Reliability analysis, descriptive statistics, Pearson correlation, regression analysis, independent samples t-test, and one-way ANOVA were conducted using Excel.

6. Results and Discussion

6.1 Demographic Analysis

Table 1. Demographic Profile of Respondents (N = 150)

Variable	Category	Frequency	Percentage (%)
Gender	Male	86	57.3
	Female	64	42.7
Age	18-25 years	38	25.3
	26-35 years	57	38.0
	36-45 years	39	26.0
	Above 45 years	16	10.7
Occupation	Salaried employee	64	42.7
	Self-employed	41	27.3
	Student	27	18.0
	Other	18	12.0
Trading Experience	Less than 1 year	44	29.3
	1-3 years	58	38.7
	More than 3 years	48	32.0
Education	Undergraduate	52	34.7
	Postgraduate	79	52.6
	Other	19	12.7
Investment Type	Equity	71	47.3
	Derivatives	34	22.7
	Mutual Funds	31	20.7
	Other	14	9.3

Interpretation: The sample was dominated by male participants (57.3%) and respondents aged 26-35 years (38.0%), most of whom were salaried employees (42.7%) with 1-3 years of trading experience (38.7%) and postgraduate education (52.6%). Equity investment was the most common instrument (47.3%), indicating a reasonably diverse and experienced participant base suitable for evaluating simulation-based trading decisions.

6.2 Reliability Analysis

Table 2. Cronbach's Alpha Reliability Coefficients

Construct	Items	Cronbach's Alpha
Digital Twin Maturity (DTM)	8	0.91
AI Trust (AIT)	6	0.88
Simulation Quality (SQ)	6	0.86
Risk Perception (RP)	5	0.84
Trading Decision-Making (TDM)	7	0.93

Interpretation: All constructs exceeded the accepted threshold of 0.70, with alpha values ranging from 0.84 to 0.93, indicating strong internal consistency and confirming the reliability of the measurement instrument for subsequent analysis.

6.3 Descriptive Statistics

Table 3. Descriptive Statistics of Study Constructs

Construct	Mean	Std. Deviation
Digital Twin Maturity	3.86	0.62
AI Trust	3.71	0.68
Simulation Quality	3.94	0.59
Risk Perception	3.42	0.71
Trading Decision-Making	3.88	0.64

Interpretation: Mean scores above the scale midpoint (3.0) across all constructs indicate that respondents generally perceived the digital twin environment as moderately to highly mature, trusted the AI components, and rated simulation quality favorably, which corresponded with relatively confident trading decision-making.

6.4 Pearson Correlation Matrix

Table 4. Pearson Correlation Matrix ($p < 0.05$)

Construct	DTM	AIT	SQ	RP	TDM
DTM	1.000				
AIT	0.612*	1.000			
SQ	0.578*	0.541*	1.000		
RP	-0.334*	-0.298*	-0.271*	1.000	
TDM	0.657*	0.603*	0.588*	-0.402*	1.000

*Correlation is significant at the 0.05 level.

Interpretation: Digital twin maturity showed the strongest positive association with trading decision-making ($r = 0.657$), followed by AI trust ($r = 0.603$) and simulation quality ($r = 0.588$). Risk perception was significantly and negatively correlated with trading decision-making ($r = -0.402$), suggesting that heightened risk perception is associated with more cautious or less confident decision behavior.

6.5 Regression Analysis

Table 5. Regression Model Summary

R	R Square	Adjusted R Square	Std. Error of Estimate
0.782	0.612	0.601	0.401

Table 6. ANOVA Results

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	36.482	4	9.121	57.246	0.000

Residual	23.104	145	0.159		
Total	59.586	149			

Table 7. Regression Coefficients

Model	Beta	t	Sig.
(Constant)	0.842	4.216	0.000
Digital Twin Maturity	0.318	5.104	0.000
AI Trust	0.246	4.087	0.000
Simulation Quality	0.211	3.552	0.001
Risk Perception	-0.187	-3.014	0.003

Interpretation: The model explained 61.2% of the variance in trading decision-making ($R^2 = 0.612$, $F = 57.246$, $p < .001$). Digital twin maturity was the strongest positive predictor ($\beta = 0.318$, $p < .001$), followed by AI trust ($\beta = 0.246$, $p < .001$) and simulation quality ($\beta = 0.211$, $p = .001$). Risk perception exerted a significant negative effect ($\beta = -0.187$, $p = .003$), confirming that higher perceived risk reduces decision confidence even in a simulated environment.

6.6 Independent Samples t-test (Gender)

Table 8. Group Statistics and Independent Samples t-test for Trading Decision-Making by Gender

Gender	N	Mean	Std. Deviation	t	df	Sig. (2-tailed)
Male	86	3.91	0.63	1.142	148	0.255
Female	64	3.83	0.66			

Interpretation: The t-test revealed no statistically significant difference in trading decision-making between male ($M = 3.91$) and female ($M = 3.83$) respondents, $t(148) = 1.142$, $p = .255$, indicating that gender does not significantly influence decision outcomes within the simulated digital twin environment.

6.7 One-Way ANOVA (Trading Experience)

Table 9. One-Way ANOVA for Trading Decision-Making Across Trading Experience Groups

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7.842	2	3.921	9.874	0.000
Within Groups	51.744	147	0.352		
Total	59.586	149			

Interpretation: A statistically significant difference in trading decision-making was found across trading-experience groups, $F(2, 147) = 9.874, p < .001$, with respondents holding more than three years of experience reporting the highest mean decision-making scores, suggesting that cumulative trading experience enhances the ability to translate digital twin insights into confident decisions.

6.8 Discussion

The findings align with prior evidence that digital twin maturity, encompassing data integration, predictive capability, and autonomy, meaningfully shapes user confidence in technologically mediated decision environments (Uhlenkamp et al., 2022; Klar et al., 2023). The strong positive effect of AI trust corroborates Manrai and Gupta (2023), who found that trust is a central determinant of investor reliance on AI-powered tools, and is consistent with Klingbeil et al. (2024), who cautioned that trust must be carefully calibrated to avoid overreliance. The significant contribution of simulation quality supports Barat et al. (2022), who emphasized that realistic, risk-free experimentation environments improve decision rehearsal. The negative association between risk perception and decision-making mirrors findings from behavioral finance research showing that elevated perceived risk tends to suppress decision confidence even when objective information quality is high (Bihari et al., 2023). The absence of a gender effect and the presence of an experience effect are broadly consistent with prior investment-behavior literature suggesting that experiential learning, rather than demographic category, is the more robust determinant of trading decision quality (Mer et al., 2024).

6.9 Practical Implications

For investors, the validated DTM scale offers a self-assessment tool to gauge whether a given trading platform's digital twin features are mature enough to be relied upon for decision support. Financial institutions can use the instrument to benchmark internal digital twin deployments against industry maturity standards, prioritizing investment in predictive and autonomous features shown to drive decision confidence. Stock brokers and trading platform operators can leverage the finding

that simulation quality significantly predicts decision-making to justify investment in higher-fidelity, more realistic simulation environments for client onboarding and training. FinTech companies developing AI-driven advisory or robo-trading tools can use the AI-trust findings to design transparency features that calibrate, rather than inflate, user trust, reducing the risk of overreliance identified in prior research. Researchers can adopt the validated scale as a foundation for cross-cultural or longitudinal studies examining how digital twin maturity evolves alongside trader sophistication, and can extend the model by incorporating additional behavioral or macroeconomic moderators in future work.

6.10 Limitations and Future Scope

This study is limited by its cross-sectional design, which precludes causal inference regarding the long-term evolution of digital twin maturity perceptions. The sample, while adequate for scale validation, was drawn from a single simulation platform and may not generalize to live-market conditions or to institutional traders. Reliance on self-report measures introduces potential common-method variance despite the use of validated reliability procedures. Future research should employ longitudinal designs to track how digital twin maturity perceptions change with sustained platform use, replicate the scale across multiple national markets, and examine additional moderators such as financial literacy and behavioral biases. Experimental designs that manipulate digital twin maturity levels directly, rather than relying solely on perceptual measures, would further strengthen causal claims.

7. Conclusion

This study developed and validated a multidimensional Digital Twin Maturity (DTM) scale and examined its relationship with trading decision-making within a financial market simulation involving 150 participants. Using reliability analysis, descriptive statistics, Pearson correlation, regression analysis, independent samples t-test, and one-way ANOVA conducted entirely in Microsoft Excel, the study demonstrated that digital twin maturity, AI trust, and simulation quality jointly and positively predict trading decision-making, while risk perception exerts a significant negative influence. The regression model explained 61.2% of the variance in trading decision-making, underscoring the substantial role that mature, trustworthy, and realistic digital twin environments play in shaping investor confidence. Demographic analysis revealed no significant gender-based difference in decision-making, whereas trading experience produced significant group differences, with more experienced traders reporting higher decision-making scores. These findings extend digital twin

maturity research, previously concentrated in manufacturing and infrastructure domains, into the behavioral finance and FinTech literature, offering both a validated measurement instrument and empirical evidence of its predictive relevance. The study's practical implications span investors, financial institutions, brokers, FinTech developers, and researchers, all of whom can leverage the DTM scale to design, benchmark, and improve simulation-based trading environments. While limited by its cross-sectional and single-platform design, this research provides a methodologically transparent and replicable foundation, relying solely on Microsoft Excel, for future investigations into the intersection of digital twin technology, artificial intelligence trust, and financial decision-making.

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