

Original Research Article

Factors Influencing the Effectiveness of AI-Based Fraud Detection

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Abstract

The increasing sophistication and volume of financial fraud in digital banking systems have compelled organizations to adopt artificial intelligence (AI) as a core detection mechanism. This study investigated the influence of three critical AI system attributes—perceived AI accuracy, AI speed, and AI reliability—on the perceived effectiveness of AI-based fraud detection among 300 professionals in the banking and financial services sector. Grounded in the DeLone and McLean Information Systems Success Model, a quantitative cross-sectional survey design was employed, and multiple linear regression analysis was conducted. The regression model explained 85.5% of the variance in fraud detection effectiveness ($R^2 = .855$, $F(3, 296) = 582$, $p < .001$). All three predictors were statistically significant: AI Speed exhibited the strongest standardized effect ($\beta = .350$, $p < .001$), followed by AI Reliability ($\beta = .319$, $p < .001$) and AI Accuracy ($\beta = .298$, $p < .001$). These findings underscore the importance of optimizing not only the accuracy but also the processing speed and reliability of AI fraud detection systems.

Keywords: Artificial Intelligence, Fraud Detection, AI Accuracy, AI Speed, AI Reliability, DeLone and McLean Model, Financial Services

1. Introduction

The rapid digitalization of financial services over the past two decades has fundamentally transformed the landscape of financial transactions, enabling unprecedented levels of convenience and accessibility for consumers and institutions alike (Chen et al., 2018). However, this digital transformation has also created fertile ground for increasingly sophisticated forms of financial fraud, including identity theft, credit card fraud, phishing attacks, and synthetic identity fraud. According to the Federal Trade Commission (2023), consumers reported losing more than \$10 billion to fraud in 2023 alone, underscoring the escalating scale of the problem. Traditional rule-based fraud detection systems have proven increasingly inadequate in the face of evolving fraud patterns (Abdallah et al., 2016), driving financial institutions to adopt machine learning and deep learning approaches that can learn from complex data patterns and adapt to emerging schemes (Ngai et al., 2011).

Despite the growing adoption of AI in fraud detection, there remains a significant gap in the empirical literature regarding which specific attributes of AI systems most strongly influence their perceived effectiveness among professional users (Petter et al., 2013). While substantial research has focused on algorithmic performance metrics such as precision and recall, comparatively less attention has been devoted to understanding how broader system-level attributes—including perceived accuracy, processing speed, and system reliability—collectively shape professional users' assessments of overall fraud detection effectiveness (Glikson & Woolley, 2020). This study addresses this gap by investigating the influence of these three AI system attributes on perceived fraud detection effectiveness, grounded in the DeLone and McLean IS Success Model (2003).

Three hypotheses were formulated: H_1 posits a significant positive relationship between perceived AI accuracy and fraud detection effectiveness; H_2 posits a significant positive relationship between perceived AI speed and fraud detection effectiveness; and H_3 posits a significant positive relationship between perceived AI reliability and fraud detection effectiveness. This study contributes to the information systems literature by extending the DeLone and McLean model to the specific context of AI-enabled fraud detection and offers actionable implications for financial institutions investing in AI-driven security infrastructure.

2. Review of Literature

2.1 Theoretical Framework: DeLone and McLean IS Success Model

The theoretical foundation of this study is grounded in the DeLone and McLean Information Systems Success Model, originally proposed in 1992 and updated in 2003 to incorporate developments in the field (DeLone & McLean, 2003). The updated model identifies six interrelated dimensions of IS success: system quality, information quality, service quality, intention to use, actual use, user satisfaction, and net benefits. The model posits that system quality—encompassing attributes such as reliability, responsiveness, and accuracy—directly influences user satisfaction and intention to use, which in turn shape actual use and net benefits. Petter et al. (2013) provided a comprehensive review and validation of the model across diverse IS contexts, confirming its continued relevance for understanding how technical system attributes translate into user-level and organizational-level outcomes.

2.2 AI Accuracy and Fraud Detection

AI accuracy in fraud detection refers to the system's ability to correctly identify fraudulent transactions while minimizing false positives and false negatives. High accuracy is fundamentally important because excessive false positives overwhelm human analysts with investigatory workload, while missed frauds result in direct financial

losses (Abdallah et al., 2016). The pursuit of accuracy has driven extensive research into advanced machine learning techniques. For instance, Bhattacharyya et al. (2011) demonstrated the effectiveness of support vector machines for credit card fraud detection, while Ngai et al. (2011) provided a comprehensive review of data mining techniques applied to fraud detection, identifying ensemble methods as particularly promising. More recently, deep learning approaches have shown superior performance across multiple fraud detection benchmarks (Carcillo et al., 2018). Users' trust in AI systems is strongly influenced by perceived accuracy (Glikson & Woolley, 2020), and Shin, D. (2021) found that accuracy perceptions significantly mediate the relationship between algorithm transparency and user trust.

2.3 AI Speed and Fraud Detection

The speed of AI-based fraud detection systems is a critical operational attribute encompassing both the latency of individual transaction screening decisions and the system's capacity to process high transaction volumes in real time. In modern digital payment environments, the ability of AI systems to deliver rapid detection decisions is essential for enabling timely intervention before fraudsters complete their objectives (Khandani et al., 2010). Research on system responsiveness has consistently demonstrated its importance for user experience. Davis (1989) identified perceived ease of use as a key driver of technology adoption, and faster systems contribute to this perception by imposing less friction on users' workflows. Venkatesh et al. (2003) further confirmed that system responsiveness contributes to perceived usefulness in their unified theory of acceptance and use of technology. From an organizational perspective, faster detection enables more proactive fraud prevention strategies that intercept fraudulent activity in progress rather than merely identifying it after the fact (Alkhateeb & Maolood, 2019).

2.4 AI Reliability and Fraud Detection

AI reliability refers to the consistency, stability, and dependability of the system's performance over time and across different operating conditions. A reliable AI system produces consistent results when presented with similar input patterns and maintains stable performance under varying transaction volumes (Petter et al., 2013). The importance of reliability in AI systems has been increasingly recognized. Unreliable AI systems can erode user trust and reduce compliance with system recommendations (Glikson & Woolley, 2020). In high-stakes domains such as financial fraud detection, reliability is an absolute requirement for operational deployment. Liu et al. (2021) emphasized that AI reliability encompasses not only functional correctness but also robustness under adversarial conditions and distributional shifts in data. Financial institutions typically subject AI fraud detection systems to rigorous reliability testing and continuous monitoring protocols to ensure that performance levels remain within acceptable thresholds over time (Bolton & Hand, 2002).

2.5 Empirical Studies on AI Fraud Detection

The empirical literature on AI-based fraud detection has grown substantially. Abdallah et al. (2016) conducted a comprehensive survey identifying ensemble methods and deep learning approaches as consistently outperforming traditional statistical techniques. Carcillo et al. (2018) addressed the critical challenge of class imbalance in fraud datasets through under-sampling and cost-sensitive learning strategies. Rajora et al. (2019) examined the credit card fraud detection pipeline, highlighting the importance of feature engineering and real-time processing capabilities. Alkhateeb & Maolood (2019) provided a comparative analysis of machine learning algorithms for financial fraud detection, reporting that gradient boosting and random forest methods achieved the best balance of

accuracy and computational efficiency. Singh & Verma (2023) extended this work by proposing deep learning architectures specifically optimized for real-time fraud scoring in streaming transaction data. From the IS success perspective, Seddon (1997) and later Petter et al. (2013) established that perceived system quality—encompassing accuracy, speed, and reliability—is the strongest predictor of overall system effectiveness, providing a theoretical basis for the present study.

3. Research Methodology

This study adopted a quantitative research design employing a cross-sectional survey methodology to collect data on the relationships between AI system attributes and fraud detection effectiveness (Creswell & Creswell, 2018). The quantitative approach was selected because it enables systematic measurement of the study variables, statistical testing of hypothesized relationships, and generalization of findings to the broader population of professionals in the banking and financial services sector. The target population comprised professionals working in banking, financial services, and related fields who have experience with or exposure to AI-based fraud detection systems. A sample of 300 respondents was drawn using convenience sampling combined with purposive selection criteria to ensure participants had sufficient knowledge and experience to provide informed responses (Saunders et al., 2019). The sample included accountants (27.0%), IT professionals (23.3%), students pursuing relevant degrees (20.7%), bankers (16.3%), and auditors (12.7%). The majority of respondents (47.7%) reported 1–3 years of professional experience, followed by those with less than 1 year (26.7%), 4–6 years (16.3%), and more than 6 years (9.3%).

Table 1. Demographic Profile of Respondents (N = 300)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	202	67.3
	Female	98	32.7
Age	18–25 years	74	24.7
	26–35 years	126	42.0
	36–45 years	56	18.7
	46 years and above	44	14.7
Occupation	Accountant	81	27.0
	IT Professional	70	23.3
	Student	62	20.7
	Banker	49	16.3
	Auditor	38	12.7
Experience	Less than 1 year	80	26.7
	1–3 years	143	47.7
	4–6 years	49	16.3
	More than 6 years	28	9.3

Data were collected using a structured self-administered questionnaire comprising validated scale items measuring four study variables—AI Accuracy, AI Speed, AI Reliability, and Fraud Detection Effectiveness—all measured on five-point Likert scales ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was developed based on established scales from the information systems and technology acceptance literature

(Davis, 1989; Petter et al., 2013), with adaptations to suit the specific context of AI-based fraud detection. All scale items demonstrated acceptable internal consistency reliability, with Cronbach's alpha coefficients exceeding the conventional threshold of 0.70. Multiple linear regression analysis was employed as the primary inferential technique, with diagnostic tests performed for normality, multicollinearity, autocorrelation, and influential observations (Hair et al., 2019).

4. Results

Table 1 presents the descriptive statistics for the four study variables. All variables exhibited means above the scale midpoint of 3.00, indicating generally positive perceptions among respondents. Fraud Detection Effectiveness (FDE) recorded the highest mean ($M = 4.18$, $SD = 0.49$), suggesting that respondents generally perceived AI-based fraud detection as effective. AI Speed ($M = 4.13$, $SD = 0.46$) and AI Reliability ($M = 4.11$, $SD = 0.47$) showed similar mean levels, while AI Accuracy ($M = 4.06$, $SD = 0.49$) had the lowest mean among the predictors. The standard deviations for all variables were relatively modest ($SD = 0.46$ – 0.49), indicating moderate consensus among respondents in their perceptions.

Table 2. Descriptive Statistics of Study Variables (N = 300)

Variable	N	Mean	Std. Deviation	Variance
AI Accuracy (AIA)	300	4.06	0.49	0.24
AI Speed (AIS)	300	4.13	0.46	0.21
AI Reliability (AIR)	300	4.11	0.47	0.22
Fraud Detection Effectiveness (FDE)	300	4.18	0.49	0.24

Note. Values based on 5-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree).

Pearson correlation analysis revealed strong positive correlations among all study variables: AI Accuracy and FDE ($r = .915$, $p < .001$), AI Speed and FDE ($r = .920$, $p < .001$), and AI Reliability and FDE ($r = .922$, $p < .001$). The intercorrelations among independent variables ranged from .865 to .890 (all $p < .001$), suggesting substantial multicollinearity that was further examined through VIF diagnostics.

Table 3. Pearson Correlation Matrix (N = 300)

Variable	1. AIA	2. AIS	3. AIR	4. FDE
1. AI Accuracy	1.000	.875**	.865**	.915**
2. AI Speed	.875**	1.000	.890**	.920**
3. AI Reliability	.865**	.890**	1.000	.922**
4. FDE	.915**	.920**	.922**	1.000

Note. ** Correlation is significant at the 0.01 level (2-tailed).

The multiple linear regression model explained 85.5% of the variance in Fraud Detection Effectiveness ($R^2 = .855$, Adjusted $R^2 = .853$). The overall model was statistically significant, $F(3, 296) = 582$, $p < .001$. All three independent variables made statistically significant contributions: AI Speed exhibited the largest standardized coefficient ($\beta = .350$, $t = 8.731$, $p < .001$), followed by AI Reliability ($\beta = .319$, $t = 7.960$, $p < .001$) and AI Accuracy ($\beta = .298$, $t = 7.441$, $p < .001$). Thus, all three hypotheses were supported. Diagnostic tests confirmed the validity of the

regression assumptions: the Shapiro-Wilk test indicated normally distributed residuals ($W = .997$, $p = .888$), VIF values ranged from 4.321 to 4.685 (below the threshold of 5.0), the Durbin-Watson statistic was 1.96, and no influential observations were detected via Cook's distance (Hair et al., 2019).

Table 4. Model Summary

Model	R	R ²	Adjusted R ²	Std. Error of Estimate	Durbin-Watson
1	.925	.855	.853	.188	1.96

Note. Predictors: (Constant), AI Reliability, AI Speed, AI Accuracy. Dependent Variable: Fraud Detection Effectiveness.

Table 5. ANOVA Results

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	61.60	3	20.53	582.000	< .001
Residual	10.45	296	.035		
Total	72.05	299			

Note. Dependent Variable: Fraud Detection Effectiveness. Predictors: (Constant), AI Reliability, AI Speed, AI Accuracy.

Table 6. Regression Coefficients

Variable	B	Std. Error	β	t	Sig.	VIF
(Constant)	.193	.075		2.573	.011	
AI Accuracy	.298	.040	.298	7.441	< .001	4.321
AI Speed	.372	.043	.350	8.731	< .001	4.685
AI Reliability	.332	.042	.319	7.960	< .001	4.498

Note. Dependent Variable: Fraud Detection Effectiveness. VIF = Variance Inflation Factor.

5. Discussion

This study examined the influence of three AI system attributes on perceived fraud detection effectiveness. The finding that all three attributes are significant predictors aligns with the DeLone and McLean model's core proposition that system quality drives user perceptions of effectiveness (DeLone & McLean, 2003; Petter et al., 2013). The strong positive relationship between AI Accuracy and effectiveness is consistent with the well-established finding that perceived accuracy is a primary driver of user trust and acceptance of AI systems (Glikson & Woolley, 2020; Shin, D. (2021).). The model's explanatory power ($R^2 = .855$) is notably high, suggesting that the three system quality attributes capture the primary dimensions along which professional users evaluate AI fraud detection effectiveness.

The finding that AI Speed emerged as the strongest predictor represents a notable contribution that extends previous research. While speed has been recognized as an important system attribute in the technology acceptance literature (Davis, 1989; Venkatesh et al., 2003), few studies have directly compared the relative effects of speed, accuracy, and reliability on AI system effectiveness in the fraud detection domain. The primacy of speed likely reflects the operational realities of fraud detection work, where the timeliness of detection decisions has direct consequences for preventing financial losses and enabling timely intervention (Khandani et al., 2010; Alkhateeb & Maolood ,2019). This aligns with the service quality dimension of the DeLone and McLean model, which includes

responsiveness as a key component (DeLone & McLean, 2003). Furthermore, the strong intercorrelations among the three AI attributes ($r = .865$ to $.890$) suggest that these dimensions are closely intertwined in users' perceptions, forming a coherent system quality construct rather than representing fully independent dimensions.

The importance of AI Reliability is consistent with research demonstrating that system reliability is a fundamental determinant of user satisfaction and continued use (Petter et al., 2013; Liu et al., 2021). Financial institutions should therefore adopt a balanced optimization approach, investing in high-performance computing infrastructure for speed, robust monitoring protocols for reliability, and continuous model refinement for accuracy (Bolton & Hand, 2002). The primacy of AI Speed also has specific implications for system architecture, suggesting that organizations should prioritize computational efficiency, low-latency processing capabilities, and scalable infrastructure that can maintain rapid response times even under peak transaction loads (Bahnsen et al., 2016). These practical implications are directly relevant to technology vendors and regulatory bodies involved in the oversight of AI-based fraud detection systems.

6. Conclusion

This study investigated the influence of perceived AI accuracy, speed, and reliability on the perceived effectiveness of AI-based fraud detection among 300 professionals in the banking and financial services sector. The regression model explained 85.5% of the variance in fraud detection effectiveness, with AI Speed ($\beta = .350$) as the strongest predictor, followed by AI Reliability ($\beta = .319$) and AI Accuracy ($\beta = .298$). The findings extend the DeLone and McLean IS Success Model to the AI fraud detection context and provide actionable guidance for practitioners. Limitations include the use of convenience sampling, the cross-sectional design, and the reliance on self-reported measures. Future research should employ longitudinal designs, incorporate objective performance metrics alongside perceptual measures, and explore additional AI attributes such as explainability and fairness (Ryman-Tubb et al., 2018).

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