“Enhancing financial security through machine learning: Adoption challenges in Jordan’s insurance fraud detection”

AUTHORS	Amer Morshed Laith T. Khrais
ARTICLE INFO	Amer Morshed and Laith T. Khrais (2025). Enhancing financial security through machine learning: Adoption challenges in Jordan’s insurance fraud detection. *Insurance Markets and Companies*, *16*(2), 85-95. doi:10.21511/ins.16(2).2025.07
DOI	http://dx.doi.org/10.21511/ins.16(2).2025.07
RELEASED ON	Friday, 31 October 2025
RECEIVED ON	Friday, 21 February 2025
ACCEPTED ON	Monday, 06 October 2025
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Insurance Markets and Companies"
ISSN PRINT	2616-3551
ISSN ONLINE	2522-9591
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
51	0	8

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

Amer Morshed (Jordan), **Laith T. Khrais** (Jordan)

ENHANCING FINANCIAL SECURITY THROUGH MACHINE LEARNING: ADOPTION CHALLENGES IN JORDAN'S INSURANCE FRAUD DETECTION

Abstract

The increasing complexity of insurance fraud in Jordan has unveiled inadequacies of traditional detection mechanisms, calling for advanced technologies. This study investigates drivers and inhibitors of machine learning adoption for fraud detection within Jordan's insurance sector, with a focus on institutional readiness, ethical concerns, and supporting regulations. By applying quantitative and exploratory research design, Partial Least Squares Structural Equation Modeling serves as an approach to analyze data collected from 291 practitioners of fraud detection, data science, and insurance compliance in the industry.

Findings show that both existing fraud detection efforts (coefficient = 0.42, p = 0.012) and knowledge of machine learning (coefficient = 0.55, p = 0.009) have favorable impacts on adoption likelihood, which underlines the relevance of bureau experience and informed professional culture. By contrast, major adoption deterrents such as limited IT capability, budgetary constraints, and moral concerns about fairness and clarity (coefficient = –0.40 and –0.38, respectively) unfavorably decrease adoption intention.

Regulatory encouragement has a two-fold role: it has a direct promoting effect on adoption (coefficient = 0.47, p = 0.011) and a buffering effect on negative ethical concerns (interaction = 0.36, p = 0.025) and adoption barriers (interaction = –0.28, p = 0.032). Perceived efficacy also mediates between awareness/experience on the one hand and adoption decisions on the other (coefficients = 0.51 and 0.44, p < 0.05).

The results demonstrate successful incorporation of machine learning into fraud detection as depending on the clarity of regulations, ethical protections, and institutional readiness, rather than on technical capability itself.

Keywords machine learning, fraud detection, insurance sector, Jordan, regulatory challenges, ethical considerations, adoption barriers, AI integration

JEL Classification G22, O33, K24

Type of the article: Research Article

Received on: 21st of February, 2025
Accepted on: 6th of October, 2025
Published on: 31st of October, 2025

Amer Morshed, Dr., Department of Accounting, Faculty of Business, Al-Zaytoonah University of Jordan. (Corresponding author)

Laith T. Khrais, Assistant Professor, Faculty of Business, Department of E-Business, Middle East University, Jordan.

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

Insurance fraud jeopardizes economic stability by inducing economic losses, increased costs of operation, and decreased customer confidence. Traditional detection methods – rule-based systems, human-centered audit, and ratio analysis – are too slow and insufficient to identify advanced real-time patterns of fraud. These shortcomings indicate a critical need for intelligent systems able to automatically process complex data of a financial nature.

Machine learning (ML) is a promising solution. Its real-time identification of abnormalities, accommodation of shifting patterns of fraud, and processing of massive datasets make it a suitable solution to modern fraud detection. Despite its proven value, however, implementation within Jordan's insurance sector is limited. This reflects a broader challenge, a disconnect between ML's technical potential and the institutional, legal, and moral framework within which it must function.

The main concern is not ML performance, but successful integration. Adoption of ML is hampered by uncertainty of regulations, lack of clarity and ethical controls, inadequate infrastructure, and limited stakeholder capability. Such related inhibitions extend beyond technology into policy, organizational culture, and trust areas.

This study looks into how alignment of regulations, ethical responsibility, institutional readiness, and stakeholder trust influences the adoption and performance of machine learning on fraud detection within Jordan's insurance sector. Getting past these obstacles is central to positioning machine learning as an ethical, efficient, and reliable technology within this important financial sector.

1. LITERATURE REVIEW AND HYPOTHESES

Insurance fraud remains a pressing concern globally, as it undermines financial stability, burdens insurers with inflated costs, and diminishes public trust. In Jordan, where the insurance sector plays a central role in economic resilience, combating fraud is particularly critical. Traditional fraud detection systems – such as ratio analysis, Benford's Law, and manual auditing – have long been the industry standard (A. R. Alshehadeh et al., 2024). However, these approaches are increasingly inadequate for identifying sophisticated or real-time fraud patterns (Ramadan & Morshed, 2024a; Mandal & Amilan, 2024). While researchers such as Mohammad Amini et al. (2023) acknowledge the historical relevance, critiques from Anowar and Sadaoui (2021) highlight key limitations, including poor scalability and an inability to address voluminous or rapidly evolving data environments. As financial crimes grow more complex, static approaches fail to keep pace.

A shift of comparison in the literature identifies increasing agreement regarding the failure of traditional systems. Morshed et al. (2024a) conclude that traditional models are incapable of handling diverse datasets or producing adaptive responses to evolving typologies of fraud. Aziz and Andriansyah (2023) also criticize traditional systems for being manpower-intensive, involving extensive manpower with low predictive input. Those shortcomings necessitate the need for something more flexible, data-intensive – something capable of learning from evolving new patterns, scaling across contexts, and adjusting based on active-fraud behaviors (Oreqat, 2021).

This analytical deficit has led to machine learning (ML) as a viable option. Lee et al. (2025) define ML as a facilitator of automated, real-time detection of fraud through the ability of ML systems to scan large datasets and spot latent anomalies that human auditors miss. ML models, like those outlined by Odufisan et al. (2025), can be programmed to expose distributed and multi-layered fraud plots with enhanced detection precision. Al-dahasi et al. (2025) note the capacity of ML systems to adapt and improve over time through ongoing learning, therefore adapting to the evolving threat environment. Alatawi (2025) further suggests that integrating methods like anomaly detection and natural language processing has exponentially increased the sophistication of fraud models. But the effectiveness of ML has been found through critical comparison to be very much reliant on its infra- and organizational context (Ahmed et al., 2023).

Technically superior though it is, ML cannot function well where there is a lack of digital preparedness or of integration capacity. Díaz-Arancibia et al. (2024) caution that ML usefulness depends directly on the digital maturity of the organization – its capacity for deploying, tracking, and interpreting sophisticated models. In developing jurisdictions such as Jordan, institutional preparedness is uneven. Omol (2024) observes that implementation of ML is often foiled by operational fragmentation and funding constraints, more so for small- and medium-sized insurers. Another limit is one of the stakeholders' knowledge and acceptance. Implementation of ML systems does not just involve technology investment – but demands cog-

http://dx.doi.org/10.21511/ins.16(2).2025.07

nitive and cultural change from decision-makers. Cardona et al. (2024) note that increasing awareness among stakeholders is one of the principal determinants of perceived usefulness and implementation effectiveness. Hernandez Aros et al. (2024) note further that they observe a correlation between the intensity of training and openness of the institution towards ML. According to Li et al. (2024), internal education mechanisms constitute foundations for building trust in predictive technology.

In contrast, Qatawneh (2024) establishes that unfamiliarity with ML – particularly in traditional insurance environments – tends to foster suspicion and reluctance to make investments. Morshed (2024a) links the reluctance to a general trend of caution in adopting new technology within Jordan's environments. Furthermore, structural barriers like a lack of data accessibility, infrastructural deficiencies, and cultural resistance remain impediments to integrating ML. According to Jreissat et al. (2024), these factors together scale down the amount and consistency of accessible training datasets needed for accuracy in models.

Underreporting of fraudulent cases, as identified through Zavitsanos et al. (2025), further limits the input of validated anomalies, impairing the predictive power of the model. Saeed and Abdulazeez (2024) support the argument by adding that low-budget insurers lack the funds and human resource capacity for switching over to ML-model systems. In reply, Di Prima et al. (2024) and Rosienkiewicz et al. (2024) support calling for the creation of a culture for innovation, whose focus lies in capacity-building and digital literacy education (Shaban & Omoush, 2025). Aside from readiness in terms of institution and technical capacity, the literature places great emphasis on the ethical difficulties of adopting machine learning (ML) for fraud detection. Perhaps one of the most frequently used arguments is the lack of transparency of ML's mode of decisioning, often described as the "black-box" issue (Krupalija et al., 2024).

Since ML models tend to lack clarity, their application in high-risk industries such as insurance presents major accountability concerns. According to Tóth and Blut (2024), such obscurity erodes trust, especially where consumers or regulators cannot question or comprehend algorithmic determinations. In addition, Xin and Huang (2024) describe possible prejudice incorporated into training sets, potentially resulting in discrimination or profiling of specific policyholders, presenting questions of equity and adherence to anti-discrimination principles.

Scholars have come up with a number of ways to solve these problems. Olivia et al. (2025) recommend the implementation of explainable artificial intelligence (XAI) models for greater explicability and more trust from stakeholders. In turn, Ashal and Morshed (2024) and Klein and Walther (2024) have spoken of fairness audits and ethics-compliance systems required for transparency, particularly for deploying predictive analytics on consumer information. Such findings echo mounting agreement: ethical controls are not add-ons – instead, they're essential for building ML legitimacy and stakeholder trust. Parallel to this, regulatory uncertainty is one of the most entrenched obstacles to adopting ML. In Jordan, while the Insurance Commission and the Central Bank have enacted financial transparency policies, there is still a large regulatory void for AI-related frameworks (Taha et al., 2023). Pantanowitz et al. (2024) note that the absence of harmonized guidance causes insurers uncertainty regarding the permissible application of ML for detecting fraud. Regulatory indeterminacy increases hesitations from institutions and hinders innovation.

On the contrary, literature highlights clear and facilitatory regulation as the key enabler. Alshammari et al. (2024) and Wilkinson et al. (2024) note that policy coherence, industry standards, and regulatory support for compliance can create the scaffolding needed for ML integration into the system. Regulatory engagement is not merely for misuse prevention but also for signaling public support, which can drive private funding for it. Lior (2021) further highlights that accurate regulation is needed for reducing the risk of misclassification – a common issue for ML-powered fraud detection systems.

Collectively, the discussed literature presents a holistic picture. Whereas ML is a scalable and adaptive solution for detecting insurance fraud, its effectiveness is contingent upon a multifaceted interdependence of determinants: obsolescence of conventional approaches, the ability of the institution to implement digital means, awareness and education of the stakeholders, the existence of ethical governance, and regulatory guidance clarity. The literature reveals not only what is attainable with ML, but also why it does not achieve full realization in places such as Jordan.

Existing research shows rising inconsistency between the technical potential of machine learning and the preparedness of nascent market institution environments. Since there is intellectual agreement within the scholarly community regarding ML's relative advantages over conventional systems, functional obstacles, particularly ethical and regulatory, remain widespread. Hence, holistic, setting-specific exploration of these interrelated factors is both urgent and required.

Based on the existing literature, the purpose of this study is to critically explore the technological, institutional, ethical, and regulatory drivers of machine learning adoption for detecting fraud in the Jordanian insurance market.

The research will spot both enablers and barriers, filling the gap between the demonstrated technical capabilities of ML and the intricate operating environment with which it will be required to interact.

H1: *The effectiveness and limitations of traditional fraud detection in Jordan's insurance sector influence machine learning adoption.*

H2: *Awareness of machine learning among Jordanian insurance professionals shapes its perception and adoption for fraud detection.*

H3: *Financial, technical, and operational barriers in Jordan's insurance industry affect machine learning implementation.*

H4: *Ethical concerns like transparency, fairness, and accountability impact trust and adoption of machine learning in fraud prevention.*

H5: *Regulatory clarity and policy support in Jordan's insurance sector influence machine learning adoption for fraud detection.*

2. METHODOLOGY

To analyze such correlations, the study employs a PLS-SEM (Partial Least Squares Structural Equation Modeling) strategy, optimal for investigating complex correlations between unobserved (latent) factors. The strategy accommodates the measurement of independent, dependent, and moderating factors simultaneously. The use of SmartPLS as the primary tool for the study has been selected because of its quality for exploratory research and for the utilization of structural equation modeling (Ali & Morshed, 2024). Compared with other conventional covariance-based SEM methods, such as AMOS, SmartPLS performs best where there are new, untested theories, without the need for a fully established model. It also accommodates reflective and formative measurement models, accepts non-normal data distributions, and operates with small and medium samples, and hence, is a perfect tool for this study. Its intuitive user interface and visualization also promote result interpretation, with a clearer understanding of the complex factors influencing ML adoption for fraud discovery (Hair Jr et al., 2014).

The study targets fraud detection, data science, and risk and compliance specialists working for insurance companies in Jordan. The specialists are major decision makers for fraud prevention and ML solution adoption. With the insurance industry's growth in Jordan, driven by more regulations and digitalization, the study has considered perspectives from small and large insurance companies. The study has only considered experts with experience in traditional fraud detection methods and ML solution-driven approaches, assuring participants' contribution of knowledgeable perspectives on ML adoption and its opportunities and challenges in the industry.

To gather data from the target group, purposive and snowball methods of sampling are employed. The purposive technique targets experts with experience in fraud identification and ML technologies, assuring the presence of relevant participants. Snowball sampling is also employed for other respondents' selection, mostly in small insurance companies where access can be more restricted (Al-Muntasir, 2022). 291 participants were invited, and 76% of them responded. The approach assures quality, variety data, and enhances reliability and

http://dx.doi.org/10.21511/ins.16(2).2025.07

Table 1. Demographics of the sample

Category	Subcategory	Number of Respondents	Percentage (%)
Position (Career)	Fraud Detection Specialist	120	25.5%
	Data Scientist	110	23.4%
	Risk & Compliance Officer	95	20.2%
	Financial Auditor	85	18.1%
	ML Adoption Consultant	60	12.8%
Experience (Years)	0-5	80	17.0%
	6-10	120	25.5%
	11-15	130	27.6%
	16-20	85	18.1%
	21+	56	11.8%
Education Level	Bachelor's	200	42.5%
	Master's	180	38.2%
	Ph.D.	91	19.3%
Gender	Male	320	68.0%
	Female	151	32.0%

generalizability of findings on ML use for fraud identification in insurance companies in Jordan (Morshed et al., 2024b).

The demographic data (see Table 1) impact the adoption trends for ML, where less senior and high-skilled individuals are more willing, and senior auditors and compliance professionals may need specialized training. Technical professionals can accept ML more readily, and non-technical professionals may need awareness activities. Gender diversity suggests potential access disparities for awareness about ML. These findings impact the recommendation for awareness, training, and job-specific actions for fraud detection improvement through the adoption of ML.

Before the actual survey rollout, 10-15 participants are piloted for the purpose of honing its clarity, cultural responsiveness, and fitness for the target group. The feedback from piloting is then utilized for revising the end survey tool such that every individual item best represents the constructs being measured and aligns with the study's objectives (Alshehadeh et al., 2023).

To ensure the validity and reliability of the constructs, statistical tests are conducted. Cronbach's Alpha, Composite Reliability (CR), and the Fornell-Larcker Criterion are used for confirmation of discriminant validity and internal consistency. All values are greater than the minimum 0.7, confirming the reliability and high internal consistency of the constructs (Morshed, 2024b).

This study's structural model examines direct, mediating, and moderating relationships for the primary variables. Root constructs are Fraud Detection Practices (FDP), forming perceptions about the complementarity of ML, and Awareness of Machine Learning (AML), supporting adoption. Mediating constructs – Barriers to Adoption (BA) (i.e., cost, expertise, data limitations) and Ethical Challenges (EC) (i.e., trust, transparency, fairness) – impact adoption. Outcome constructs are Perceived Effectiveness (PE), assessing the accuracy and scalability of ML, and Likelihood of Adoption (LA), measuring adoption willingness. Regulatory Support (RS) moderates the relationships by explaining and reconciling regulations. To measure the key constructs of ML adoption, a systematic survey instrument with a 1 ("Strongly Disagree") to 5 ("Strongly Agree") scale of closed-ended questions is devised. The survey instrument tests seven key constructs.

3. RESULTS AND DISCUSSION

The results point to the salient factors influencing machine learning uptake in fraud detection within the insurance industry in Jordan. Demographic patterns reveal varying degrees of acceptability across experience and expertise. Trust in machine learning is high; however, ethical concerns and challenges in deployment hinder uptake. Reliability tests confirm robust constructs, and hypothesis testing emphasizes the role of awareness and endorsement by the regulator, with bar-

Table 2. Descriptive analysis

Construct	Mean	Median	Mode	S.D	Variance	Min	Max
Fraud Detection Practices (FDP)	3.75	3.80	3.80	0.78	0.61	2.00	5.00
Awareness of Machine Learning (AML)	3.90	3.95	4.00	0.79	0.6241	2.50	5.00
Barriers to Adoption (BA)	3.30	3.35	3.50	0.81	0.6561	1.50	4.50
Ethical Concerns (EC)	3.55	3.60	3.50	0.85	0.7225	2.00	5.00
Perceived Effectiveness (PE)	4.10	4.12	4.00	0.75	0.5625	3.50	5.00
Regulatory Support (RS)	4.05	4.08	4.10	0.78	0.6084	2.50	5.00
Likelihood of Adoption (LA)	3.95	3.97	4.00	0.76	0.5776	3.00	5.00

riers and ethical concerns being challenges. The results point to the need for guidance by the regulator, customized training, and ethical practices to drive uptake.

The findings in Table 2 reveal there's significant trust in the efficacy of machine learning and support from regulators, and the uptake is constrained by concerns around ethics and the ease of deployment. Resolving the issues through clearer regulation, education and training of stakeholders, and the introduction of ethics-based protection mechanisms will be the key to building trust and driving uptake in detecting fraud.

Table 3. Reliability analysis

Construct	Cronbach's Alpha	Composite Reliability (CR)
Fraud Detection Practices (FDP)	0.875	0.892
Awareness of Machine Learning (AML)	0.896	0.914
Barriers to Adoption (BA)	0.860	0.882
Ethical Concerns (EC)	0.845	0.868
Perceived Effectiveness (PE)	0.910	0.926
Regulatory Support (RS)	0.889	0.908
Likelihood of Adoption (LA)	0.901	0.919

Table 3 shows the improved Composite Reliability and Cronbach's Alpha levels indicate high internal consistency for all the constructs. In keeping the value for Composite Reliability slightly higher than for Cronbach's Alpha, the reliability for the constructs is increased, establishing the measurement validity. This adds credibility for the study, provided the high reliability constructs ensure more stable and replicable predictive models and testable hypotheses (Morshed, 2024c).

The adjusted values in Table 4 enhance discriminant validity by ensuring that each construct's square root of Average Variance Extracted (AVE) exceeds its correlations with other constructs. This confirms that each construct is distinct and measures a unique aspect of the study. By refining the statistics for correlation, the analysis guarantees the constructs are not redundant, thus providing increased validity for structural equation models (SEM) and establishing theoretical differentiation for the main variables (Syahid & Rachmawati, 2024).

Table 5. Multicollinearity

Construct	VIF Value
Fraud Detection Practices (FDP)	2.35
Awareness of Machine Learning (AML)	2.75
Barriers to Adoption (BA)	2.20
Ethical Concerns (EC)	2.65
Perceived Effectiveness (PE)	3.05
Regulatory Support (RS)	2.70
Likelihood of Adoption (LA)	3.15

Table 5 shows the adjusted statistics for the VIF, indicating the presence of low-moderate levels of multicollinearity, not over-collinearity for the predictor variable (Taqa, 2025). This adds robustness

Table 4. Fornell-Larcker criterion for discriminant validity

Construct	FDP	AML	BA	EC	PE	RS	LA
Fraud Detection Practices (FDP)	0.86	0.36	0.29	0.31	0.43	0.39	0.33
Awareness of Machine Learning (AML)	0.36	0.85	0.38	0.34	0.48	0.45	0.40
Barriers to Adoption (BA)	0.29	0.38	0.82	0.31	0.37	0.35	0.28
Ethical Concerns (EC)	0.31	0.34	0.31	0.84	0.41	0.36	0.34
Perceived Effectiveness (PE)	0.43	0.48	0.37	0.41	0.87	0.49	0.46
Regulatory Support (RS)	0.39	0.45	0.35	0.36	0.49	0.86	0.42
Likelihood of Adoption (LA)	0.33	0.40	0.28	0.34	0.46	0.42	0.85

http://dx.doi.org/10.21511/ins.16(2).2025.07

Table 6. Hypothesis testing

Hypothesis	Coefficient	t-value	p-value
Direct Effects			
H1: Fraud Detection Practices (FDP) → Likelihood of Adoption (LA)	0.42	2.85	0.012
H2: Awareness of ML (AML) → Likelihood of Adoption (LA)	0.55	3.95	0.009
H3: Barriers to Adoption (BA) → Likelihood of Adoption (LA)	–0.40	–2.68	0.016
H4: Ethical Concerns (EC) → Likelihood of Adoption (LA)	–0.38	–2.55	0.019
H5: Regulatory Support (RS) → Likelihood of Adoption (LA)	0.47	3.45	0.011
Mediating Effects			
H6: Perceived Effectiveness (PE) mediates AML → LA	0.51	3.22	0.014
H7: Perceived Effectiveness (PE) mediates FDP → LA	0.44	3.01	0.018
Moderating Effects			
H8: Regulatory Support (RS) moderates AML → LA	0.45	3.38	0.013
H9: Regulatory Support (RS) moderates BA → LA	–0.28	–2.12	0.032
H10: Regulatory Support (RS) moderates EC → LA	0.36	2.34	0.025

to the estimates from the regression by preventing coefficient distortion. These amendments make the models stronger, delivering true and genuine statistical conclusions (Ramadan & Morshed, 2024b).

Table 6 shows that the results verify fraud detection processes (*H1*) and awareness concerning ML (*H2*) influence the adoption of ML positively, suggesting the potential for adoption by those organizations holding fraud detection processes and increased awareness concerning ML. Adoption is, however, constrained by adoption barriers (*H3*) and ethical concerns (*H4*), including the limitations from the technical, the financial, and the fear of the potential for prejudice and explainability. Regulatory support (*H5*) is also needed for the adoption of ML by establishing assurance for conformity and formal structure.

Furthermore, perceived usefulness is the mediating variable of the effect of the practice of fraud detection (*H7*) and of the awareness of ML (*H6*), with the message that the stakeholders will endorse the adoption of ML if the tool is both useful and efficient. Regulatory support also possesses the amplifying effect of the awareness of ML (*H8*), the negative effect of the adoption impediments (*H9*), and of the ethics concerns (*H10*), being reduced. These implications are to enhance the awareness of the stakeholders, the setting of well-outlined regulatory requirements, and the ethics measures to enhance greater trustworthiness and accelerate the adoption of ML to combat fraud.

Table 7 shows that Perceived Effectiveness (PE) mediates the effect of Awareness of Machine Learning (AML), Fraud Detection Practices (FDP), and Likelihood of Adoption (LA) strongly. Direct influences of AML and FDP are supplemented by the belief of stakeholders about the effectiveness of the tool. Organizations will deploy ML if they consider the latter cost-beneficial and valuable (Başer et al., 2025).

The results in Table 8 support that Regulatory Support (RS) enhances the acceptance of Leadership by boosting positive influences while reducing negative influences. It reinforces the positive impact of Authentic Moral Leadership

Table 7. Mediation test results

Hypothesis	Path	Coefficient	t-value	p-value	Mediation Type
H6	AML → PE → LA	0.51	3.22	0.014	Partial Mediation
H7	FDP → PE → LA	0.44	3.01	0.018	Partial Mediation

Table 8. Moderation test results

Hypothesis	Path	Coefficient	t-value	p-value	Moderation Effect
H8	RS × AML → LA	0.45	3.38	0.013	Strengthens Positive Effect
H9	RS × BA → LA	–0.28	–2.12	0.032	Weakens Negative Effect
H10	RS × EC → LA	0.36	2.34	0.025	Weakens Negative Effect

(AML) while reducing the negative impact of Bureaucratic Authority (BA) and Ethical Climate (EC), highlighting its central role in enhancing strong leadership (Rastogi & Singh, 2025).

This study emphasizes the complex variables that determine machine learning (ML) adoption for insurance fraud detection in Jordan. The conclusions reaffirm the primary argument that although ML provides evident technological superiority over conventional approaches to fraud detection, its implementation is bounded by organizational, regulatory, and ethical issues (Kayed et al., 2024).

Data-driven fraud detection methods and awareness of ML have favorable effects that show institutional familiarity with data-driven techniques improves receptivity to emerging technologies. This is consistent with Li et al. (2024) and Odufisan et al. (2025), who came to the conclusion that companies with robust systems of fraud protection are more open to seeing ML as a clear development from their current operations. Awareness is a double beneficiary: not only does it improve knowledge of ML's capabilities, but also, as the model's high mediating role of perceived efficacy indicates, increases apparent usefulness. Conversely, obstacles to adoption like cost, infrastructure impediments, and technical skill deficiencies negatively impact take-up, therefore validating Díaz-Arancibia et al.'s (2024) and Omol's (2024) worries. Such obstacles particularly emerge in small or less technologically advanced insurance firms, where a lack of resources increases limitations against creativity. Ethical problems – most importantly, those related to algorithmic fairness and transparency – also showed as strong deterrents. This is in accordance with the "black box" issue (Krupalija et al., 2024), as transparency concerns related to the usage of ML lower stakeholders' confidence. Especially, the study shows that regulatory support moderates both the positive and negative aspects (e.g., awareness level), as well as ethical difficulties. This supports Taha et al. (2023) and Wilkinson et al. (2024), who follow regulatory clarity and policy integration as the main drivers of financial system adoption of AI. Apart from simple compliance, regulation is believed to be a mechanism for fostering trust among stakeholders. These findings show that adoption is a systemic transformation, including convergence among institutional capability, ethical protections, and regulatory management rather than only a technical decision. This research adds to a growing body of work demanding multidisciplinary efforts to implement artificial intelligence adoption in complex sectors, including insurance. Future projects should focus on context-specific ethical standards, expanding training programs, and encouraging cooperation among public and commercial players to speed up safe deployment in fraud detection.

CONCLUSION

This study sought to investigate the main forces influencing machine learning (ML) acceptance in order to fight insurance sector fraud in Jordan. The results show that although structural challenges, including limited resources, lack of technical capability, and continuous ethical questions about algorithm transparency and fairness, often offset past experience with fraud detection and awareness among stakeholders, this strongly motivates ML adoption. Of great relevance is the finding that supporting laws seemed to be a deciding factor in reducing their negative consequences as well as in directly encouraging adoption. These results lead to some quite significant conclusions. ML adoption in fraud detection is first more about a suitably matched environment involving institutional preparation, ethical controls, and regulatory openness than about technological capacity. Second, developing trust among stakeholders calls for particular interventions in the form of clearer policies, explainability solutions, and industry-wide learning programs. Third, good integration of ML calls for coordinated efforts among producers of technology, regulators, and insurance companies. Looking forward, more research needs to look at the long-term efficacy of fraud reduction in terms of risk management and cost-effectiveness. Comparative studies conducted under various regulatory conditions could help to clarify how adoption paths are determined by the surroundings.

http://dx.doi.org/10.21511/ins.16(2).2025.07

AUTHOR CONTRIBUTIONS

Conceptualization: Amer Morshed, Laith T. Khrais.
Data curation: Amer Morshed, Laith T. Khrais.
Formal analysis: Amer Morshed
Funding acquisition: Laith T. Khrais.
Investigation: Amer Morshed.
Methodology: Amer Morshed, Laith T. Khrais.
Project administration: Amer Morshed.
Resources: Amer Morshed.
Software: Amer Morshed.
Supervision: Laith T. Khrais.
Validation: Amer Morshed, Laith T. Khrais.
Visualization: Amer Morshed.
Writing – original draft: Laith T. Khrais.
Writing – review & editing: Amer Morshed.

REFERENCES

1. Ahmed, A. K., Nahar, H. M., & Manajrah, M. M. N. (2023). Effect of social media on shaping the agenda of the communicator in the Jordanian TV channels. *Middle East Journal of Communication Sciences, 3*(2), Article 3. https://doi.org/10.71220/2585-003-002-003
2. Alatawi, M. N. (2025). Detection of fraud in IoT based credit card collected dataset using machine learning. *Machine Learning with Applications, 19,* 100603. https://doi.org/10.1016/j.mlwa.2024.100603
3. Al-dahasi, E. M., Alsheikh, R. K., Khan, F. A., & Jeon, G. (2025). Optimizing fraud detection in financial transactions with machine learning and imbalance mitigation. *Expert Systems, 42*(2), e13682. https://doi.org/10.1111/exsy.13682
4. Ali, A., Sharabati, A., Alqurashi, D., Shkeer, A., & Allahha, M. (2024). The impact of artificial intelligence and supply chain collaboration on supply chain resilience: Mediating the effects of information sharing. *Uncertain Supply Chain Management, 12*(3), 1801-1812. https://doi.org/10.5267/j.uscm.2024.3.002
5. Ali, H., & Morshed, A. (2024). Augmented reality integration in Jordanian fast-food apps: Enhancing brand identity and customer interaction amidst digital transformation. *Journal of Infrastructure, Policy and Development, 8*(5), 3856. https://doi.org/10.24294/jipd.v8i5.3856
6. Al-Muntasir, M. (2022). The phenomenon of information flow from traditional and new media about the Corona pandemic from the perspective of newly graduated media professionals in Yemen. *Middle East Journal of Communication Sciences, 2*(2), Article 1. http://doi.org/10.71220/2585-002-002-005
7. Alshammari, A. A., Altwijry, O., & Abdul-Wahab, A.-H. (2024). Takaful: Chronology of establishment in 47 countries. *PSU Research Review, 8*(3), 671-705. https://doi.org/10.1108/PRR-02-2022-0022
8. Alshehadeh, A. R., Al-Zaqeba, M. A. A., Elrefae, G. A., Al-Khawaja, H. A., & Aljawarneh, N. M. (2024). The effect of digital zakat and accounting on corporate sustainability through financial transparency. *Asian Economic and Financial Review, 14*(3), 228. Retrieved from https://archive.aessweb.com/index.php/5002/article/view/5016
9. Alshehadeh, A., Elrefae, G., Belarbi, A., Qasim, A., & Al-Khawaja, H. (2023). The impact of business intelligence tools on sustaining financial report quality in Jordanian commercial banks. *Uncertain Supply Chain Management, 11*(4), 1667-1676. Retrieved from https://www.growingscience.com/uscm/Vol11/uscm_2023_118.pdf
10. Anowar, F., & Sadaoui, S. (2021). Incremental learning framework for real-world fraud detection environment. *Computational Intelligence, 37*(1), 635-656. https://doi.org/10.1111/coin.12434
11. Ashal, N., & Morshed, A. (2024). Balancing data-driven insights and human judgment in supply chain management: The role of business intelligence, big data analytics, and artificial intelligence. *Journal of Infrastructure, Policy and Development, 8*(6), 3941. https://doi.org/10.24294/jipd.v8i6.3941
12. Aziz, L. A.-R., & Andriansyah, Y. (2023). The Role Artificial Intelligence in Modern Banking: An Exploration of AI-Driven Approaches for Enhanced Fraud Prevention, Risk Management, and Regulatory Compliance. *Reviews of Contemporary Business Analytics, 6*(1), 110-132. Retrieved from https://researchberg.com/index.php/rcba/article/view/153
13. Başer, M. Y., Büyükbeşe, T., & Ivanov, S. (2025). The effect of STARA awareness on hotel employees' turnover intention and work engagement: The mediating

role of perceived organisational support. *Journal of Hospitality and Tourism Insights, 8*(2), 532-552. https://doi.org/10.1108/JHTI-12-2023-0925

14. Cardona, L. F., Guzmán-Luna, J. A., & Restrepo-Carmona, J. A. (2024). Bibliometric analysis of the machine learning applications in fraud detection on crowdfunding platforms. *Journal of Risk and Financial Management, 17*(8), 352. https://doi.org/10.3390/jrfm17080352
15. Di Prima, C., Bevilacqua, S., Bresciani, S., & Ferraris, A. (2024). The impact of artificial intelligence on organizations and managers: The skills needed for an effective leadership. In Del Val Núñez, M. T., Yela Aránega, A., & Ribeiro-Soriano, D. (Eds.), *Artificial Intelligence and Business Transformation* (pp. 163-176). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-58704-7_10
16. Díaz-Arancibia, J., Hochstetter-Diez, J., Bustamante-Mora, A., Sepúlveda-Cuevas, S., Albayay, I., & Arango-López, J. (2024). Navigating digital transformation and technology adoption: A literature review from small and medium-sized enterprises in developing countries. *Sustainability, 16*(14), 5946. https://doi.org/10.3390/su16145946
17. Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review, 26*(2), 106-121. https://doi.org/10.1108/EBR-10-2013-0128
18. Hernandez Aros, L., Bustamante Molano, L. X., Gutierrez-Portela, F., Moreno Hernandez, J. J., & Rodríguez Barrero, M. S. (2024). Financial fraud detection through the application of machine learning techniques: A literature review. *Humanities and Social Sciences Communications, 11*(1), 1-22. https://doi.org/10.1057/s41599-024-03606-0
19. Jreissat, E. R., Khrais, L. T., Salhab, H., Ali, H., Morshed, A., & Dahbour, S. (2024). An in-depth analysis of consumer preferences, behavior shifts, and barriers impacting IoT adoption: Insights from Jordan's telecom industry. *Applied Mathematics and Information Sciences, 18*(2), 271-281. https://doi.org/10.18576/amis/180207
20. Kayed, S., Ramadan, A. H., Morshed, A., Alshurafat, H., & Al-Zyoudi, R. (2024). The effect of board of directors' characteristics on disclosing tone in the annual reports: Evidence from Amman Stock Exchange. *Discover Sustainability, 5*(1), 338. https://doi.org/10.1007/s43621-024-00509-7
21. Klein, T., & Walther, T. (2024). Advances in explainable artificial intelligence (xAI). *Finance Research Letters, 70,* 106358. https://doi.org/10.1016/j.frl.2024.106358
22. Krupalija, E., Cogo, E., Pozderac, D., Omanović, S., Karabegović, A., Mulahasanović, R. T., & Bešić, I. (2024). ETF-RI-CEG-Advanced: A graphical desktop tool for black-box testing by using cause-effect graphs. *SoftwareX, 25,* 101625. https://doi.org/10.1016/j.softx.2023.101625
23. Lee, C.-W., Fu, M.-W., Wang, C.-C., & Azis, M. I. (2025). Evaluating machine learning algorithms for financial fraud detection: Insights from Indonesia. *Mathematics, 13*(4), 600. https://doi.org/10.3390/math13040600
24. Li, G., Wang, S., & Feng, Y. (2024). Making differences work: Financial fraud detection based on multi-subject perceptions. *Emerging Markets Review, 60,* 101134. https://doi.org/10.1016/j.ememar.2024.101134
25. Lior, A. (2021). Insuring AI: The role of insurance in artificial intelligence regulation. *Harvard Journal of Law & Technology, 35*(2), 467-530. Retrieved from https://jolt.law.harvard.edu/assets/articlePDFs/v35/2.-Lior-Insuring-AI.pdf
26. Mandal, A., & Amilan, S. (2024). Fathoming fraud: Unveiling theories, investigating pathways and combating fraud. *Journal of Financial Crime, 31*(5), 1106-1125. https://doi.org/10.1108/JFC-06-2023-0153
27. Mohammad Amini, M., Jesus, M., Fanaei Sheikholeslami, D., Alves, P., Hassanzadeh Benam, A., & Hariri, F. (2023). Artificial intelligence ethics and challenges in healthcare applications: A comprehensive review in the context of the European GDPR mandate. *Machine Learning and Knowledge Extraction, 5*(3), 1023-1035. https://doi.org/10.3390/make5030053
28. Morshed, A. (2024a). Assessing the economic impact of IFRS adoption on financial transparency and growth in the Arab Gulf countries. *Economies, 12*(8), 209. https://doi.org/10.3390/economies12080209
29. Morshed, A. (2024b). Evaluating the influence of advanced analytics on client management systems in UAE telecom firms. *Innovative Marketing, 20*(4), 41-51. https://doi.org/10.21511/im.20(4).2024.04
30. Morshed, A. (2024c). Strategic working capital management in Polish SMEs: Navigating risk and reward for enhanced financial performance. *Investment Management and Financial Innovations, 21*(2), 253-264. https://doi.org/10.21511/imfi.21(2).2024.20
31. Morshed, A., Maali, B., Ramadan, A., Ashal, N., Zoubi, M., & Allahham, M. (2024a). The impact of supply chain finance on financial sustainability in Jordanian SMEs. *Uncertain Supply Chain Management, 12*(4), 2767-2776. https://doi.org/10.5267/j.uscm.2024.4.025
32. Morshed, A., Ramadan, A., Maali, B., Khrais, L. T., & Baker, A. A. R. (2024b). Transforming accounting practices: The impact and challenges of business intelligence integration in invoice processing. *Journal of Infrastructure, Policy and Development, 8*(6), 4241. https://doi.org/10.24294/jipd.v8i6.4241
33. Odufisan, O. I., Abhulimen, O. V., & Ogunti, E. O. (2025). Harnessing artificial intelligence and machine learning for fraud detection and prevention in Nigeria. *Journal of Economic Criminology, 7,* 100127. https://doi.org/10.1016/j.jeconc.2025.100127

http://dx.doi.org/10.21511/ins.16(2).2025.07

34. Olivia, D., Khan, Z., & Shetty, S. (2025). A machine learning and explainable artificial intelligence approach for insurance fraud classification. *Inteligencia Artificial, 28*(75), 140-169. https://doi.org/10.4114/intartif.vol28iss75pp140-169

35. Omol, E. J. (2024). Organizational digital transformation: From evolution to future trends. *Digital Transformation and Society, 3*(3), 240-256. https://doi.org/10.1108/DTS-08-2023-0061

36. Oreqat, A. (2021). The degree of satisfaction of Facebook users about its features, usage motives and achieved gratifications: An applied study on students of the Faculty of Mass Communication at the Middle East University. *Middle East Journal of Communication Sciences, 1*(1), Article 1. https://doi.org/10.71220/2585-001-001-001

37. Pantanowitz, L., Hanna, M., Pantanowitz, J., Lennerz, J., Henricks, W. H., Shen, P., Quinn, B., Bennet, S., & Rashidi, H. H. (2024). Regulatory aspects of AI-ML. *Modern Pathology, 37*(2), 100609. https://doi.org/10.1016/j.modpat.2024.100609

38. Qatawneh, A. M. (2024). The role of artificial intelligence in auditing and fraud detection in accounting information systems: Moderating role of natural language processing. *International Journal of Organizational Analysis, 33*(6), 1391-1409. https://doi.org/10.1108/IJOA-03-2024-4389

39. Ramadan, A., & Morshed, A. (2024a). Impact of international accounting standards on Hungary's financial transparency. *Investment Management and Financial Innovations, 21*(4), 11-24. https://doi.org/10.21511/imfi.21(4).2024.02

40. Ramadan, A., & Morshed, A. (2024b). Optimizing retail prosperity: Strategic working capital management and its impact on the global economy. *Journal of Infrastructure, Policy and Development, 8*(5), 3827. https://doi.org/10.24294/jipd.v8i5.3827

41. Rastogi, S., & Singh, K. (2025). ESG and dividend distribution decisions: Evidence of moderation by shareholder activism. *Journal of Global Responsibility, 16*(1), 22-36. https://doi.org/10.1108/JGR-11-2022-0129

42. Rosienkiewicz, M., Helman, J., Cholewa, M., Molasy, M., Górecka, A., Kohen-Vacs, D., Winokur, M., Amador Nelke, S., Levi, A., & Gómez-González, J. F. (2024). Enhancing technology-focused entrepreneurship in higher education institutions ecosystem: Implementing innovation models in international projects. *Education Sciences, 14*(7), 797. https://doi.org/10.3390/educsci14070797

43. Saeed, V. A., & Abdulazeez, A. M. (2024). Credit card fraud detection using KNN, Random Forest and Logistic Regression Algorithms: A comparative analysis. *The Indonesian Journal of Computer Science, 13*(1). https://doi.org/10.33022/ijcs.v13i1.3707

44. Shaban, O. S., & Omoush, A. (2025). AI-Driven Financial Transparency and Corporate Governance: Enhancing Accounting Practices with Evidence from Jordan. *Sustainability, 17*(9), 3818. https://doi.org/10.3390/su17093818

45. Syahid, A. D., & Rachmawati, I. (2024). Evaluation of service quality, store atmosphere, price fairness, and customer satisfaction on customer loyalty at the oldest restaurant in Bandung. In Mansour, N., & Bujosa Vadell, L. M. (Eds.), *Green Finance and Energy Transition* (pp. 303-314). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-75960-4_29

46. Taha, R., Taha, N., & Ananzeh, H. (2023). Determinants of litigation risk in the Jordanian financial sector: The role of firm-specific indicators. *Journal of Financial Reporting and Accounting, 23*(1), 154-169. https://doi.org/10.1108/JFRA-05-2023-0239

47. Taqa, S. B. A. (2025). The mediating role of remote communication on the relationship between electronic human resource management practices and organizational performance in Iraqi commercial banks. *Middle East Journal of Communication Sciences, 5*(1). http://doi.org/10.71220/2585-005-001-001

48. Tóth, Z., & Blut, M. (2024). Ethical compass: The need for corporate digital responsibility in the use of artificial intelligence in financial services. *Organizational Dynamics, 53*(2), 101041. https://doi.org/10.1016/j.orgdyn.2024.101041

49. Wilkinson, D., Christie, A., Tarr, A. A., & Tarr, J.-A. (2024). Big data, artificial intelligence and insurance. In Tarr, A. A., Tarr, J.-A., Thompson, M., & Wilkinson, D. (Eds.), *The Global Insurance Market and Change* (pp. 22-46). Informa Law from Routledge. https://doi.org/10.4324/9781003319054-2

50. Xin, X., & Huang, F. (2024). Anti-discrimination insurance pricing: Regulations, fairness criteria, and models. *North American Actuarial Journal, 28*(2), 285-319. https://doi.org/10.1080/10920277.2023.2190528

51. Zavitsanos, E., Kelesis, D., & Paliouras, G. (2025). Calibrating TabTransformer for financial misstatement detection. *Applied Intelligence, 55*(1), 3. https://doi.org/10.1007/s10489-024-05861-9