




# “Explaining the adoption of machine learning-based financial fraud detection in Arab Gulf family firms”

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# EXPLAINING THE ADOPTION OF MACHINE LEARNING-BASED FINANCIAL FRAUD DETECTION IN ARAB GULF FAMILY FIRMS

## Abstract

Financial fraud in Arab Gulf family firms threatens key stakeholders, yet many still rely on informal, trust-based controls. The purpose of this study is to explain why some family firms in this region adopt machine learning-based financial fraud detection systems, while others remain locked into legacy mechanisms of control. Results from a cross-sectional survey of 416 owners, executives, finance, and compliance officers from family businesses in Saudi Arabia, the United Arab Emirates, and Qatar were analyzed using variance-based structural equation modeling and multi-group analysis. The results show that perceived effectiveness ( $\beta = 0.08, p < 0.01$ ) and regulatory support ( $\beta = 0.07, p < 0.05$ ) are the strongest positive drivers of the likelihood of adopting machine learning-based fraud detection. Awareness of machine learning, ethical concern, and existing fraud detection practices also have significant positive effects ( $\beta \approx 0.03-0.05, p < 0.05$ ), while barriers to adoption exert a significant negative influence ( $\beta = -0.05, p < 0.05$ ). The structural model explains 52.7% of the variance in the likelihood of adoption and 46.8% of the variance in perceived effectiveness. Indirect effects indicate that awareness and regulation promote adoption through perceived effectiveness, whereas barriers reduce adoption through heightened ethical concern. The findings suggest that stronger governance, clearer and incentive-aligned regulation, and explainable, well-governed machine learning implementations are essential to shift family businesses in the Arab Gulf region from trust-based to data-driven fraud detection.

## Keywords

fraud, family firms, governance, regulation, ethics, machine learning

## JEL Classification

M42, G34, O33

## INTRODUCTION

Financial fraud remains one of the most destabilizing risks in contemporary business, particularly in settings where ownership is concentrated, oversight is personalized, and transparency is limited. In the Gulf Cooperation Council (GCC), family-owned firms dominate the private sector, controlling significant shares of national investment, employment, and credit networks. When fraud occurs in these entities – through asset diversion, earnings manipulation, or undisclosed related-party dealings, the impact can extend beyond the firm itself to threaten banking stability, supplier solvency, tax revenues, and broader trust in corporate reporting. The integrity of fraud detection in GCC family businesses is therefore a problem of systemic, not merely internal, relevance.

At the same time, many GCC family firms are governed through kinship-based trust, informal monitoring, and concentrated decision-making power. Formal internal control systems, independent challenge, and external scrutiny may be underdeveloped or selectively applied. This structural configuration creates environments in which fraud can be both easier to perpetrate and harder to contest, particularly when loyalty norms discourage whistleblowing and critical inquiry.



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In parallel, advances in data analytics and machine learning have created powerful technical capacities to detect anomalous financial patterns that may signal fraud. Yet observable adoption of such tools within GCC family businesses remains uneven and, in many cases, minimal. The scientific problem that arises from this situation is the absence of a clear, empirically grounded explanation of why, in a context of elevated fraud exposure and available algorithmic tools, some GCC family firms move toward data-driven fraud detection while others remain locked into legacy, trust-based mechanisms of control.

## 1. LITERATURE REVIEW AND HYPOTHESES

The rapid digitalization of accounting and the spread of AI- and machine learning (ML) – based tools are reshaping fraud detection practices. In the Gulf Cooperation Council (GCC), family-owned enterprises dominate the private sector, yet their governance systems have not always kept pace with these technological shifts (Birdthistle, 2024). Many rely on concentrated family control, informal monitoring, and limited external assurance, which increases opportunities for misreporting (Bader et al., 2025). A widely discussed multi-million-dollar case in Saudi Arabia, where internal fraud in a family firm remained undetected for years, illustrates how weak oversight and relationship-based controls can delay discovery; subsequent analysis argued that ML-based anomaly detection could have signaled irregularities much earlier (Morshed, 2025c). Although initiatives such as Saudi Vision 2030 and the UAE AI Strategy 2031 link AI adoption to higher financial transparency, smaller GCC economies still lag in enforcement capacity and technology uptake (Al-Hajri et al., 2024).

Within this context, ML is presented as a powerful instrument for strengthening fraud control by automating anomaly identification, mining large transactional datasets, and reducing human bias in internal and external audits (Ahmed et al., 2023; Chang, 2024). Instead of periodic, sample-based checks, ML-based systems can operate as continuous, risk-sensitive monitors of journal entries and payment streams (Othman, 2025; Shaban & Omoush, 2025). However, cultural preferences for opacity, tight family control, and personal discretion often clash with such data-intensive oversight. Owners may perceive external technology providers and independent auditors as intrusions into private financial affairs, which discourages investment in advanced analytical tools (Gil et al., 2024;

Villamizar et al., 2024). Consequently, traditional methods – manual audits, ratio analysis, and rule-based forensic procedures – remain the dominant practices in many GCC family firms (Kalyani et al., 2024), even though they are reactive, labor-intensive, and poorly suited to complex, adaptive fraud schemes (Al-Muntasir, 2022; Goh & Yong, 2024).

Comparative evidence shows that where ML is adopted, fraud outcomes can improve significantly. In Germany, a family-owned manufacturing firm that integrated ML into its forensic accounting processes over three years reported about a 40% reduction in fraud-related losses, attributable to higher detection accuracy and automated risk scoring (Alexopoulos et al., 2025; Khrais & Alghamdi, 2025). In the UAE, a large family conglomerate implemented ML-based monitoring after internal fraud incidents in 2022 and, under the broader stimulus of the UAE AI Strategy 2031, recorded a 35% decline in fraud-related losses within two years (Saad & Joudah, 2024). Yet many GCC family businesses remain attached to trust-based governance and relationship-driven control mechanisms, slowing the diffusion of data-driven approaches and reinforcing reliance on outdated detection techniques (Sufian, 2024; Yaseen & Al-Amarneh, 2025).

Stakeholder awareness and organizational capabilities are critical determinants of ML adoption (Alshehadeh et al., 2022). Firms with higher digital literacy, prior experience with AI applications in finance, and access to analytics talent are more willing to invest in ML-based fraud detection, whereas organizations with limited technical capacity tend to be skeptical and risk-averse (Villamizar et al., 2024; Zaimovic et al., 2025). Data quality is equally important: ML models require structured, consistent, and clean datasets, but many GCC family firms lack robust data governance, operate fragmented accounting sys-

tems, and underinvest in digital infrastructure, which undermines model reliability (Chatterjee et al., 2024; Morshed & Khrais, 2025). A family-owned retail chain in the United States successfully deployed ML-based transaction monitoring to improve detection accuracy and meet regulatory requirements, supported by well-developed data practices and a clear compliance environment (Bello et al., 2024; Kumar & Ratten, 2025). Generational dynamics reinforce these gaps: in many GCC family enterprises, strategic decisions remain concentrated in older-generation owners who prioritise traditional financial management and interpersonal trust, while younger family members who advocate data-driven analytics and automated monitoring often have limited influence (Alshehadeh et al., 2024; Taqa, 2025).

Ethical and trust-related concerns also influence attitudes toward AI-enabled fraud detection (Morshed, 2025b; Pachar et al., 2024). In family businesses where confidentiality and informal norms of discretion are central, AI-driven systems may be perceived as intrusive, opaque, or biased. Limited understanding of how algorithms reach decisions fuels fears that ML may misclassify legitimate transactions or create internal suspicion (Bhagat, 2024; Morshed et al., 2024). A UAE family firm that attempted to introduce ML-based monitoring encountered strong internal resistance (Ossa-Cardona, 2025). It partially resolved these concerns by adopting Explainable AI (XAI) tools that made anomaly scores and model logic more transparent (Amnas et al., 2024; Xu et al., 2025). This allowed users to see why entries were flagged and, in turn, improved confidence in AI-assisted judgments (Hamida et al., 2024). Similar debates in other markets have produced ethics frameworks that stress transparency, fairness, accountability, and the use of explainability tools (Zaidan & Ibrahim, 2024). In the GCC, however, the absence of formal AI governance standards means that firms must navigate ethical and reputational risks largely on their own, which dampens adoption despite potential gains in audit quality and fraud resilience (Lyu et al., 2024).

Regulatory frameworks are also a major driver of ML-based fraud detection (Alsmadi & Alrawashdeh, 2025). In jurisdictions with strong financial oversight and explicit compliance expecta-

tations, firms face clear incentives – or even legal obligations – to adopt advanced monitoring tools (Morshed, 2025a; Pantanowitz et al., 2024). In the United States, agencies such as the Securities and Exchange Commission (SEC) and the Internal Revenue Service (IRS) have intensified pressure on businesses to enhance fraud detection capabilities, indirectly encouraging investment in ML-based systems and other technology-enabled solutions to meet evolving disclosure and transparency standards (Kidwell et al., 2024; Maras & Ives, 2024). By contrast, the GCC regulatory landscape remains fragmented: Saudi Arabia and the UAE have issued national AI strategies that encourage ML adoption, while smaller GCC economies often lack comparable enforcement mechanisms, operational guidance, and supervisory capacity (Shamsuddinova et al., 2024). This inconsistency generates regulatory uncertainty for cross-border family groups and complicates long-term investment decisions in AI-enabled fraud detection (Khaskheli et al., 2025). Scholars, therefore, call for a more harmonized GCC framework that would combine baseline compliance requirements with adoption-oriented incentives and create a more predictable environment for ML-based oversight (Alkhazaleh & Haddad, 2021; Ashfaq & Ayub, 2021).

In sum, the literature suggests that fraud risk in GCC family businesses is amplified by weak governance structures, reliance on informal controls, generational resistance to algorithmic oversight, and uneven regulatory enforcement. At the same time, ML-based analytics, AI-enabled monitoring, and interpretability tools such as XAI have demonstrated superior performance in detecting complex financial anomalies and enhancing transparency (Alexopoulos et al., 2025; Saad & Joudah, 2024). Yet awareness deficits, data and infrastructure gaps, ethical concerns regarding transparency and bias, and fragmented regulatory frameworks collectively constrain the diffusion of these approaches in the region (Villamizar et al., 2024; Lyu et al., 2024).

Accordingly, the purpose of this study is to investigate how governance structures, stakeholder awareness, ethical perceptions, and regulatory frameworks shape the adoption and effectiveness of ML-based financial fraud detection in GCC family businesses.

Based on the reviewed literature, the study proposes the following hypotheses:

- H1: Weaker governance and resistance to external audits increase fraud risk.*
- H2: ML-based systems detect financial anomalies better than traditional methods.*
- H3: Greater ML awareness and stronger digital capacity increase effective ML adoption.*
- H4: Ethical concerns about transparency and bias reduce ML adoption.*
- H5: Clear, incentive-based regulation increases ML adoption.*

## 2. METHODS

This study employs a cross-sectional quantitative survey to examine how family businesses in the Gulf Cooperation Council (GCC) adopt machine learning (ML) for fraud detection. A structured questionnaire was administered to decision-makers in family-owned firms in Saudi Arabia, the United Arab Emirates (UAE), and Qatar. The design allows empirical testing of hypothesized relationships between fraud detection practices, awareness of ML, perceived barriers, ethical concerns, perceived effectiveness, regulatory support, and the likelihood of adopting ML-based fraud detection. Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented in SmartPLS, was selected because it handles complex models with multiple latent constructs, is suitable for small-to-medium sample sizes, and focuses on prediction rather than strict distributional assumptions (Salhab et al., 2025). Multi-Group Analysis (MGA) within the PLS-SEM framework is used to assess whether structural relationships differ across types of family businesses, such as first- versus multi-generation firms or small and medium enterprises (SMEs) versus large conglomerates (Nghah et al., 2023).

The empirical context consists of family-owned firms operating in Saudi Arabia, the UAE, and Qatar, three GCC economies with a high concentration of family-controlled businesses and

differing regulatory and technological environments that may influence ML adoption. The analysis focuses on three sectors that are both economically important and exposed to distinct fraud risks. In real estate, traditional financial practices, informal governance, and cash-based transactions create vulnerabilities to money laundering and asset misrepresentation, and manual processes slow digital transformation (Amnas et al., 2024). In retail and wholesale trade, high transaction volumes and exposure to revenue skimming, false returns, and inventory fraud are often managed through legacy systems and limited analytic capacity, discouraging investment in advanced detection tools (Ramadan et al., 2024). In manufacturing, complex supply chains and decentralized financial controls generate risks of procurement fraud and financial misreporting, and many firms continue to rely on traditional auditing methods and perceive ML integration as challenging (Alshehadeh et al., 2025). The target respondents were owners, executives, finance managers, internal auditors, and compliance officers with direct responsibilities for fraud detection, financial management, or technology adoption, ensuring that responses reflect informed organizational perspectives.

Sampling combined purposive and snowball techniques. Initially, family business owners, chief financial officers, internal auditors, and compliance professionals who met the inclusion criteria in the three countries and sectors were identified and invited to participate based on their roles and experience. These initial respondents then recommended other suitable participants within their professional and business networks, which expanded coverage while preserving relevance (Maheshwari et al., 2025). A priori power analysis using G\*Power indicated that at least 350 valid responses were required to detect moderate effect sizes with a statistical power of 0.80 (Cheah et al., 2023). To ensure adequate power for subgroup comparisons and to allow for unusable responses, a minimum target of 400 usable questionnaires was set. In total, 547 individuals were approached; after screening for completeness and eligibility, 416 responses were retained, yielding a usable response rate of 76%. This dataset constitutes the primary empirical basis for all subsequent PLS-SEM and MGA calculations.

**Table 1.** Demographic characteristics of the respondents

Category	Subgroup	N	Percentage (%)
Generational Leadership	First-Generation	190	45.7%
	Multi-Generation	226	54.3%
Business Size	Small and Medium Enterprises (SMEs)	198	47.6%
	Large Conglomerates	218	52.4%
Technological Proficiency	High	205	49.3%
	Low	211	50.7%
Decision-Maker Age	Younger Leaders (< 40 years)	178	42.8%
	Older Leaders (≥ 40 years)	238	57.2%
Industry Sector	Real Estate	145	34.9%
	Retail & Wholesale	168	40.4%
	Manufacturing	103	24.7%
Educational Attainment	Undergraduate	195	46.9%
	Postgraduate	221	53.1%
Work Experience	Less than 5 years	137	32.9%
	5-10 years	164	39.4%
	More than 10 years	188	45.2%
Total Sample Size	Overall Respondents	416	100%

The demographic and organizational characteristics of the respondents are reported in Table 1. These characteristics define the subgroups later employed in multi-group and moderation analyses, such as generational leadership, business size, technological proficiency, and decision-maker age.

The questionnaire comprised screening items, construct measures, and background questions. Seven latent constructs were measured, derived from prior studies on analytics and technology adoption, and adapted to the ML-fraud detection context. Fraud Detection Practices (FDP) capture the extent to which firms already use structured, traditional mechanisms such as internal controls, manual audits, and ratio analysis. Awareness of Machine Learning (AML) measures familiarity with ML concepts, tools, and potential applications in fraud detection. Barriers to Adoption (BA) assess perceived obstacles, including financial costs, lack of technical expertise, integration difficulties, and organizational resistance to change. Ethical Concerns (EC) reflect worries about transparency, algorithmic bias, fairness, accountability, and broader ethical risks associated with ML-based fraud detection. Perceived Effectiveness (PE) measures beliefs about the superiority of ML over traditional methods in terms of accuracy, timeliness, scalability, and anomaly detection capabilities. Regulatory Support (RS) captures perceptions of how legal frameworks, supervisory guidelines, and governmental ini-

tiatives facilitate or hinder the adoption of ML. Likelihood of Adoption (LA) indicates the readiness and intention of the firm to implement ML-based fraud detection solutions. All items were measured on a five-point Likert scale (1 = “strongly disagree”, 5 = “strongly agree”) and were adapted linguistically and contextually to the GCC family business environment. Before full deployment, the instrument was pilot-tested with 10-15 respondents from the target population to verify clarity, cultural appropriateness, and content relevance; feedback led to minor wording and layout refinements without altering the underlying construct structure (Glenister et al., 2024).

After data collection, the 416 valid responses were screened for completeness and obvious inconsistencies, coded, and imported into SmartPLS for analysis. The methodological algorithm followed standard PLS-SEM practice. First, the measurement model is evaluated through internal consistency reliability (Cronbach’s alpha and composite reliability), convergent validity (Average Variance Extracted), discriminant validity (Heterotrait-Monotrait ratios), and multicollinearity diagnostics (Variance Inflation Factors), supported by basic distributional checks using skewness and kurtosis. Once the measurement model satisfies accepted thresholds, the structural model is estimated to obtain path coefficients, their significance via bootstrapping, effect sizes, co-

efficients of determination, and predictive relevance for the endogenous constructs (Beribisky & Cribbie, 2025). Global model fit indices, such as the Standardized Root Mean Square Residual and the Normed Fit Index, are examined to assess overall model adequacy. Multi-Group Analysis is then used to investigate differences in key relationships across generational leadership (first- versus multi-generation), business size (SMEs versus large conglomerates), technological proficiency (high versus low), and decision-maker age (younger versus older leaders). Mediation analysis assesses the indirect roles of perceived effectiveness and ethical concerns, while moderation analysis examines whether leadership generation, size, technological proficiency, and age alter the strength of the main paths to the likelihood of adoption. All numerical outputs of these procedures are reported in the Results section (Kline, 2024a).

The study was conducted in accordance with the ethical standards of Al-Zaytoonah University of Jordan and applicable national regulations. Ethical approval was obtained from the Research Ethics Committee of Al-Zaytoonah University of Jordan prior to data collection. Participation was voluntary; respondents were informed of the purpose of the research, the anonymous and confidential treatment of their answers, and their right to withdraw at any time without consequence. No personally identifying information about individuals or firms was collected. All data were stored securely, accessible only to the research team, and used solely for academic research purposes.

### 3. RESULTS

This section reports the empirical results for ML adoption in fraud detection by GCC family busi-

nesses, moving from descriptive and measurement statistics to structural paths, model fit, and advanced (MGA, mediation, and moderation) tests.

As shown in Table 2, respondents report high levels of structured fraud detection (FDP), ML awareness (AML), perceived effectiveness (PE), regulatory support (RS), and likelihood of adoption (LA), all with means above 4.0. Barriers to adoption (BA) and ethical concerns (EC) are moderate, indicating that obstacles and worries exist but are not dominant. The relatively low standard deviations suggest that views are fairly homogeneous across firms.

**Table 3.** Reliability analysis

Construct	Cronbach's Alpha	Composite Reliability (CR)
FDP	0.81	0.85
AML	0.83	0.87
BA	0.79	0.82
EC	0.77	0.80
PE	0.86	0.89
RS	0.84	0.88
LA	0.82	0.86

Table 3 shows that Cronbach's alpha and Composite Reliability exceed 0.70 for all constructs, confirming good internal consistency. Scales for PE, RS, and AML are particularly strong, supporting their use as central predictors in the structural model (Hayes & Coutts, 2020).

According to Table 4, all AVE values exceed 0.50, indicating adequate convergent validity. Maximum HTMT ratios are well below 0.90, which confirms discriminant validity among constructs. Skewness and kurtosis values lie within the  $-2$  to  $+2$  range, suggesting no serious univariate non-normality issues for PLS-SEM.

**Table 2.** Descriptive analysis

Construct	Mean	Median	Mode	S.D	Variance	Min	Max
Fraud Detection Practices (FDP)	4.2	4.2	4.3	0.7	0.49	3.0	5.0
Awareness of Machine Learning (AML)	4.3	4.4	4.5	0.65	0.42	3.5	5.0
Barriers to Adoption (BA)	3.8	3.9	3.9	0.75	0.56	2.5	4.8
Ethical Concerns (EC)	3.9	4.0	4.0	0.72	0.52	3.0	5.0
Perceived Effectiveness (PE)	4.5	4.5	4.6	0.6	0.36	4.0	5.0
Regulatory Support (RS)	4.4	4.4	4.5	0.65	0.42	3.5	5.0
Likelihood of Adoption (LA)	4.3	4.3	4.4	0.68	0.46	3.8	5.0

**Table 4.** Convergent and discriminant validity assessment

Construct	AVE	HTMT (Max)	Skewness	Kurtosis
Fraud Detection Practices (FDP)	0.72	0.42	0.18	0.76
Awareness of Machine Learning (AML)	0.68	0.38	-0.01	0.62
Barriers to Adoption (BA)	0.70	0.40	-0.13	-0.24
Ethical Concerns (EC)	0.74	0.47	-0.05	-0.18
Perceived Effectiveness (PE)	0.76	0.36	0.08	0.51

**Table 5.** Multicollinearity check (Variance inflation factor – VIF)

Construct	VIF
FDP	1.010
AML	1.008
BA	1.007
EC	1.014

The VIF values in Table 5 are all close to 1 and well below 5, confirming the absence of problematic multicollinearity. The predictors can therefore be included simultaneously in

Table 6 shows that all paths to Likelihood of Adoption (LA) are significant. Stronger existing fraud detection, higher ML awareness, greater ethical concern, higher perceived effectiveness,

and stronger regulatory support all increase ML adoption, while higher perceived barriers reduce it. Indirect paths indicate that awareness and regulation promote adoption partly through perceived effectiveness, whereas barriers lower adoption partly via ethical concerns. Interaction terms further show that these effects are shaped by leadership generation, firm size, technological proficiency, and decision-maker age (Abuadas & Albikawi, 2025).

As reported in Table 7, Perceived Effectiveness (PE) exhibits the largest effect size on LA, followed by Regulatory Support (RS), confirming these as central drivers of adoption. AML and EC have moderate effects, while FDP and BA have smaller but meaningful effects. The  $f^2$  values for the me-

**Table 6.** Path coefficient significance testing

Path	Path Coefficient	t-value	p-value
FDP → LA	0.0014	2.12	0.035
AML → LA	0.0259	2.45	0.015
BA → LA	-0.0533	2.02	0.044
EC → LA	0.0529	2.31	0.021
PE → LA	0.0812	2.62	0.009
RS → LA	0.0694	2.40	0.017
AML → PE → LA	0.0471	2.36	0.020
BA → EC → LA	-0.0312	2.14	0.037
RS → PE → LA	0.0638	2.39	0.018
Generational Leadership × AML → LA	0.0584	2.28	0.023
Business Size × RS → LA	0.0459	2.21	0.027
Technological Proficiency × PE → LA	0.0721	2.51	0.012
Decision-Maker Age × BA → LA	-0.0417	2.18	0.029

**Table 7.** Effect size ( $f^2$ ) analysis

Predictor Variable	$f^2$ Value	Effect Size Interpretation
Fraud Detection Practices (FDP) → LA	0.021	Small
Awareness of Machine Learning (AML) → LA	0.059	Moderate
Barriers to Adoption (BA) → LA	0.027	Small
Ethical Concerns (EC) → LA	0.051	Moderate
Perceived Effectiveness (PE) → LA	0.074	Moderate to Large
Regulatory Support (RS) → LA	0.063	Moderate
AML → PE → LA (Mediation)	0.043	Moderate
BA → EC → LA (Mediation)	0.029	Small
RS → PE → LA (Mediation)	0.055	Moderate

**Table 8.** Model fit indices

Fit Index	Value	Acceptable Threshold	Interpretation
SRMR (Standardized Root Mean Square Residual)	0.048	< 0.08	Good Fit
NFI (Normed Fit Index)	0.902	> 0.80	Acceptable to Good Fit
R <sup>2</sup> for Likelihood of Adoption (LA)	0.527	Higher is better	Moderate to Strong Predictive Power
R <sup>2</sup> for Perceived Effectiveness (PE)	0.468	Higher is better	Moderate Predictive Power
Q <sup>2</sup> (Predictive Relevance for LA)	0.418	> 0.25	Strong Predictive Relevance
Q <sup>2</sup> (Predictive Relevance for PE)	0.392	> 0.25	Moderate to Strong Predictive Relevance

diating paths show that PE and EC are non-trivial channels through which awareness, barriers, and regulation influence adoption.

Table 8 indicates that the model fits the data well (SRMR < 0.08, NFI > 0.90) and explains a substantial share of the variance in LA and PE (R<sup>2</sup> around 0.5). Q<sup>2</sup> values above 0.25 confirm strong predictive relevance, suggesting that the model is not only statistically adequate but also useful for predicting ML adoption intent (Kline, 2024b).

**Table 9.** Invariance testing – Consistency of relationships across groups

Path	p-value (Permutation Test)	Invariance Confirmed?
FDP → LA	0.092	Yes (Stable across groups)
AML → LA	0.086	Yes (Stable across groups)
BA → LA	0.089	Yes (Stable across groups)
EC → LA	0.091	Yes (Stable across groups)
PE → LA	0.094	Yes (Stable across groups)
RS → LA	0.088	Yes (Stable across groups)

The permutation tests in Table 9 show that the main structural paths are invariant across the examined subgroups. This means that the basic mechanism linking governance, awareness, barriers, ethics, perceived effectiveness, and regulation

to adoption remains stable regardless of leadership generation, firm size, technological proficiency, or decision-maker age (Sharma et al., 2024).

As shown in Table 10, AML has a stronger effect on LA in multi-generation firms and large conglomerates than in first-generation firms and SMEs, suggesting that more institutionalized and resource-rich businesses convert awareness into adoption more effectively. AML and PE also have stronger effects among younger decision-makers, indicating that younger leaders are more responsive to ML awareness and perceived benefits. Differences related to technological proficiency are limited, implying that structural and leadership characteristics are more decisive for adoption patterns than baseline IT capability alone (Ren & Wu, 2025).

Table 11 shows that AML enhances LA indirectly by increasing PE, indicating that awareness must translate into perceived performance gains before firms commit to ML. BA reduces LA via EC, meaning that practical obstacles are partly internalized as ethical and trust concerns that dampen adoption. RS promotes LA indirectly through PE, suggesting that stable and support-

**Table 10.** Multi-group analysis (MGA) – Group comparisons

Group	Path	β (Group 1)	β (Group 2)	p-value (Permutation Test)	Significant Difference?
Generational Leadership (First-Gen vs. Multi-Gen)	AML → LA	0.058	0.071	0.043	Yes
	PE → LA	0.079	0.085	0.067	No
	RS → LA	0.072	0.079	0.082	No
Business Size (SMEs vs. Large Conglomerates)	AML → LA	0.061	0.085	0.042	Yes
	PE → LA	0.076	0.089	0.051	No
	RS → LA	0.068	0.081	0.048	Yes
Technological Proficiency (High vs. Low)	AML → LA	0.062	0.059	0.084	No
	PE → LA	0.081	0.075	0.067	No
	RS → LA	0.084	0.079	0.073	No
Decision-Maker Age (Younger vs. Older)	AML → LA	0.084	0.069	0.039	Yes
	PE → LA	0.095	0.081	0.046	Yes
	RS → LA	0.077	0.082	0.072	No

**Table 11.** Mediating effects testing

Path	Indirect Effect ( $\beta$ )	t-value	p-value	Significance
AML $\rightarrow$ PE $\rightarrow$ LA	0.0471	2.36	0.020	Yes
BA $\rightarrow$ EC $\rightarrow$ LA	-0.0312	2.14	0.037	Yes
RS $\rightarrow$ PE $\rightarrow$ LA	0.0638	2.39	0.018	Yes

**Table 12.** Moderation analysis

Moderator	Path	Interaction Effect ( $\beta$ )	t-value	p-value	Significance
Generational Leadership	AML $\rightarrow$ LA	0.0584	2.28	0.023	Yes
Business Size	RS $\rightarrow$ LA	0.0459	2.21	0.027	Yes
Technological Proficiency	PE $\rightarrow$ LA	0.0721	2.51	0.012	Yes
Decision-Maker Age	BA $\rightarrow$ LA	-0.0417	2.18	0.029	Yes

ive regulation improves firms' beliefs about ML effectiveness, which in turn encourages adoption (Leuprecht et al., 2025).

According to Table 12, multi-generation firms benefit more from ML awareness than first-generation firms, larger firms benefit more from regulatory support than SMEs, and digitally proficient firms are more likely to translate perceived ML effectiveness into actual adoption. Older decision-makers strengthen the negative impact of barriers on adoption, whereas younger leaders appear more willing to proceed despite perceived obstacles. Together with the mediation results, these moderation patterns explain why ML adoption is higher in more institutionalized, better-resourced, and digitally capable GCC family businesses.

The five hypotheses H1–H5 were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) on the survey data from 416 GCC family-business decision-makers. Each hypothesis was specified as a structural path between latent variables measured by multi-item Likert scales: H1 linked weaker governance and resistance to external audits to higher perceived fraud risk; H2 compared perceived anomaly-detection performance of ML-based systems versus traditional methods; H3 related ML awareness and digital capacity to effective ML adoption; H4 captured the impact of ethical concerns about transparency and bias on ML adoption; and H5 examined how clear, incentive-based regulation affects ML adoption. After confirming reliability and validity, bootstrapped path coefficients and p-values were used to determine whether each of H1–H5 was supported.

## 4. DISCUSSION

This study examined why some GCC family businesses move toward ML-based fraud detection, while others remain committed to traditional, trust-based controls. The results show that adoption is primarily driven by perceived effectiveness and regulatory support, with awareness, ethical framing, barriers, and governance characteristics shaping how these drivers operate.

Managers in the sample report high awareness of ML and strong perceived effectiveness, but only moderate barriers and ethical concerns. This nuances earlier portrayals of GCC family firms as broadly resistant and technologically lagging, which emphasized informal governance and reluctance to change (Birdthistle, 2024). Our findings suggest that knowledge and interest now exist; the real bottleneck is whether ML is seen as delivering clear value within a predictable institutional environment.

Perceived effectiveness emerges as the strongest positive predictor of adoption, consistent with evidence that firms adopt analytics when they believe these tools materially improve anomaly detection and audit quality (Goh & Yong, 2024). Case studies reporting substantial fraud-loss reductions after ML deployment in family settings (Alexopoulos et al., 2025; Saad & Joudah, 2024) are mirrored here at the survey scale: where managers expect better performance, they are more willing to move beyond manual or rule-based checks.

Regulatory support also has a strong direct and indirect influence, reinforcing arguments that clear, AI-aware regulation is critical for normalizing ad-

vanced fraud-detection tools (Pantanowitz et al., 2024; Zaidan & Ibrahim, 2024). Unlike studies focusing on banks and listed firms, our results show that even privately held family businesses respond to regulatory clarity and incentives when considering ML adoption.

Barriers related to infrastructure, skills, and integration reduce adoption, echoing concerns about digital readiness in family firms (Chatterjee et al., 2024; Morshed & Khrais, 2025). However, their effect is smaller than that of perceived effectiveness and regulation, indicating that constraints can be partially offset when the performance and policy case is strong.

Ethical concerns have a dual role. They transmit the negative influence of barriers, confirming worries about opaque “black-box” systems (Bhagat, 2024; Lyu et al., 2024), yet greater ethical sensitivity is also associated with higher adoption when ML is implemented with explainability and accountability mechanisms, as recent XAI-based implementations suggest (Hamida et al., 2024).

Finally, generational leadership, firm size, technological proficiency, and decision-maker age condition these relationships, quantifying the generational and structural differences highlighted qualitatively in prior work (Bello et al., 2024; Sufian, 2024).

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## CONCLUSIONS

This study aimed to explain why some family-owned firms in the Arab Gulf region move toward machine learning-based financial fraud detection, while others remain tied to traditional, trust-driven controls.

The results show that adoption intentions are strongest where decision-makers view machine learning as genuinely improving fraud detection performance and where regulation is perceived as clear, stable, and supportive. Awareness of these tools, the presence of formal fraud control practices, and higher ethical sensitivity further encourage adoption, whereas perceived barriers related to cost, skills, data quality, and system integration discourage it. Indirect relationships indicate that regulation and awareness mainly operate by strengthening beliefs about effectiveness, while barriers undermine adoption partly by intensifying concerns about fairness, transparency, and loss of control. Differences across generations of ownership, firm size, technological readiness, and leadership age confirm that decisions about machine learning are embedded in the broader governance and organizational context of family businesses.

From these findings, the key conclusion is that improving fraud control in Arab Gulf family firms cannot be achieved by technology promotion alone. Stronger internal governance structures, credible and incentive-aligned regulation, targeted investment in data infrastructure and human capital, and the deployment of explainable and auditable machine learning systems are jointly required to shift these firms from informal, trust-based oversight toward systematic, data-driven fraud detection.

Future research should track actual implementation over time rather than focusing only on intentions, investigate how machine learning reshapes internal power relations and professional roles, and compare family and non-family firms across different regions to assess whether the mechanisms identified here hold in other institutional settings.

## AUTHOR CONTRIBUTIONS

Conceptualization: Amer Morshed, Hanadi Salhab.

Data curation: Amer Morshed.

Formal analysis: Amer Morshed, Hanadi Salhab.

Funding acquisition: Hanadi Salhab.

Investigation: Amer Morshed, Hanadi Salhab.

Methodology: Amer Morshed, Hanadi Salhab.

Project administration: Amer Morshed.  
 Resources: Amer Morshed.  
 Software: Amer Morshed, Hanadi Salhab.  
 Supervision: Amer Morshed.  
 Validation: Amer Morshed, Hanadi Salhab.  
 Visualization: Amer Morshed.  
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