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AI-Driven Banking Accounting and Organizational Resilience: Decision Intelligence as Mediator and Digital Leadership as Moderator

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Abstract

Purpose: This study examines how artificial intelligence (AI) adoption in banking accounting affects organizational resilience (OR) among Jordanian listed banks, and whether real-time decision intelligence (RTDI) mediates and digital leadership (DL) moderates those effects, including a moderated mediation pathway. **Design/methodology/approach:** A cross-sectional survey of 320 professionals drawn from all 14 Amman Stock Exchange-listed banks was analyzed via partial least squares structural equation modeling (PLS-SEM) using SmartPLS 4 with 5,000 bias-corrected bootstrap subsamples. AI was operationalized as a reflective–formative second-order hierarchical component model comprising four first-order dimensions: financial reporting, audit, risk management, and regulatory compliance. **Findings:** AI significantly enhances RTDI ($\beta = 0.224$, $p = 0.008$) and OR ($\beta = 0.780$, $p < 0.001$), explaining 77.6% of OR variance. RTDI partially mediates the AI–OR relationship ($\beta = 0.031$, $p = 0.043$, VAF = 3.8%). DL exerts a negative moderation on AI → OR ($\beta = -0.091$, $p = 0.001$), indicating a ceiling/substitution effect. The moderated mediation is significant ($\beta = -0.012$, $p = 0.027$). Importance–performance map analysis (IPMA) identifies AI as the highest-priority construct for resilience improvement. **Originality/value:** This is the first study to integrate AI in banking accounting, RTDI, DL, and OR within a single moderated mediation model grounded in dynamic capabilities view (DCV), technology–organization–environment (TOE) framework, and upper echelons theory (UET) in an emerging-economy banking context. The negative moderation finding challenges the prevailing assumption that digital leadership unconditionally amplifies technology–performance relationships.

Keywords: artificial intelligence; banking accounting; organizational resilience; real-time decision intelligence; digital leadership; PLS-SEM; moderated mediation; IPMA; Jordan; emerging economies

JEL Classification: G21; M41; O33; C39

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1. Introduction

The global banking industry is undergoing profound transformation driven by artificial intelligence (AI), which is being applied to fundamental accounting processes—including financial reporting, auditing, risk management, and regulatory compliance [10,14,57,61]. By 2024, approximately 58% of financial services firms had adopted AI-powered accounting tools, with the market projected to reach USD 10 billion by 2025 [20,41]. JPMorgan Chase alone invested USD 18 billion in technology in 2025, expecting AI to reduce operational servicing costs by approximately 30% [64]. These investments signal a strategic repositioning of financial institutions toward intelligent, data-driven operations [66].

Despite these advances, banks continue to face intensifying pressures on their *organizational resilience* (OR)—the capacity to anticipate, prepare for, respond to, and adapt to disruptive events [21,31]. From the COVID-19 pandemic to cyberattacks and dynamic regulatory environments, resilience has become a strategic imperative rather than a contingency plan [1,36,38,56]. While AI creates a strong

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foundation for resilience-building, the mechanisms through which AI in accounting translates into organizational resilience remain empirically under-explored [11,23].

The Jordanian banking context provides a theoretically and practically significant setting for this inquiry. Jordan's 14 ASE-listed banks hold total assets of approximately JOD 60 billion, operate 869 branches, and employ 22,996 professionals [8]. A 2024 report by the Association of Banks in Jordan (ABJ) projected that generative AI could boost productivity by 30% and revenue by 6%. Nevertheless, the sector faces a critical digital-skills gap, with approximately 2,613 new hires in 2024—nearly half being fresh graduates lacking adequate digital capabilities [33]. Recent evidence confirms strong AI adoption readiness (mean = 4.3) in the sector, with API integration ($\beta = 0.78$) and government incentives ($\beta = 0.51$) as key enablers [2,4,13].

Four research gaps motivate this study. **First**, no prior study has examined the collective impact of AI across multiple banking-accounting functions on OR. **Second**, the mechanisms through which AI produces resilience remain a "black box"—this study introduces RTDI as a theoretically grounded mediator. **Third**, the moderating role of digital leadership in the AI–resilience relationship is untested. **Fourth**, no study has investigated a moderated mediation in which DL conditions the indirect AI $\rightarrow$ RTDI $\rightarrow$ OR pathway. This study fills all four gaps by synthesizing the dynamic capabilities view (DCV; Teece [59], Teece et al. [60]), the TOE framework [63], and upper echelons theory (UET; Hambrick [27], Hambrick & Mason [28]).

The remainder of the paper is organized as follows: Section 2 presents the theoretical framework, literature review, and hypotheses. Section 3 details the methodology. Section 4 reports PLS-SEM results including mediation, moderation, moderated mediation, and IPMA. Section 5 discusses implications. Section 6 concludes with limitations and future directions.

2. Literature Review and Hypotheses Development

2.1. Theoretical Foundations

2.1.1. Dynamic Capabilities View (DCV)

The DCV [59,60] posits that sustainable competitive advantage derives from an organization's ability to sense opportunities, seize them, and reconfigure resources in response to environmental changes. In the present study, AI in banking accounting represents the *sensing* capability—continuously scanning and processing financial, audit, and compliance data at machine speed [18,40]. Real-time decision intelligence constitutes the *seizing* capability— transforming AI-generated insights into timely, actionable decisions [19,67]. Organizational resilience embodies the *reconfiguring* capability—adapting structures and processes in response to disruptions [11,56]. Importantly, Teece [59] argues that dynamic capabilities require managerial orchestration, providing theoretical grounding for digital leadership as a conditioning factor across the entire sensing–seizing–reconfiguring pipeline.

2.1.2. Technology–Organization–Environment (TOE) Framework

The TOE framework [63] describes three contexts that influence technology adoption and its outcomes: the *technological* context (the characteristics of the technology itself), the *organizational* context (firm characteristics and resources), and the *environmental* context (industry and regulatory pressures). This study operationalizes the technological context through the four AI accounting dimensions; the organizational context through digital leadership; and the environmental context through the Jordanian banking regulatory environment [4,15,65]. The TOE framework explains why the effect of AI on resilience is not universal but conditioned by organizational and environmental factors.

2.1.3. Upper Echelons Theory (UET)

UET [27,28] argues that organizational outcomes are partially reflective of the cognitive bases and values of top management teams. Digital leadership—encompassing the promotion of technology adoption, articulation of a digital vision, fostering data-driven decision-making, and championing innovation—determines whether AI investments translate into organizational outcomes [39,42,45,62].

UET therefore underpins the role of DL as a moderator of both the direct and indirect pathways from AI to organizational resilience.

2.2. AI in Banking Accounting

AI in banking accounting encompasses machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and predictive analytics applied across core accounting functions [35,43,52,58]. This study conceptualizes AI as a reflective–formative second-order construct with four first-order dimensions:

AI in Financial Reporting (FR) transforms reporting through automated data aggregation, natural language generation (NLG), anomaly detection, and real-time consolidation. ML-based automation can reduce manual processing by up to 80% [4,10,61].

AI in Audit (AUD) enables continuous auditing, anomaly detection, predictive risk assessment, and intelligent document review. The Big Four accounting firms have collectively invested over USD 9.5 billion in AI-related audit capabilities [6,14,32,46].

AI in Risk Management (RM) encompasses predictive credit scoring, real-time monitoring, scenario simulation, and early warning systems [9,24,51].

AI in Regulatory Compliance (RC) automates AML/KYC processes, transaction surveillance, and regulatory reporting [2,3,5,7].

2.3. Organizational Resilience and H1

Organizational resilience is a dynamic, multi-dimensional capability comprising anticipation, preparation, response, and adaptation to disruptive events [1,21,31,38]. Technology adoption has been positively associated with resilience [11,23], and AI capabilities specifically enhance resilience by improving information processing speed, decision quality, risk identification accuracy, and compliance assurance [56,68].

H1: AI in banking accounting has a significant positive effect on organizational resilience. *(DCV, TOE)*

2.4. Real-Time Decision Intelligence as Mediator (H2–H4)

Real-time decision intelligence refers to the organizational capability to generate, process, and act upon continuously updated multi-source analytics within compressed decision windows [19,50,67]. From the DCV perspective, RTDI represents the "seizing" micro-foundation: translating AI-generated sensing into organization-wide adaptive action [18,40]. AI investments in banking accounting directly build RTDI by providing continuous data streams, anomaly alerts, and decision-support dashboards that compress the time from data to decision [58**?**]. In turn, RTDI contributes to OR by enabling faster, evidence-based responses to financial disruptions, credit deteriorations, and regulatory changes [11,56].

H2: AI in banking accounting has a significant positive effect on RTDI. *(DCV)*

H3: RTDI has a significant positive effect on organizational resilience. *(DCV)*

H4: RTDI mediates the relationship between AI and organizational resilience. *(DCV)*

2.5. Digital Leadership as Moderator (H5)

Digital leadership encompasses the strategic orientation, technological vision, resource allocation, and culture-shaping behaviors of senior managers with respect to digital transformation [42,45,62]. Grounded in UET, DL is expected to moderate the AI–OR relationship by either amplifying or constraining the translation of AI capabilities into resilience outcomes [15,56]. At low DL, AI investments may struggle to translate into resilience due to weak governance, limited data literacy, and resistance to AI-driven recommendations [39,66]. However, at high DL, the marginal contribution of AI to OR may diminish because digitally mature leaders may have already established overlapping resilience structures—a "ceiling" or substitution effect consistent with the too-much-of-a-good-thing (TMGT) proposition [47].

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H5: Digital leadership moderates the relationship between AI and organizational resilience. *(UET, TOE)*

2.6. Moderated Mediation (H6)

Beyond moderating the direct pathway, DL may also condition the indirect AI → RTDI → OR pathway. Under the DCV, digital leaders orchestrate the entire sensing–seizing–reconfiguring pipeline by allocating resources to decision infrastructure, building data-driven cultures, and ensuring that AI insights flow efficiently into resilience-building actions [27,59]. At high DL, the sensing–seizing pipeline may become less dependent on AI because established governance structures and decision routines partially substitute for AI-driven RTDI, attenuating the indirect effect—a pattern consistent with the TMGT effect at the mediated-path level [29,47].

H6: Digital leadership moderates the indirect effect of AI on organizational resilience through RTDI (moderated mediation). *(DCV+UET)*

Table 1 summarizes the hypotheses.

Table 1. Summary of Research Hypotheses.

H	Path	Type	Theory	Expected Direction
H1	AI → OR	Direct	DCV, TOE	+
H2	AI → RTDI	Direct	DCV	+
H3	RTDI → OR	Direct	DCV	+
H4	AI → RTDI → OR	Mediation	DCV	+
H5	DL × AI → OR	Moderation	UET, TOE	±
H6	DL mod. AI→RTDI→OR	Mod. Med.	DCV+UET	±

AI = artificial intelligence in banking accounting; OR = organizational resilience; RTDI = real-time decision intelligence; DL = digital leadership; DCV = dynamic capabilities view; TOE = technology–organization–environment framework; UET = upper echelons theory.

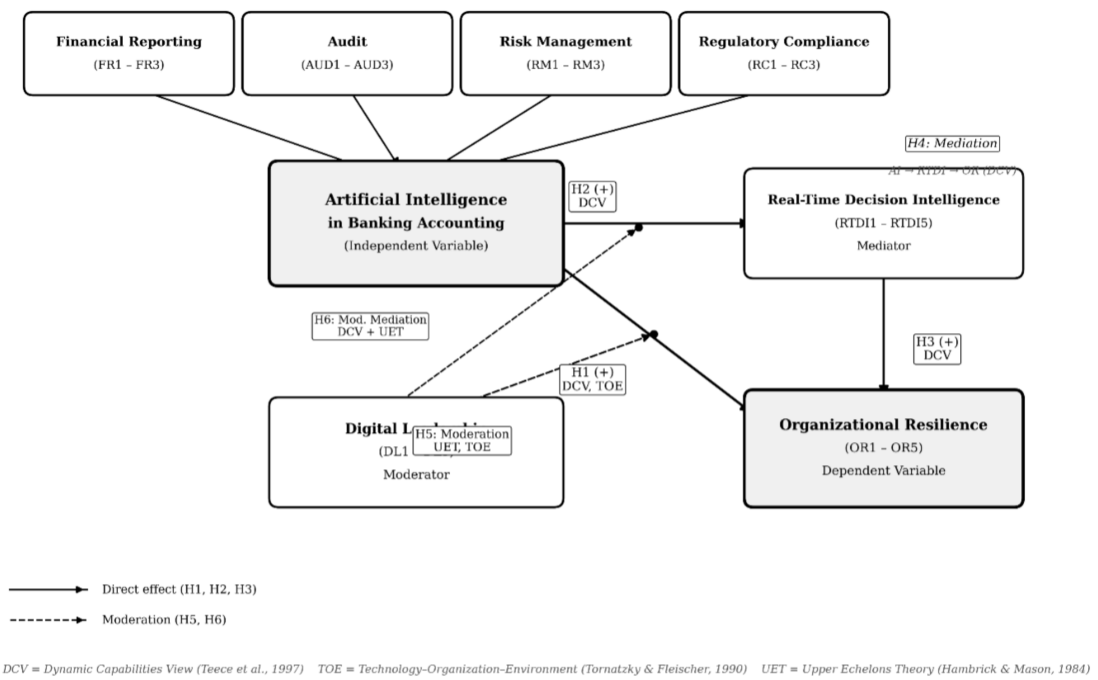

Figure 1. Proposed conceptual framework with theoretical foundations for each pathway. AI in banking accounting is modeled as a reflective–formative second-order construct (FR, AUD, RM, RC). Solid arrows = direct paths; dashed arrow = indirect (mediation) path; dotted line = moderation path. DCV = dynamic capabilities view; TOE = technology–organization–environment framework; UET = upper echelons theory.

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3. Research Methodology

3.1. Research Design and Context

This study adopts a quantitative, cross-sectional design using PLS-SEM guidelines [16,25,26]. The research context encompasses all 14 ASE-listed banks in Jordan: Arab Bank, Housing Bank for Trade and Finance, Bank of Jordan, Jordan Ahli Bank, Jordan Kuwait Bank, Cairo Amman Bank, Capital Bank of Jordan, Arab Jordan Investment Bank, Jordan Commercial Bank, Investbank, Société Générale de Banque–Jordanie, Bank al Etihad, ABC Bank Jordan, and Jordan Islamic Bank. These banks collectively represent approximately 95% of Jordan's total banking sector assets [8].

3.2. Population, Sampling, and Data Collection

The target population consists of accounting managers, auditors, compliance officers, risk managers, and IT officers who interact directly with AI systems in their professional roles. Based on ABJ (2024) sector-level employment data (22,996 total employees), the relevant professional subset is estimated at approximately 3,500. Applying the Krejcie & Morgan [37] formula yields a minimum required sample of 346.

Data were collected via a structured Google Forms questionnaire administered through the ABJ network and bank HR departments from January to April 2025, using stratified random sampling proportional to each bank's workforce size. Of 450 questionnaires distributed, 342 were returned (76.0% response rate). After listwise deletion of 22 incomplete responses, 320 usable responses were retained—satisfying both the Krejcie–Morgan minimum and PLS-SEM's ten-times rule [25].

3.3. Survey Instrument

The instrument comprises 34 items measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) distributed across five constructs. The AI in banking accounting scale (12 items, FR1–FR3, AUD1–AUD3, RM1–RM3, RC1–RC3) was adapted from Kokina & Blanchette [35], Issa et al. [32], Appelbaum et al. [6], Rabbani et al. [51], and Arner et al. [7]. RTDI (5 items, RTDI1–RTDI5) was adapted from Delen & Zolbanin [19]. Digital leadership (5 items, DL1–DL5) was adapted from Oberer & Erkollar [45]. Organizational resilience (5 items, OR1–OR5) was adapted from Duchek [21].

The instrument was translated into Arabic using the forward–backward translation protocol, with the translation team comprising two bilingual academics and one professional translator. Content validity was established through expert review by five academics and three banking practitioners (Content Validity Index, CVI = 0.91), exceeding the recommended threshold of 0.80 [49].

3.4. Common Method Bias Assessment

Procedural remedies included guaranteed anonymity, counter-balanced item ordering, varied scale anchors, and reverse-coded items [48]. Statistical assessment employed Harman's single-factor test (maximum single-factor variance = 29.4% < 50%) and full collinearity VIF assessment (range: 1.028–3.932, all < 5.0), confirming the absence of systematic common method bias [34,48].

3.5. Analytical Approach: PLS-SEM

PLS-SEM via SmartPLS 4 [54] was selected based on five rationale: (1) the study's exploratory–confirmatory nature; (2) the presence of reflective–formative second-order constructs; (3) the predictive emphasis of the research objectives; (4) non-normal data distributions common in survey research; and (5) the complexity of the model incorporating mediation, moderation, moderated mediation, and a hierarchical component model [25,26,55].

The two-stage analytical procedure of Hair et al. [25] was followed. **Stage 1 (Measurement Model):** Outer loadings ≥ 0.708, Cronbach's $\alpha \geq 0.70$, composite reliability (CR) ≥ 0.70, and AVE ≥ 0.50 [22]; Fornell–Larcker discriminant validity. **Stage 2 (Structural Model):** Inner VIF < 5.0; 5,000 bias-corrected bootstrap subsamples for path coefficients; R^2, Q^2, f^2, and SRMR < 0.08 [25]. Mediation was assessed via specific indirect effects [44]; moderation via the product indicator approach [30]; moderated

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mediation via the index of moderated mediation [29]. IPMA was performed following Ringle & Sarstedt [53].

4. Results

4.1. Sample Characteristics

Table 2 presents the demographic profile of the 320 respondents. The sample is predominantly male (58.4%) and dominated by professionals with 5–15 years of experience (62.5%), broadly consistent with ABJ (2024) sector-level data. Finance and audit departments account for 54.4% of the sample, ensuring good representation of the most AI-intensive banking functions.

Table 2. Respondent Demographics ($n = 320$).

Characteristic	Category	Freq.	%
Gender	Male	187	58.4
	Female	133	41.6
Position	Accountant/Accounting Manager	85	26.6
	Auditor	71	22.2
	Compliance Officer	62	19.4
	IT/Systems Officer	56	17.5
	Risk Manager/Other	46	14.4
Department	Finance	100	31.3
	Audit	74	23.1
	Risk Management	58	18.1
	Compliance	52	16.3
	Information Technology	36	11.3
Experience	$<$ 5 years	47	14.7
	5–10 years	111	34.7
	11–15 years	89	27.8
	$>$ 15 years	73	22.8
Bank Type	Local Commercial	200	62.5
	Islamic	86	26.9
	International Branch	34	10.6

4.2. Descriptive Statistics

Table 3 reports construct-level descriptive statistics. All construct means exceed the scale midpoint of 3.0, indicating generally positive perceptions of AI adoption and its outcomes across Jordanian banks. Financial Reporting records the highest AI-dimension mean ($M = 4.269$, $SD = 0.801$), suggesting it is the most widely perceived application, followed by Risk Management ($M = 4.183$), Audit ($M = 4.165$), and Regulatory Compliance ($M = 4.077$, $SD = 0.926$). The elevated standard deviation for Regulatory Compliance reflects heterogeneity in RegTech deployment across the 14 banks. Organizational Resilience records the highest overall mean ($M = 4.300$, $SD = 0.799$), while RTDI exhibits the lowest mean and highest variability ($M = 4.048$, $SD = 0.952$), suggesting that conversion of AI outputs into real-time actionable intelligence remains uneven.

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Table 3. Descriptive Statistics.

Construct	Items	Mean	SD	Min	Max
Financial Reporting	3	4.269	0.801	1.33	5.00
Audit	3	4.165	0.863	1.00	5.00
Risk Management	3	4.183	0.871	1.00	5.00
Regulatory Compliance	3	4.077	0.926	1.00	5.00
AI (Second-Order)	12	4.173	0.869	1.08	5.00
Real-Time Decision Intelligence	5	4.048	0.952	1.20	5.00
Digital Leadership	5	4.143	0.882	1.00	5.00
Organizational Resilience	5	4.300	0.799	1.40	5.00

4.3. Measurement Model Assessment

4.3.1. Outer Loadings

Table 4 presents outer loadings for all reflective indicators. The twelve first-order AI-dimension indicators load comfortably above the 0.708 threshold [25], ranging from 0.844 (AUD1) to 0.901 (AUD3). AUD3 (reduction of human bias in audit procedures) records the highest individual loading, reflecting strong perceived impact of AI-based audit automation in the Jordanian context. Digital Leadership loadings range from 0.832 to 0.875, and Organizational Resilience loadings from 0.823 to 0.925, with OR3 (collaborative crisis problem-solving) recording the highest loading overall, emphasizing the salience of collective adaptive response in banking resilience perceptions.

Table 4. Outer Loadings.

Item	FR	AUD	RM	RC	RTDI	DL	OR
FR1	0.859						
FR2	0.899						
FR3	0.884						
AUD1		0.844					
AUD2		0.886					
AUD3		0.901					
RM1			0.859				
RM2			0.854				
RM3			0.889				
RC1				0.849			
RC2				0.880			
RC3				0.884			
RTDI1					0.816		
RTDI2†					0.553		
RTDI3†					0.599		
RTDI4†					0.569		
RTDI5†					0.582		
DL1						0.872	
DL2						0.865	
DL3						0.875	
DL4						0.870	
DL5						0.832	
OR1							0.823
OR2							0.850
OR3							0.925
OR4							0.893
OR5							0.883

† Loadings below 0.708 retained: removal did not improve CR or AVE; construct AVE = 0.691 > 0.50 [25]. FR = Financial Reporting; AUD = Audit; RM = Risk Management; RC = Regulatory Compliance; RTDI = Real-Time Decision Intelligence; DL = Digital Leadership; OR = Organizational Resilience.

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Four RTDI indicators (RTDI2–RTDI5) produced loadings below 0.708 (range: 0.553–0.599). Following Hair et al. [25], item removal was evaluated systematically; however, removal of any single item did not meaningfully improve composite reliability or AVE beyond thresholds already satisfied (AVE $= 0.691 > 0.50$). All five RTDI items were therefore retained to preserve construct content validity—ensuring that all theoretical dimensions of RTDI (multi-source integration, situational insight, disruption response, and AI-supported dashboards) remain represented in the measurement model.

4.3.2. Reliability and Convergent Validity

Table 5 reports internal consistency and convergent validity statistics. All constructs exceed the recommended thresholds: Cronbach's $\alpha \geq 0.70$, CR ≥ 0.70, and AVE ≥ 0.50 [22,25]. The second-order AI construct records the highest reliability ($\alpha = 0.948$, CR $= 0.954$), reflecting the breadth and internal coherence of the 12-item measurement scale across four accounting functions. RTDI records the lowest—though still acceptable—reliability ($\alpha = 0.772$, CR $= 0.764$), consistent with the lower outer loadings of RTDI2–RTDI5. Importantly, Hair et al. [25] note that Cronbach's α tends to underestimate reliability in PLS-SEM; composite reliability is the preferred indicator. The AVE for the second-order AI construct (0.636) reflects the construct's formative aggregation of four heterogeneous dimensions, while all six first-order and process constructs show AVE values between 0.691 and 0.776—well above the 0.50 threshold.

Table 5. Construct Reliability and Convergent Validity.

Construct	**Cronbach's α**	**CR (ρ_c)**	**AVE**
Financial Reporting	0.856	0.912	0.776
Audit	0.850	0.909	0.769
Risk Management	0.835	0.901	0.752
Regulatory Compliance	0.841	0.904	0.759
AI (Second-Order)	0.948	0.954	0.636
Real-Time Decision Intelligence	0.772	0.764	0.691
Digital Leadership	0.914	0.936	0.745
Organizational Resilience	0.923	0.943	0.767

All values exceed recommended thresholds: $\alpha \geq 0.70$, CR ≥ 0.70, AVE ≥ 0.50 [22,25].

4.3.3. Discriminant Validity: Fornell–Larcker Criterion

Table 6 presents the Fornell–Larcker matrix. For all seven constructs, the square root of the AVE (diagonal) exceeds all inter-construct correlations (off-diagonal), confirming discriminant validity [22]. Notably, RTDI exhibits the smallest inter-construct correlations (range: 0.627–0.680), reinforcing its empirical distinctiveness as a mediating mechanism that is conceptually separable from both the AI input constructs and the resilience outcome. Two pairs warrant comment: the DL–OR correlation ($r = 0.871$) is marginally below OR's AVE square root (0.876), and the AUD–RM correlation ($r = 0.849$) is marginally below RM's AVE square root (0.867). Both pass the Fornell–Larcker criterion. These theoretically expected near-boundaries are consistent with the overlapping operational spheres of audit and risk management under AI, and with the inherent connection between digital leadership and resilient organizational culture [55,56].

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Table 6. Fornell–Larcker Matrix ($\sqrt{\text{AVE}}$ on Diagonal).

	FR	AUD	RM	RC	RTDI	DL	OR
Financial Reporting	**0.881**						
Audit	0.781	**0.877**					
Risk Management	0.723	0.849	**0.867**				
Regulatory Compliance	0.691	0.799	0.818	**0.871**			
RTDI	0.637	0.650	0.631	0.627	**0.831**		
Digital Leadership	0.750	0.784	0.799	0.811	0.736	**0.863**	
Org. Resilience	0.735	0.789	0.820	0.851	0.680	0.871	**0.876**

Bold diagonal values = $\sqrt{\text{AVE}}$. Discriminant validity supported when diagonal > all off-diagonal values in the same row and column [22].

4.3.4. Second-Order Construct Validity

All second-order paths from the AI second-order construct to its four first-order dimensions are highly significant: AI $\rightarrow$ FR ($\beta = 0.873$, $R^2 = 0.762$), AI $\rightarrow$ AUD ($\beta = 0.941$, $R^2 = 0.885$), AI $\rightarrow$ RM ($\beta = 0.929$, $R^2 = 0.864$), and AI $\rightarrow$ RC ($\beta = 0.906$, $R^2 = 0.821$), all at $p < 0.001$. The dominance of AUD ($\beta = 0.941$) suggests that audit is the most representative dimension of AI adoption in the banking sector [55], consistent with the substantial AI investment in audit automation documented by Appelbaum et al. [6] and Osasona et al. [46].

4.4. Structural Model Assessment

4.4.1. Model Fit and Predictive Power

Inner VIF values range from 1.028 to 3.932 (all < 5.0), confirming the absence of multicollinearity [25]. SRMR $= 0.058 < 0.08$, indicating acceptable model fit. The model explains 57.0% of RTDI variance ($R^2_{\text{RTDI}} = 0.570$) and 77.6% of OR variance ($R^2_{\text{OR}} = 0.776$), both classified as substantial [17]. Stone–Geisser Q^2 values (RTDI $= 0.328$, OR $= 0.591$) confirm high predictive relevance for both endogenous constructs [25].

4.4.2. Hypothesis Testing

Table 7 presents full structural model results. Figure 2 displays the PLS-SEM path diagram with standardized coefficients and significance levels. All six hypotheses are supported.

H1 ($\beta = 0.780$, $t = 16.630$, $p < 0.001$, $f^2 = 0.812$): AI exerts a dominant, large-effect positive influence on OR, confirming the DCV sensing–reconfiguring mechanism and extending Shatila [56] to the specific domain of banking accounting.

H2 ($\beta = 0.224$, $t = 2.660$, $p = 0.008$): AI positively enhances RTDI, consistent with the information-processing view [18,67] and the DCV seizing capacity.

H3 ($\beta = 0.137$, $t = 2.507$, $p = 0.012$): RTDI positively affects OR, confirming that the seizing capacity links to organizational reconfiguration [11,19].

H4 (indirect $\beta = 0.031$, $t = 2.027$, $p = 0.043$, 95% CI $= [0.001, 0.061]$, VAF $= 3.8\%$): RTDI partially mediates the AI–OR relationship. The predominantly direct path indicates that AI's resilience benefits are largely structural (automated risk detection, continuous audit, real-time compliance) rather than fully mediated through the decision intelligence channel.

H5 ($\beta = -0.091$, $t = 3.250$, $p = 0.001$, 95% CI $= [-0.146, -0.036]$): DL negatively moderates AI $\rightarrow$ OR, consistent with the TMGT effect [47]. At high DL, the marginal contribution of AI to OR diminishes because digitally mature leaders have established overlapping resilience structures that partially substitute for AI-specific contributions.

H6 ($\beta = -0.012$, $t = 2.215$, $p = 0.027$, 95% CI $= [-0.024, -0.001]$): The moderated mediation index is significant, confirming that DL also conditions the indirect AI $\rightarrow$ RTDI $\rightarrow$ OR pathway.

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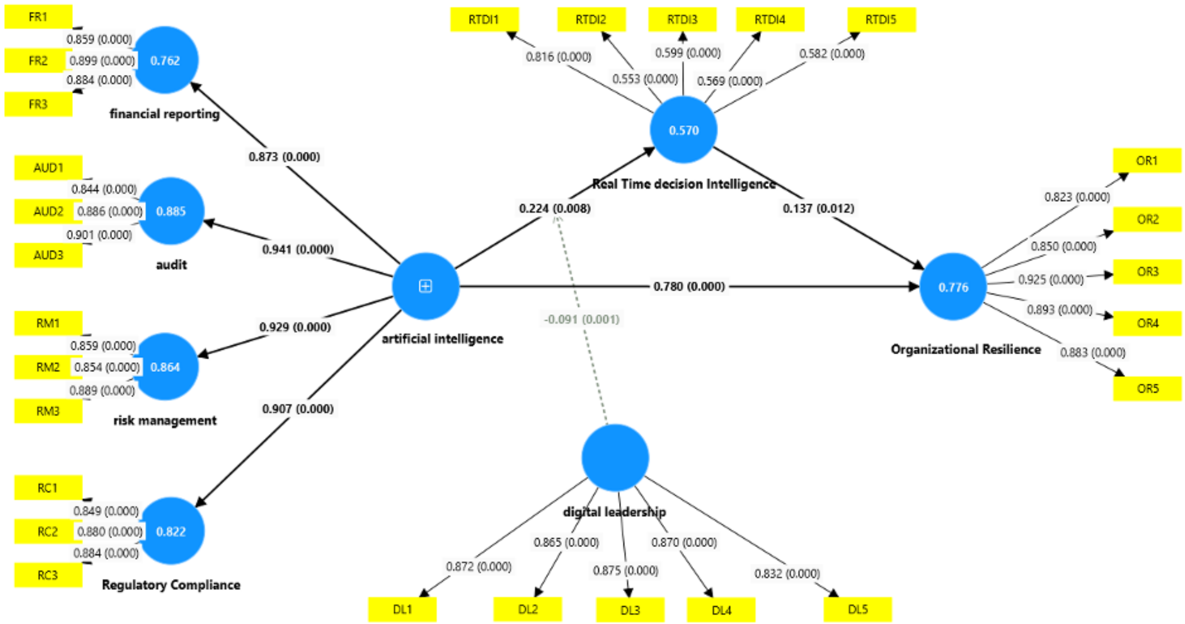

Figure 2. PLS-SEM structural model results. Path coefficients (β) are standardized; asterisks indicate significance levels ($^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$). R^2 values reported inside endogenous construct circles. Bootstrap: 5,000 bias-corrected subsamples. AI = artificial intelligence; RTDI = real-time decision intelligence; DL = digital leadership; OR = organizational resilience.

Table 7. Structural Model Results: Hypothesis Testing.

Hypothesis / Path	β	SD	t	p	95% CI	Result
H1: AI $\rightarrow$ OR	0.780	0.047	16.630	< 0.001	$[0.688, 0.872]$	Supported***
H2: AI $\rightarrow$ RTDI	0.224	0.084	2.660	0.008	$[0.059, 0.389]$	Supported**
H3: RTDI $\rightarrow$ OR	0.137	0.055	2.507	0.012	$[0.030, 0.244]$	Supported*
H4: AI$\rightarrow$RTDI$\rightarrow$OR (indirect)	0.031	0.015	2.027	0.043	$[0.001, 0.061]$	Supported*
H5: DL$\times$AI $\rightarrow$ OR	-0.091	0.028	3.250	0.001	$[-0.146, -0.036]$	Supported**
H6: DL mod. AI$\rightarrow$RTDI$\rightarrow$OR	-0.012	0.006	2.215	0.027	$[-0.024, -0.001]$	Supported*

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Bootstrap: 5,000 bias-corrected subsamples [25]. CI = bias-corrected bootstrap confidence interval. $f^2 = 0.812$ for H1 (large effect); VAF $= 3.8\%$ for H4 (partial mediation).

4.4.3. Moderation Interaction

The negative moderation coefficient ($\beta = -0.091$) indicates that as digital leadership increases, the marginal contribution of AI to OR decreases, producing a flattening interaction plot. Three complementary explanations are consistent with the data and theory: (1) digitally mature leaders have established overlapping resilience governance structures that substitute for AI-specific contributions [27]; (2) absorptive capacity constraints may plateau at high DL levels, limiting further integration of AI outputs [66]; and (3) resource reallocation associated with high DL may disperse attention away from accounting-specific AI applications [47].

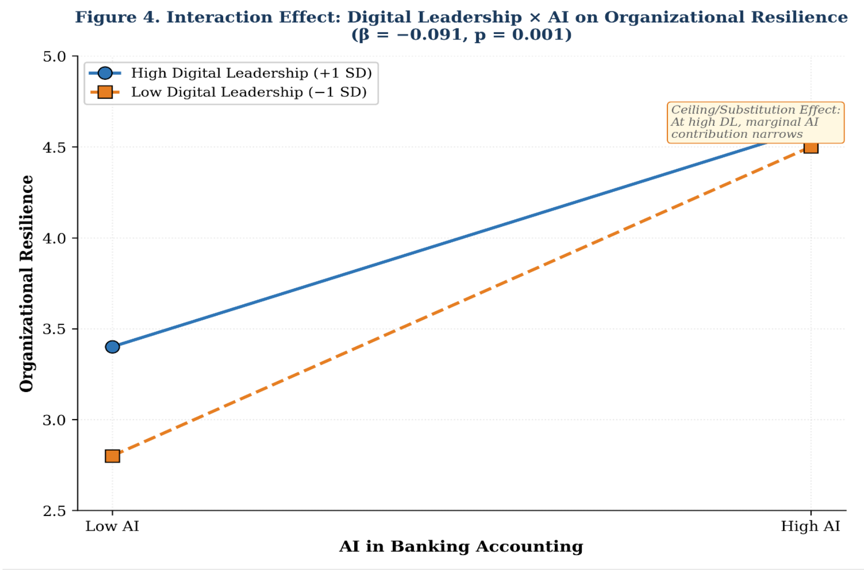

Figure 3. Interaction effect of digital leadership (DL) on the relationship between AI and organizational resilience (OR). High and low DL are plotted at ± 1 SD from the mean. The converging lines indicate a negative moderation (ceiling/substitution effect): at high DL, the marginal contribution of AI to OR diminishes [47].

4.4.4. Importance–Performance Map Analysis (IPMA)

Table 8 presents IPMA results for the target construct OR, contrasting the total effect (importance) of each predecessor construct with its performance (mean scores rescaled 0–100) [53]. AI records the highest importance (total effect = 0.811) and a performance of 78.2, placing it in the strategic "Concentrate Here" quadrant—high importance with meaningful improvement potential. RTDI records moderate importance (0.137) but the highest performance (81.3), suggesting it is relatively well-leveraged. DL shows the lowest importance (0.068) at a performance of 79.1.

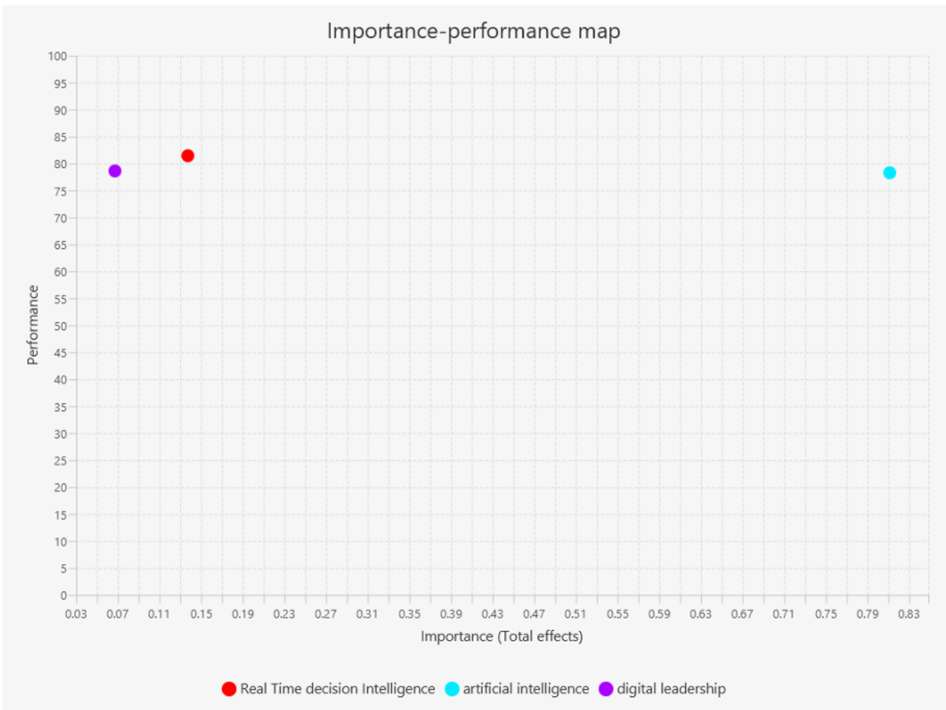

Figure 4. Importance–Performance Map Analysis (IPMA) for organizational resilience. The horizontal axis represents importance (total effect on OR); the vertical axis represents performance (mean scores rescaled 0–100). AI occupies the "Concentrate Here" zone (high importance, improvement potential). RTDI is in "Keep Up the Good Work" (moderate importance, high performance) [53].

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Table 8. IPMA Results (Target Construct: Organizational Resilience).

Construct	Importance (Total Effect)	Performance (0–100)
Artificial Intelligence (AI)	0.811	78.2
Real-Time Decision Intelligence	0.137	81.3
Digital Leadership	0.068	79.1

IPMA following Ringle & Sarstedt [53]. Importance = total effect on organizational resilience; performance = construct mean scores rescaled to 0–100.

5. Discussion

5.1. Key Findings and Theoretical Contributions

H1 ($\beta = 0.780$, $f^2 = 0.812$): The dominant, large-effect influence of AI on OR affirms AI in banking accounting as a major resilience-building capability, extending Shatila [56]'s general AI–resilience findings to the specific domain of accounting functions. The DCV sensing–reconfiguring mechanism is validated: AI in continuous audit, predictive risk management, and real-time compliance automation directly strengthens banks' adaptive capacity [11,59]. This finding endorses the ABJ (2024) strategic focus on AI as a productivity and resilience driver, and aligns with evidence from comparable emerging-economy contexts [2,4].

H2 ($\beta = 0.224$): AI's positive effect on RTDI is consistent with the information-processing view [18,67] and confirms the DCV seizing capacity. The moderate $R^2 (= 0.570)$ indicates that factors beyond AI—including data infrastructure quality, analytical culture, and process maturity—also shape RTDI, echoing **?**]'s argument that AI value depends on complementary organizational assets.

H3 ($\beta = 0.137$): RTDI's positive effect on OR confirms its theorized role as a seizing capability translating AI outputs into adaptive action, consistent with Browder et al. [11] and Garrido-Moreno et al. [23].

H4 (indirect $\beta = 0.031$, VAF $= 3.8\%$): The partial mediation finding—with the predominantly direct path—indicates that AI's resilience benefits operate largely through structural mechanisms (automated anomaly detection, continuous audit trails, compliance monitoring) rather than primarily through the cognitive decision channel. This pattern aligns with Delen & Zolbanin [19]'s observation that in maturing AI contexts, direct operational benefits precede sophisticated cognitive integration.

H5 ($\beta = -0.091$): The negative moderation represents this study's most theoretically novel finding. Three mechanisms are proposed: (1) *ceiling effect*—digitally mature leaders have established resilience governance that overlaps with and partially substitutes for AI contributions [27]; (2) *absorptive capacity saturation*—at high DL, marginal absorption of additional AI outputs may plateau [66]; and (3) *resource reallocation*—high DL organizations may redirect resources from accounting AI to broader digital transformation initiatives [39,65]. This finding challenges UET's conventionally positive assumptions about digital leadership and is consistent with the TMGT effect [47].

H6 ($\beta = -0.012$): The significant moderated mediation index is a novel contribution to the AI–resilience literature. At high DL, the sensing–seizing pipeline from AI through RTDI to OR becomes less dependent on AI's direct input, because established decision governance structures partially substitute for AI-generated intelligence in the seizing phase [27,59]. This finding has not been previously documented in the banking AI literature.

5.2. Theoretical Contributions

Six theoretical contributions emerge. **First**, the DCV is extended to AI-driven banking accounting, empirically validating the sensing (AI) $\rightarrow$ seizing (RTDI) $\rightarrow$ reconfiguring (OR) chain in a financial services context [11,59]. **Second**, the TOE framework is enriched with evidence of non-linear organizational conditioning effects, showing that the organizational context (DL) can dampen rather than amplify technological outcomes. **Third**, UET's prevailing positive view of digital leadership is qualified by the TMGT effect, identifying a boundary condition relevant to AI–resilience research [27,47]. **Fourth**, the reflective–formative second-order AI model is validated for banking accounting, pro-

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viding a reusable measurement template for future research [55]. **Fifth**, RTDI is established as a partial mediator in the AI–OR mechanism, contributing to the "black box" literature on AI's organizational outcomes [19,67]. **Sixth**, this is the first study to provide moderated mediation evidence in the AI–resilience domain from an emerging-economy banking context.

5.3. Practical Implications

IPMA positions AI as the highest-priority construct (importance = 0.811, performance = 78.2), providing an evidence-based case for continued investment across all four accounting dimensions. The audit dimension ($\beta_{\mathrm{AI}\rightarrow\mathrm{AUD}} = 0.941$) should receive strategic priority, consistent with the global trend of Big Four AI investment [6,46]. For the Central Bank of Jordan, findings endorse AI incentivization policies alongside governance frameworks that condition AI deployment with adequate decision intelligence infrastructure. For bank boards and senior management, the negative moderation finding suggests that leadership readiness evaluations should be coupled with technological readiness assessments—high DL without corresponding governance structures may not amplify AI investments optimally. For the ABJ, the identified digital-skills gap requires targeted training programs combining AI-driven accounting literacy with digital governance capabilities. The moderated mediation finding implies that banks with weaker digital leadership will realize the greatest resilience gains from AI investments via the RTDI channel, making them priority targets for AI adoption support programs.

6. Conclusions, Limitations, and Future Research

6.1. Conclusion

This study provides comprehensive empirical evidence for the role of AI in banking accounting as a driver of organizational resilience in the Jordanian banking sector. Drawing on 320 professionals across all 14 ASE-listed banks and employing PLS-SEM via SmartPLS 4, all six hypotheses are supported. AI is the dominant predictor of OR ($\beta = 0.780$, $R^2 = 0.776$), with RTDI serving as a partial mediator and DL producing ceiling effects on both the direct ($\beta = -0.091$) and indirect ($\beta = -0.012$) pathways. IPMA identifies AI as the construct of highest strategic priority for resilience improvement. Grounded in DCV, TOE, and UET, the study establishes AI-driven accounting as a strategic dynamic capability that enhances banks' capacity to endure, adapt to, and learn from disruptions—while simultaneously revealing that digital leadership is not an unconditional amplifier of that capability.

6.2. Limitations

The study has five limitations. **First**, the cross-sectional design precludes causal inference and temporal dynamics. **Second**, the single-country focus limits generalizability to other MENA or emerging-economy contexts. **Third**, self-reported perceptual data are subject to response bias despite the procedural and statistical remedies applied. **Fourth**, four RTDI indicators recorded loadings below 0.708, reflecting modest representational breadth of the construct. **Fifth**, bank-type disaggregation (commercial vs. Islamic vs. international) was not conducted, leaving potential heterogeneity unexplored.

6.3. Future Research

Longitudinal designs would allow the identification of temporal dynamics in AI's effect on resilience. Comparative MENA studies would test boundary conditions across different regulatory and cultural environments. PLS-MGA comparing commercial and Islamic banks would reveal whether Islamic banking principles moderate the AI–resilience relationship. Additional mediators—organizational agility, knowledge management, and digital absorptive capacity—could enrich the model. Qualitative investigation of the negative moderation finding is warranted to identify the specific mechanisms through which DL creates substitution effects. Finally, integrating objective financial performance metrics with perceptual resilience measures would provide a more complete picture of AI's value creation in banking.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AML	Anti-Money Laundering
AUD	Audit
AVE	Average Variance Extracted
CI	Confidence Interval
CR	Composite Reliability
CVI	Content Validity Index
DCV	Dynamic Capabilities View
DL	Digital Leadership
FR	Financial Reporting
HTMT	Heterotrait–Monotrait ratio
IPMA	Importance–Performance Map Analysis
KYC	Know Your Customer
ML	Machine Learning
NLG	Natural Language Generation
NLP	Natural Language Processing
OR	Organizational Resilience
RC	Regulatory Compliance
RM	Risk Management
RPA	Robotic Process Automation
RTDI	Real-Time Decision Intelligence
SEM	Structural Equation Modeling
SRMR	Standardized Root Mean Square Residual
TOE	Technology–Organization–Environment
TMGT	Too-Much-of-a-Good-Thing
UET	Upper Echelons Theory
VAF	Variance Accounted For
VIF	Variance Inflation Factor
ASE	Amman Stock Exchange
ABJ	Association of Banks in Jordan
PLS	Partial Least Squares

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