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STUDIES RESEARCH JOURNAL

e-ISSN: 2175--5825

OPERATIONALIZING FORESIGHT: DESIGNING AND VALIDATING A CONTEXTUAL MODEL FOR FORECASTING EMERGING TECHNOLOGIES IN IRAN'S BANKING INDUSTRY

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ABSTRACT

Objective: This study aims to introduce and empirically validate the Technology Prediction Processor (FPRO), a strategic foresight framework designed to enhance technology anticipation and decision-making within the banking and fintech sectors of developing economies.

Originality/Value: FPRO advances the literature by integrating foresight capacity, information infrastructure, predictive accuracy with systematic validation, and strategic agility into a unified operational model. Unlike traditional forecasting tools, the framework is specifically tailored to environments facing accelerated digital transformation and technological uncertainty, demonstrating high transferability across emerging markets.

Method: A mixed-methods design was applied. First, qualitative insights were collected through semi-structured interviews with sixteen senior banking and fintech experts. A three-round fuzzy Delphi technique refined the thematic structure. Quantitative validation was conducted using survey data from 286 industry professionals, analyzed through Structural Equation Modeling (SEM).

Results: The FPRO model presented excellent statistical robustness (RMSEA = 0.022; CFI = 0.97; χ^2/df = 1.14). The findings confirm that the four strategic drivers—foresight capacity, information infrastructure, predictive accuracy, and strategic agility—jointly enhance institutional decision-making and digital transformation performance in the financial sector.

Conclusion: The Technology Prediction Processor is a reliable foresight tool capable of supporting policymakers, executives, and financial organizations in navigating technological disruptions. While validated in Iran, the model shows strong applicability to other developing markets undergoing digital transformation.

Keywords: Strategic foresight capacity. Technology prediction processor (FPRO). Banking industry. Digital transformation. Operational research. Structural equation modeling.

FUTURE STUDIES RESEARCH JOURNAL
Scientifc Editor: Renata Giovinazzo Spers
Evaluation: Double Blind Review, pelo SEER/OJS
Received: 18/05/2025
Accepted: 09/09/2025

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OPERACIONALIZANDO A PROSPECÇÃO: PROJETO E VALIDAÇÃO DE UM MODELO CONTEXTUAL PARA PREVER TECNOLOGIAS EMERGENTES NO SETOR BANCÁRIO DO IRÃ

RESUMO

Objetivo: O estudo tem como objetivo apresentar e validar empiricamente o Technology Prediction Processor (FPRO), um framework de prospectiva estratégica desenvolvido para fortalecer a capacidade de antecipação tecnológica e apoiar a tomada de decisão no setor bancário e fintechs de economias em desenvolvimento.

Originalidade/Valor: O FPRO contribui ao integrar, em um modelo operacional unificado, quatro pilares estratégicos: capacidade de prospectiva, infraestrutura informacional, precisão preditiva com validação sistemática e agilidade estratégica. Diferentemente de modelos tradicionais de previsão, o framework é projetado para contextos marcados por intensa transformação digital e elevada incerteza tecnológica, demonstrando alta transferibilidade para outros mercados emergentes.

Método: Aplicou-se um desenho de métodos mistos. Primeiramente, entrevistas semiestruturadas com dezesseis especialistas seniores forneceram insights qualitativos. Em seguida, um Delphi fuzzy de três rodadas refinou as prioridades temáticas. A validação quantitativa utilizou dados de survey com 286 profissionais do setor, analisados por Modelagem de Equações Estruturais (SEM).

Resultados: O modelo FPRO apresentou excelente robustez estatística (RMSEA = 0.022; CFI = 0.97; $\chi^2/df = 1.14$). Os resultados confirmam que os quatro motores estratégicos—capacidade de prospectiva, infraestrutura informacional, precisão preditiva e agilidade estratégica—atuam conjuntamente para otimizar a tomada de decisão institucional e os resultados da transformação digital no setor financeiro.

Conclusão: O Technology Prediction Processor constitui uma ferramenta confiável de prospectiva estratégica capaz de apoiar formuladores de políticas, executivos e instituições financeiras na gestão de disrupções tecnológicas. Embora validado no Irã, o modelo demonstra forte aplicabilidade a outros mercados em desenvolvimento.

Palavras-chave: Capacidade de prospectiva estratégica; Technology Prediction Processor (FPRO); Indústria bancária; Transformação digital; Pesquisa operacional; Modelagem de equações estruturais.

1. INTRODUCTION

Over the past decade, the global banking industry has undergone profound technological disruption, driven by the convergent rise of artificial intelligence, blockchain ecosystems, open banking frameworks, and cloud-based service infrastructures. Financial institutions in mature markets such as the United States, the European Union, and East Asia have already integrated predictive analytics and strategic foresight systems into their core operations, enhancing customer interaction, regulatory adaptability, and overall market agility (PricewaterhouseCoopers, 2024; BIS, 2025; BIS, 2024; Noreen et al., 2023; Wang et al., 2024). While these transformations have consolidated digital maturity in advanced economies, emerging markets are experiencing similar pressures under far more constrained conditions. For example, studies of the Jordanian banking sector reveal that despite strong digital ambitions, institutions must still contend with structural inefficiencies and evolving regulatory landscapes that limit the full realization of technological potential (Alqararah et al., 2025).

Extensive literature on digital banking adoption in emerging economies underscores a common set of challenges: legacy IT infrastructure, inconsistent data governance, low integration between predictive tools and strategic planning, and a shortage of specialized foresight expertise (Acosta-Prado, et al.2024; Melnychenko et al., 2020; Legowo et al., 2021). These issues are amplified in developing financial markets, where institutional resilience hinges on the capacity to anticipate and adapt to global technology trends—yet adaptation must be context-sensitive, balancing innovation opportunities against regulatory and cultural realities (Ahmadi et al., 2021; Obeng, et al.2024).

Iran's banking sector embodies many of these conditions. While strategic interest in digital transformation is firmly established, operational execution often stalls due to regulatory fragmentation, data silos, and insufficient organizational readiness (Taghipour & Moradhasel, 2019; Hashemi et al., 2020). External foresight models, when imported without modification, tend to underperform by neglecting the environmental, legal, and institutional constraints unique to the Iranian financial system. Addressing this gap requires an integrated, evidence-based forecasting architecture that can translate the conceptual strengths of international foresight practices into operationally feasible strategies.

Building on this rationale, the proposed contextual model aims to bridge foresight practice with organizational sustainability and strategic intelligence, thereby reinforcing its relevance to sustainable competitiveness. This study responds to that need by developing and validating the Technology Prediction Processor (FPRO)—a multi layered foresight framework synthesized from qualitative insights, Delphi based expert consensus, and quantitative structural equation modeling.

By aligning global best practices with local operational imperatives, the FPRO model seeks to strengthen institutional foresight capacity, ensure predictive accuracy with systematic validation, and enhance strategic agility in the face of complex technological transitions. Furthermore, its design emphasizes transferability to other emerging markets, making it a relevant tool for policymakers and industry leaders navigating similar digital transformation trajectories (Capatina, et al.2024; BIS, 2024; PricewaterhouseCoopers, 2025).

2. THEORETICAL FOUNDATION OR CONCEPTUAL BACKGROUND

2.1 Strategic Foresight

Digital transformation is no longer a complementary improvement in the banking industry; it has evolved into a structural necessity (PricewaterhouseCoopers, 2024; McKinsey & Company, 2024). The accelerated adoption of artificial intelligence, blockchain, cloud computing, and open-banking frameworks has profoundly reshaped how financial services are delivered, how customers are engaged, and how regulators oversee the system (Mosteanu & Faccia, 2020; Melnychenko et al., 2020). Empirical evidence further indicates that mobile internet connectivity and collateral systems can broaden banking outreach while enhancing the predictive accuracy of technology adoption (D'Andrea et al., 2024). These disruptive forces have generated both strategic opportunities and operational pressures, compelling banks to embed foresight capabilities into everyday decision-making processes (Saritas & Smith, 2011).

In advanced economies, foresight mechanisms have already been institutionalized. Financial institutions continuously scan weak signals and evaluate potential technological trajectories to anticipate change (PwC, 2024; BIS, 2024). Evidence from the Jordanian banking sector (Alqararah et al., 2025) demonstrates that strong digital transformation capabilities—enabled by process automation and intelligent data integration—significantly enhance efficiency and customer satisfaction. Likewise, the bibliometric study by Acosta-Prado et al. (2024) shows that trust, security, and perceived usefulness are dominant drivers of digital-banking adoption in emerging economies, with regulatory adaptability serving as a critical enabling factor.

2.2 Digital Transformation & Banking Sustainability

The situation in developing markets, however, tends to be more nuanced. Research on financial inclusion and digital ecosystems (Amaliah et al., 2024) confirms that technology adoption can directly foster sustainable economic growth when supported by inclusive regulatory frameworks, yet limited digital literacy and fragmented infrastructures continue to constrain these benefits. Illustratively, Cambodia's experience with building a secure, nationwide digital-payment network shows that coordinated action between government and industry can accelerate both adoption and impact (Ly & Ly, 2024).

For banks in emerging contexts, integrating digital transformation with sustainability objectives is increasingly central to institutional competitiveness. The interplay between foresight and digitalization strengthens the ability to anticipate regulatory shifts, optimize environmental performance, and expand access to underserved populations—aligning technological progress with broader socio-economic goals.

2.3 Institutional Capabilities & Innovation

Within Iran, empirical studies identify several persistent structural impediments: outdated IT infrastructure, fragmented data systems, poor integration between forecasting outputs and strategic planning, and the absence of continuous scenario-based validation (Hashemi et al., 2020). Taghipour and Moradhasel (2019) further emphasize that weak cultural readiness and incomplete regulatory coherence exacerbate transformation bottlenecks.

From a methodological standpoint, scholars have recommended integrated frameworks that combine Delphi-based expert consensus, structural equation modeling, and scenario planning to effectively adapt global foresight practices to local realities (Okoli & Pawlowski, 2004; Hu & Bentler, 1999; Mietzner & Reger, 2005).

Recent contributions in foresight research also stress the importance of uniting qualitative insight with quantitative verification to ensure models remain theoretically sound while retaining operational relevance (Ahmadi et al., 2021).

Overall, the literature converges on one conclusion: in markets such as Iran, imported foresight frameworks often deliver limited success because they overlook national institutional contexts. Bridging this gap demands the creation of contextualized models—such as the Technology Prediction Processor (FPRO)—that align validated international mechanisms with local operational conditions. Building on this recognition, the present study designs and empirically validates a foresight-driven framework specifically customized for Iran's banking sector, while remaining adaptable to other emerging-market environments.

3. METHODOLOGY

This study adopts a mixed-methods framework to design and validate a practical model for forecasting emerging technologies in Iran's banking sector. The integration of qualitative thematic analysis with quantitative statistical validation—including the Delphi technique and structural equation modeling (SEM)—ensures both depth of insight and methodological robustness. The following subsections detail the research process and instruments used in each phase.

3.1 Research Population and Sampling

Qualitative Phase:

At the qualitative stage, a purposive sample of 16 distinguished experts was selected for their extensive experience in banking digital transformation (minimum 15 years), senior leadership roles, and specialized knowledge in technology adoption and futures studies. These participants represented a diverse cross-section of public and private banks, digital finance firms, and regulatory authorities. Recruitment followed a systematic snowball sampling approach, ensuring theoretical saturation by the 15th interview, with a final assurance interview (M16) completing the process.

Quantitative Phase:

The quantitative phase comprised the development of a structured questionnaire informed by qualitative themes. This instrument was distributed among 286 senior banking professionals—including IT managers, fintech entrepreneurs, and regulatory specialists—across multiple financial institutions, resulting in a robust dataset for subsequent SEM analysis.

3.2 Data Collection Instruments

Qualitative Instruments:

Semi-structured interviews focused on ten core questions regarding technological trends, implementation challenges, key model features, and organizational readiness. Each interview lasted approximately 60–70 minutes; all sessions were recorded, transcribed, and systematically coded for detailed thematic analysis.

Quantitative Instruments:

The survey instrument was constructed drawing from validated constructs in futures studies literature (Brown & Clarke, 2006; Travers, 2010) as well as insights obtained from the expert interviews. Reliability and validity were assured through pilot testing, involving Cronbach's alpha assessment and factor analysis.

3.3 Research Process Flow

The overall methodological flow is presented in Figure 1, illustrating how the sequential phases—qualitative exploration, Delphi-based expert validation, and quantitative model testing—were systematically integrated to develop and confirm the **Technology Prediction Processor (FPRO)**.

Figure 1 visualizes the triangulated design, from the initial interview phase through to SEM evaluation, ensuring the coherence and scientific reliability of the foresight model.

Description of the Process:

1. **Qualitative Expert Interviews** → Identification of major foresight dimensions and local constraints.
2. **Thematic Coding (Brown & Clarke, 2006)** → Extraction of conceptual categories: foresight capacity, information infrastructure, validation accuracy, agility.
3. **Fuzzy Delphi Round I–III** → Consensus refinement among expert panel (n = 16) on relevance and uncertainty of key trends.
4. **Survey Design & Data Collection** → Structured questionnaire distributed among 286 senior banking professionals.
5. **SEM Analysis (LISREL)** → Statistical testing of latent constructs, path coefficients, and fit indices.
6. **Model Validation** → Finalization of the FPRO operational framework; verification via Cronbach's Alpha, CFA, and RMSEA criteria.

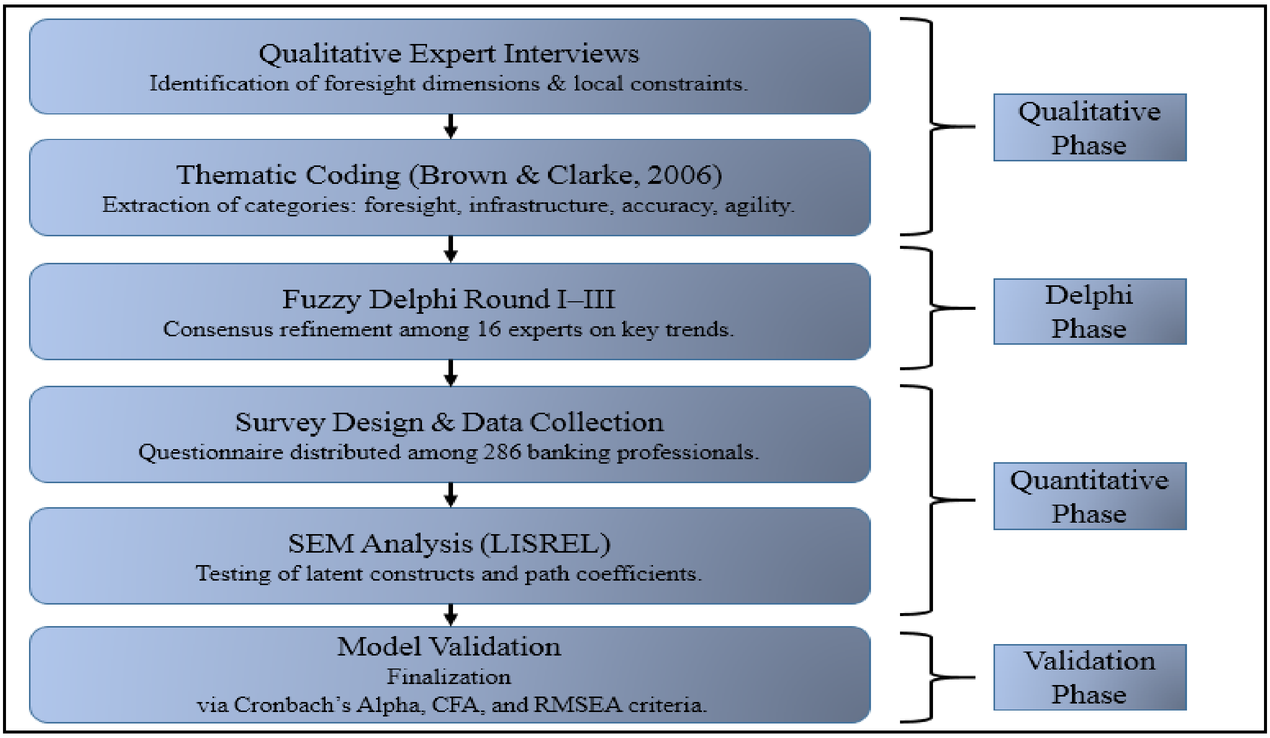

Figure 1. Research Process Flow for the Design and Validation of the Technology Prediction Processor (FPRO) Model

This flow illustrates the integration of qualitative insights, Delphi-based expert consensus, and quantitative SEM validation, ensuring both theoretical soundness and operational reliability in constructing the FPRO model.

3.4 Quantitative Validation: Delphi Technique & SEM

Fuzzy Delphi Technique:

To further refine core thematic trends from the qualitative phase, a three-round Delphi procedure was conducted among the same expert panel. Participants rated the relevance and uncertainty of 21 key trends, facilitating consensus and minimizing individual bias. Items were retained if their mean Likert score met or exceeded 3.5, thereby strengthening the rigor of the trend selection process.

Structural Equation Modeling (SEM):

Quantitative survey responses from 286 professionals were analyzed using LISREL to evaluate model fit, estimate path coefficients, and assess overall reliability. Confirmatory

Factor Analysis (CFA) validated the significance and robustness of all latent constructs and their interrelationships.

Major fit indices—including RMSEA, CFI, Chi-square/df, IFI, NFI, RFI, PNFI, and TLI—were systematically evaluated. All criteria met or surpassed standard thresholds, confirming both the structural and measurement validity of the conceptual model, as detailed below.

Table 1. Model fit indices for the Technology Prediction Processor (FPRO) model

Fit Index	Criteria/Acceptable Value	Model Value	Evaluation
χ^2/df (Chi-square/df)	< 3	1.14	Excellent
CFI (Comparative Fit Index)	≥ 0.90	0.97	Excellent
IFI (Incremental Fit Index)	≥ 0.90	0.97	Excellent
RFI (Relative Fit Index)	≥ 0.80	0.85	Adequate
NFI (Normed Fit Index)	≥ 0.80	0.86	Adequate
PNFI (Parsimony Normed Fit Index)	≥ 0.50	0.80	Excellent
NNFI/TLI (Non-Normed Fit/Tucker-Lewis Index)	≥ 0.90	0.97	Excellent

As demonstrated in Table 1, all key metrics—such as RMSEA = 0.022, CFI = 0.97, and χ^2/df = 1.14—strongly support the model's statistical reliability and confirm its appropriateness for operational use in Iran's banking sector.

The next figure presents the finalized structural equation model, visually summarizing the pathways and standardized coefficients for the latent variables underpinning technology foresight.

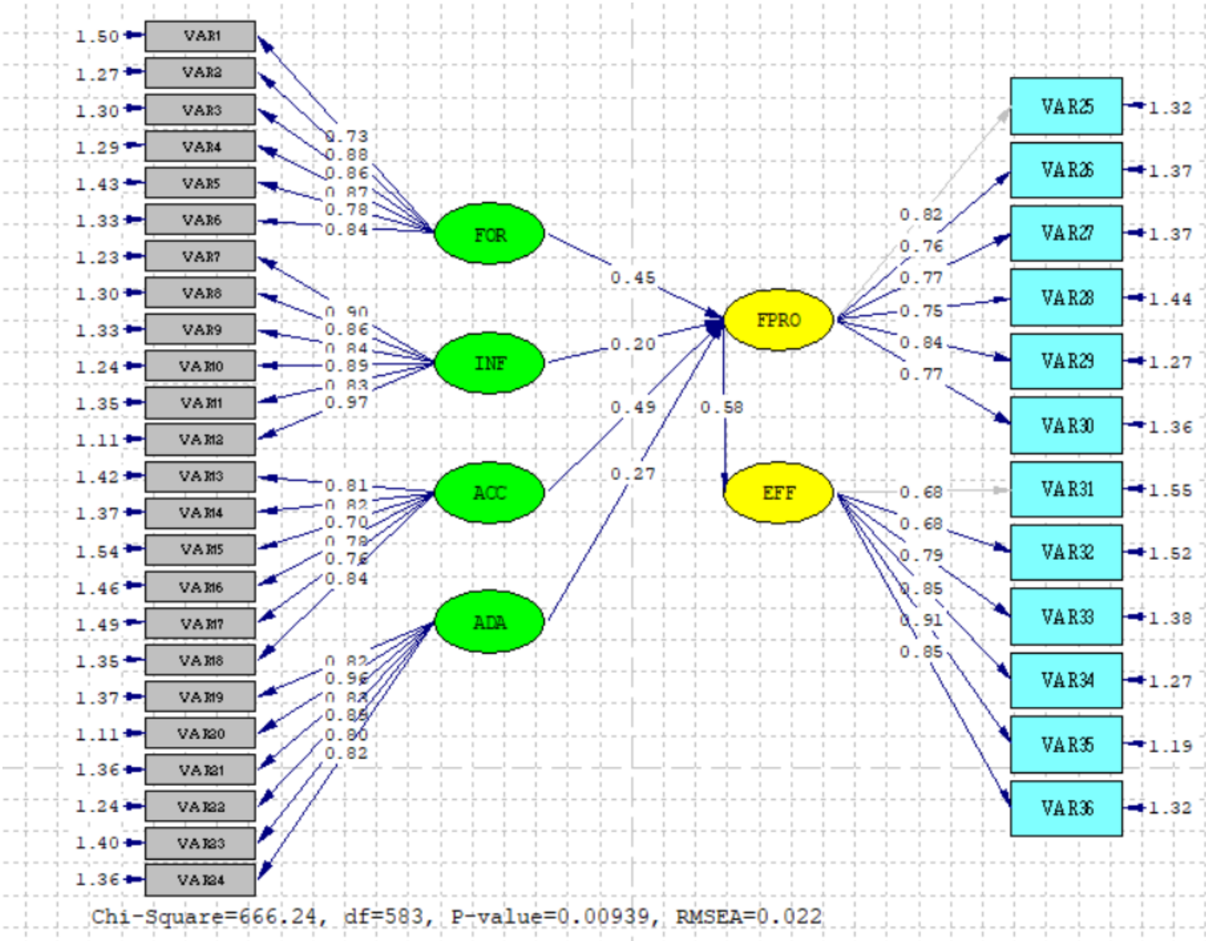

Figure 2. Structural equation model (SEM) output for the Technology Prediction Processor (FPRO) model in Iran's banking sector.

This figure provides empirical evidence of the direct and significant effects that strategic foresight capacity, information infrastructure, predictive accuracy, and strategic agility exert on the core Technology Prediction Processor (FPRO). The model's output underscores the theoretical and operational validity, confirming its practical utility for institutional decision-making and risk governance.

3.5 Reliability and Rigor

To guarantee the credibility and robustness of findings, both qualitative and quantitative results were subjected to multiple validation procedures:

- **Qualitative credibility** was ensured through saturation, iterative peer review, participant verification, and alignment with established literature.

- **Quantitative reliability** was established, with Cronbach's alpha exceeding 0.80 across all constructs, and composite validity as well as AVE confirming measurement accuracy.

To assess the internal consistency and reliability of the measurement instrument, Cronbach's Alpha coefficients were calculated for each construct and for the overall questionnaire. As shown in Table 2, all coefficients exceed the minimum acceptable threshold of 0.70 (Nunnally, 1978), indicating satisfactory reliability across all constructs.

Table 2. Cronbach's Alpha reliability coefficients for all constructs

Construct	Number of Items	Cronbach's Alpha	Reliability Status
Strategic Foresight Capacity (FOR)	6	0.742	Acceptable
Information Infrastructure (INF)	6	0.780	Acceptable
Predictive Accuracy & Validation (ACC)	6	0.710	Acceptable
Strategic Agility & Adaptiveness (ADA)	6	0.762	Acceptable
Technology Prediction Processor (FPRO)	6	0.725	Acceptable
Banking Effectiveness (EFF)	6	0.719	Acceptable
Overall Questionnaire	**36**	**0.806**	**Acceptable**

These results confirm that the items within each construct are homogenous and measure the same underlying concept. Therefore, the instrument demonstrates adequate reliability for subsequent statistical analyses, including Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

3.6 Ethical Considerations

All study participants provided informed consent, and all data collection and storage procedures complied with prevailing local and international research ethics standards. Confidentiality and privacy were rigorously maintained throughout the research process.

4. RESULTS AND FINDINGS

4.1 Conceptual Model Derivation and Key Findings

In this section, the central findings of the mixed-methods research are summarized, highlighting the emergence and empirical validation of a practical model for technology foresight in Iran's banking industry.

Drawing upon in-depth qualitative analysis of expert interviews—combined with robust quantitative assessment via structural equation modeling (SEM)—four fundamental dimensions have been identified as critical to effective technology prediction:

- **Strategic Foresight Capacity (FOR):** The organization's ability to continuously scan for future trends and detect emerging signals in the banking technology landscape.
- **Information Infrastructure (INF):** The comprehensiveness, accessibility, and quality of data resources that underpin predictive functions.
- **Predictive Accuracy & Validation (ACC):** Mechanisms to systematically verify and validate predictive outputs, strengthening reliability.
- **Strategic Agility & Adaptiveness (ADA):** The institution's capacity for flexible, rapid response to dynamic technological changes and external disruptions.

These four components converge and are operationalized through a central mechanism referred to as the **Technology Prediction Processor (FPRO)**. When effectively implemented, the FPRO not only integrates diverse sources of input but directly drives **Banking Effectiveness (EFF)** by enhancing quality of decision-making and reducing operational risk across digital transformation initiatives.

This empirically validated conceptual model represents a systematic integration of thematic insights and quantitative evidence, forming a coherent and actionable framework for banking technology foresight and organizational planning.

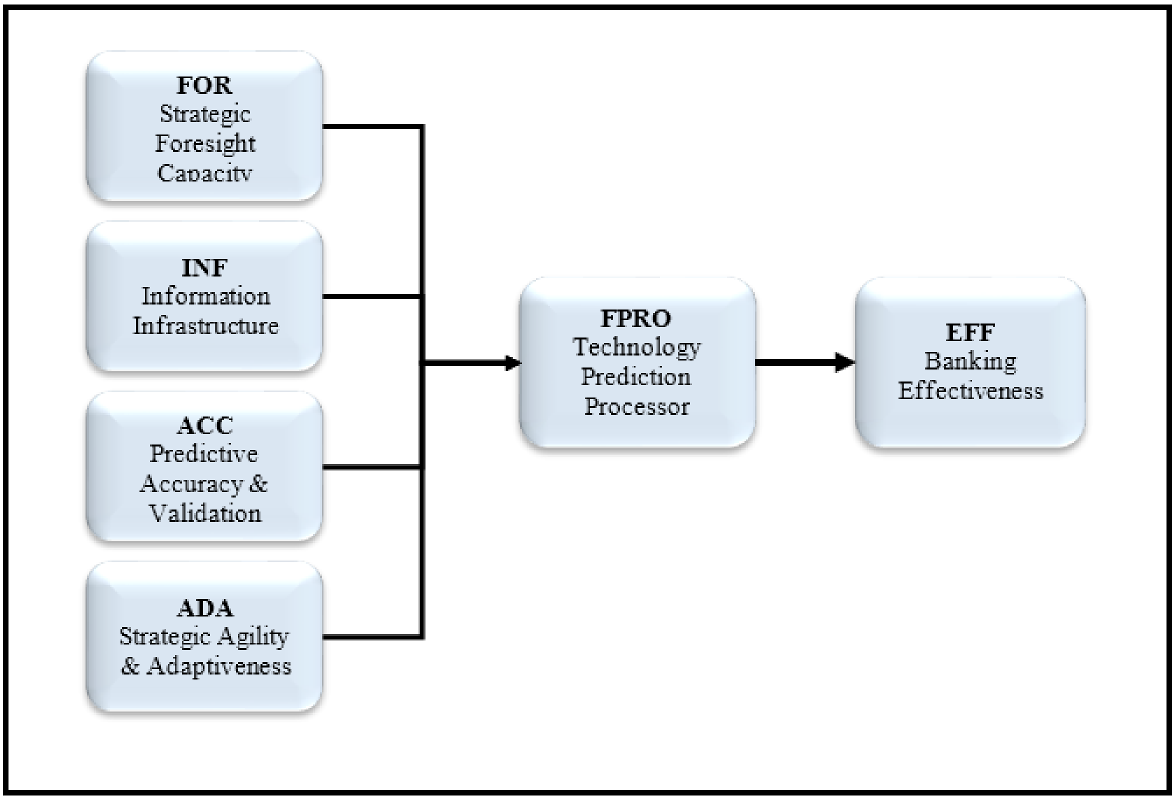

Figure 3. Validated conceptual and operational model of technology foresight for the Iranian banking industry.

As depicted in Figure 3, the input dimensions collectively establish a multi-layered approach to strategic technology anticipation. Through the central FPRO, actionable and validated recommendations are delivered, enabling financial institutions to better anticipate change, allocate resources efficiently, and strengthen their organizational resilience. The logical consistency and empirical support for this operational model provide a sound basis for subsequent policy recommendations and practical application.

5. RESULTS AND DISCUSSIONS

5.1 Interpretive Analysis of the Final Model

The finalized operational foresight model unveils a clear and empirically tested causal chain for predicting technological trajectories within Iranian banking institutions.

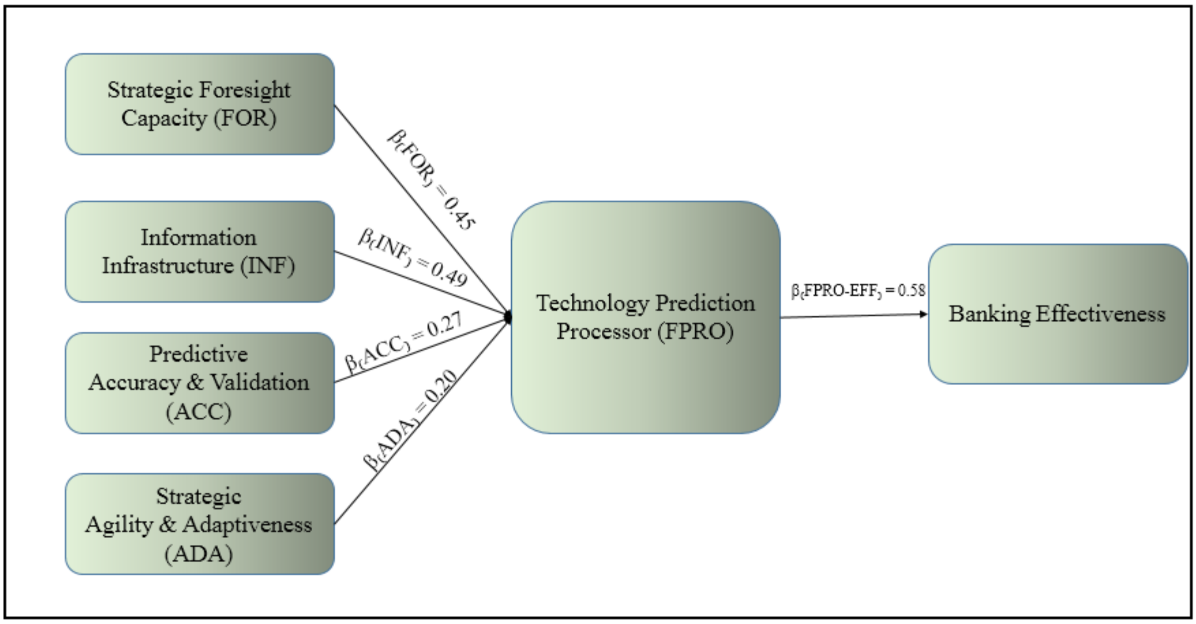

Figure 4. Structural path diagram of the FPRO model showing standardized coefficients among latent constructs.

The diagram visually confirms that: Strategic Foresight Capacity (FOR), Information Infrastructure (INF), Predictive Accuracy & Validation (ACC), and Strategic Agility & Adaptiveness (ADA) exert direct and statistically significant influences on the Technology Prediction Processor (FPRO)—with standardized coefficients of $\beta = 0.45$, $\beta = 0.49$, $\beta = 0.27$, and $\beta = 0.20$, respectively.

Furthermore, the foresight engine (FPRO) demonstrates a positive and significant effect on Banking Effectiveness (EFF) ($\beta = 0.58$, $p < 0.05$), thereby completing the validated causal chain derived from the LISREL SEM analysis.

Each driver—Strategic Foresight Capacity (FOR)**,** Information Infrastructure (INF)**,** Predictive Accuracy & Validation (ACC), and Strategic Agility & Adaptiveness (ADA)—operates as a fundamental pillar, feeding into and amplifying the central Technology Prediction Processor (FPRO)**.**

The analysis confirms that FOR exerts the strongest influence on FPRO, echoing global findings that institutionalized futures-scanning and weak-signal detection markedly increase preparedness for market volatility and innovation shocks (PwC, 2024; BIS, 2024). INF functions as the backbone of predictive architecture—quality, accessibility, and seamless integration of data directly determine forecast credibility. Without a robust infrastructure, even the most advanced analytical engines deliver suboptimal outputs.

ACC ensures integrity by embedding verification cycles, peer review, and error correction—mechanisms long recognized as essential in foresight practice (Saritas & Smith, 2011). These safeguards reduce operational risk by reinforcing internal trust in predictive deliverables. ADA, finally, bridges analysis and action; agile governance frameworks shorten response times, enabling swift mobilization of cross-functional teams to act upon early warnings.

At the model's core, FPRO orchestrates multidimensional inputs—scenario simulations, Delphi-based consensus, and trend mining—to produce tangible outputs: actionable early alerts, decision packages, and timing strategies that integrate seamlessly into banking operational plans. The resulting boost in Banking Effectiveness (EFF) manifests in more precise investment decisions, lower risk in technology adoption, improved project delivery rates, and superior customer service.

Qualitative insights corroborated quantitative patterns, showing that expert consensus on institutional agility parallels the strong SEM-based loadings of ADA on FPRO. This cross-method alignment reinforces the model's internal validity, confirming that themes identified through expert narratives resonate strongly with statistical evidence.

5.2 Broader Implications for Industrial Engineering and Management

Beyond banking, the model holds transferability to diverse branches of industrial engineering—from manufacturing and logistics to energy and service operations. Embedding a structured foresight engine like FPRO into these systems can elevate strategic planning, facilitate proactive supply-chain adjustments, and improve resource utilization.

In manufacturing or logistics, FOR enables detection of early industry signals; INF supports integration of real-time operational data for accurate capacity forecasts; ACC mitigates risks linked to investing in process innovation; and ADA ensures rapid pivoting when regulatory or technological landscapes shift. Integrating these capabilities fosters organizational resilience and sustains competitiveness in turbulent environments (Rotolo et al., 2015).

5.3 Comparison with Previous Models

Prior models often lacked contextual tailoring, suffered from incomplete operational embedding, and failed to align with organizational structures in emerging market settings (Rotolo et al., 2015; Van der Heijden, 2005). The proposed framework counters these weaknesses through a dual-track methodology: qualitative expert input grounded in local realities, paired with rigorous quantitative testing via SEM. This blend produces a foresight system that is both conceptually sound and operationally practical for Iranian banks, while offering scalability for other regions.

5.4 Policy and Managerial Recommendations

For Bank Executives:

- Establish continuous foresight programs anchored in environmental scanning.
- Invest in centralized, high-integrity data infrastructures capable of supporting advanced predictive analytics.
- Standardize prediction validation procedures, embed error-tracking protocols, and ensure transparent reporting.
- Streamline governance to enable fast, agile decision-making by empowered cross-functional teams.
- Integrate FPRO outputs directly into executive dashboards and decision-support platforms.

For Policymakers:

- Encourage cross-bank information sharing and collaborative foresight initiatives.
- Mandate data harmonization and interoperability standards sector-wide to strengthen predictive capabilities.
- Fund targeted training programs to enhance foresight skills and data literacy across organizational tiers.

The FPRO model contributes to policy resilience by institutionalizing foresight within banking governance frameworks. Its principles support public-policy alignment with the UN SDGs and national transformation plans, thereby enhancing adaptive capacity and sustainable competitiveness in Iran's financial sector.

5.5 Limitations and Future Research

The model, while robust, carries boundaries:

- **Contextual scope**: Indicators are tuned to Iran's banking industry; applying them to other domains will require re-validation.
- **Temporal scope**: Digital innovation cycles are dynamic; extended longitudinal studies are necessary to track the model's adaptability.
- **Validation scope**: Current focus is organizational-level; future work should add micro-level variables and simulate exogenous shocks.
- **Data scope**: Broader, cross-sector sampling and real-time data integration will strengthen external validity.

Acknowledging these limits creates pathways for refining the model and testing its resilience in other financial and industrial contexts.

5.6 Transition to Conclusion

Ultimately, predictive strength in Iranian banking hinges on integrating foresight, data infrastructure, validation rigor, and agility—coordinated through the FPRO engine. This synergy transforms scenario planning from a conceptual exercise into a driver of measurable performance gains. The next section distills these contributions into the broader conclusions of the study.

6. CONCLUSION

6.1 Theoretical Contributions

This study advances foresight theory by operationalizing a contextual forecasting framework specifically adapted to emerging financial environments. The integration of qualitative consensus-building mechanisms (interviews + Delphi) with robust quantitative validation (SEM) demonstrates how methodological complementarity can strengthen theoretical soundness. The FPRO model—anchored in four interconnected drivers of **strategic foresight capacity, information infrastructure, predictive accuracy and validation, and strategic agility**—extends current foresight literature by translating abstract constructs into measurable, empirically testable dimensions. In doing so, it bridges the longstanding gap between conceptual foresight models and their practical execution within organizational systems.

6.2 Practical Implications

Practically, the FPRO framework provides a clear roadmap for embedding foresight within banking governance and strategic operations. By linking data infrastructure with validation protocols and agile decision-making, it enables institutions to anticipate technological disruptions earlier and respond more coherently. The model thus promotes improved resource allocation, enhanced innovation readiness, and stronger resilience under market volatility. For bank executives, this means transforming foresight from a peripheral analytical exercise into a core, performance-driven management process. Its design is equally transferable to other sectors—such as energy, logistics, and public administration—where technological turbulence and regulatory complexity demand adaptive governance.

6.3 Future Research

Future research should expand the reach and precision of the FPRO framework. Three directions appear most valuable:

(1) applying the model across different industries and national contexts to strengthen external validity;

(2) integrating additional mediators—such as leadership dynamics or organizational learning capacity—to capture systemic interactions; and

(3) conducting longitudinal studies to test foresight sustainability over time. As technological change accelerates, continuous learning, adaptive feedback loops, and multi-stakeholder collaboration will be essential. Ultimately, turning *anticipation into action—swiftly, accurately, and decisively* remains the defining challenge for institutions seeking to thrive in a data-driven future.

Declarations

Ethical Approval and Consent to Participate

Not applicable. This study did not involve human participants or animals that require formal ethics committee approval.

Consent for Publication

Not applicable. This manuscript contains no individual person's data, images, or videos.

Funding

Not applicable. The authors received no financial support for the research, authorship, or publication of this article.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

REFERENCES

Acosta-Prado, J. C., Rojas Rincón, J. S., Mejía Martínez, A. M., & Riveros Tarazona, A. R. (2024). Trends in the literature about the adoption of digital banking in emerging economies: A bibliometric analysis. *Journal of Risk and Financial Management, 17*(12), 545. https://doi.org/10.3390/jrfm17120545

Ahmadi, A., Zargar, A., & Adami, A. (2021). The role of emerging technologies in national security and power of countries: Opportunities and threats *[In Persian]*. *International Studies Journal (ISJ), 18*(4), 139–159. https://doi.org/10.22034/isj.2021.279840.1427

Ali Alqararah, E., Shehadeh, M., & Yaseen, H. (2025). The role of digital transformation capabilities in improving banking performance in Jordanian commercial banks. *Journal of Risk and Financial Management, 18*(4), 196. https://doi.org/10.3390/jrfm18040196

Amaliah, I., Ali, Q., Sudrajad, O. Y., Rusgianto, S., Nu'man, H., & Aspiranti, T. (2024). Does digital financial inclusion forecast sustainable economic growth? Evidence from an emerging economy. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(2), 100262. https://doi.org/10.1016/j.joitmc.2024.100262

Bank for International Settlements. (2024). *BIS annual economic report 2024*. https://www.bis.org/publ/arpdf/ar2024e.pdf

Bank for International Settlements. (2025). *Leveraging tokenisation for payments and financial transactions*. https://www.bis.org/publ/othp92.pdf

Brown, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Capatina, A., Bleoju, G., & Kalisz, D. (2024). Falling in love with strategic foresight, not only with technology: European deep-tech startups' roadmap to success. *Journal of Innovation & Knowledge, 9*(3), 100515. https://doi.org/10.1016/j.jik.2024.100515

D'Andrea, A., Hitayezu, P., Kpodar, K., Limodio, N., & Presbitero, A. F. (2024). *Mobile internet, collateral, and banking (IMF Working Paper No. WP/24/70)*. International Monetary Fund. https://www.imf.org/media/Files/Publications/WP/2024/EWP2470.pdf

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

Hashemi, M., Safdari Ranjbar, M., & Noorbakhsh, A. (2021). Identifying blockchain windows of opportunity in Iran's banking industry *[In Persian]*. *Science and Technology Policy Letters, 11*(2), 35–53. https://dor.isc.ac/dor/20.1001.1.24767220.1400.11.2.3.3

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Legowo, M. B., Nurdiansyah, R., Setiawan, A., & Perwitasari, D. (2021). Fintech and bank: Past, present, and future. *Jurnal Khatulistiwa Informatika, 7*(1), 94–99. https://doi.org/10.31294/jtk.v7i1.9726

Ly, R., & Ly, B. (2024). Digital payment systems in an emerging economy. *Computers in Human Behavior Reports, 16*, 100517. https://doi.org/10.1016/j.chbr.2024.100517

McKinsey & Company. (2024). *Banking update 2024: What leaders need to know.* https://www.mckinsey.com/~/media/mckinsey/email/leadingoff/2024/11/18/2024-11-18b.html

Melnychenko, S., Volosovych, S., & Baraniuk, Y. (2020). Dominant ideas of financial technologies in digital banking. *Baltic Journal of Economic Studies, 6*(1), 92–99. https://doi.org/10.30525/2256-0742/2020-6-1-92-99

Mietzner, D., & Reger, G. (2005). Advantages and disadvantages of scenario approaches for strategic foresight. *International Journal of Technology Intelligence and Planning, 1*(2), 220–239. https://doi.org/10.1504/IJTIP.2005.006516

Mosteanu, N. R., & Faccia, A. (2020). Digital systems and new challenges of financial management – FinTech, XBRL, blockchain, and cryptocurrencies. *Quality – Access to Success, 21*(174), 159–166. https://www.srac.ro/calitatea/en/arhiva/2020/QAS_Vol.21_No.174_Feb.2020.pdf

Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial intelligence (AI) in the banking industry and consumers' perspective. *Sustainability, 15*(4), 3682. https://doi.org/10.3390/su15043682

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.

Obeng, E., Amankwah-Amoah, J., Aboagye, M. O., & Sarpong, D. (2024). Role of digital ecosystems in driving inclusive finance in developing countries. *Technological Forecasting and Social Change, 196*, 122569. https://doi.org/10.1016/j.techfore.2022.122569

Okoli, C., & Pawlowski, S. D. (2004). The Delphi method as a research tool: An example, design considerations, and applications. *Information & Management, 42*(1), 15–29. https://doi.org/10.1016/j.im.2003.11.002

PricewaterhouseCoopers. (2024). *Leveraging GenAI in banking.* https://www.pwc.com/m1/en/publications/leveraging-generative-ai-in-banking.html

PricewaterhouseCoopers. (2025). *Global M&A trends in financial services: 2025 mid-year outlook.* https://www.pwc.com/gx/en/services/deals/trends/financial-services.html

Rotolo, D., Hicks, D., & Martin, B. R. (2015). What is an emerging technology? *Research Policy, 44*(10), 1827–1843. https://doi.org/10.1016/j.respol.2015.06.006

Saritas, O., & Smith, J. E. (2011). The big picture Trends, drivers, wild cards, discontinuities, and weak signals. *Futures, 43*(3–4), 292–312. https://doi.org/10.1016/j.futures.2010.11.007

Taghipour, Z., & Moradhasel, N. (2020). The role of artificial intelligence in modern banking *[In Persian]. In Proceedings of the 1st International Conference on New Challenges and Solutions in Industrial Engineering, Management, and Accounting.* Tehran, Iran.

Travers, M. (2010). *Qualitative research through case studies.* SAGE Publications Ltd.

Van der Heijden, K. (2005). *Scenarios: The art of strategic conversation* (2nd ed.). Wiley. ISBN 978-0-470-02368-6

Wang, S., Asif, M., Shahzad, M. F., & Ashfaq, M. (2024). Data privacy and cybersecurity challenges in the digital transformation of the banking sector. *Computers & Security, 147*, Article 104051. https://doi.org/10.1016/j.cose.2024.104051