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Predictive Modeling of NFT Adoption for Enhancing FinTech Applications in Iran's Banking Sector

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***Abstract*— This research proposes a data-driven modeling framework for the expansion of financial technology (FinTech) in Iran's banking system through the integration of non-fungible tokens (NFTs). Using a data-mining approach, the study analyzes behavioral data collected from customers of Iranian cryptocurrency exchanges from 2020 to 2025. After preprocessing, the dataset was evaluated with decision trees, Naïve Bayes, neural networks, and rough set algorithms. The results demonstrate that the rough set model achieved the highest predictive accuracy (0.98) in identifying user behavior patterns and the principal factors influencing NFT adoption.**

From a banking and policy-making perspective, the findings highlight the potential of NFT-enabled FinTech platforms to offer innovative tools for digital asset management, enhance transparency, reduce transaction costs, and promote financial inclusion. At the same time, risks such as regulatory uncertainty, cyber fraud, and price volatility emphasize the urgent need for tailored supervisory and governance frameworks that are suited to Iran's economic environment.

The originality of this study lies in offering a quantitative and simulation-oriented model that bridges theoretical insights with practical applications. By doing so, it provides actionable guidance for the Central Bank of Iran, financial institutions, and regulators to strengthen the digital financial ecosystem and advance the transition toward smart banking.

Keywords: FinTech, NFT, Data Mining, Smart Banking, Blockchain

I. Introduction

The rapid advancement of information and communication technologies, along with widespread internet penetration, has transformed global economic structures and underscored the need for innovation in financial and banking systems. Financial Technology FinTech, a synthesis of finance and technology emerging from the Fourth Industrial Revolution, plays a central role in reshaping financial business models and facilitating digital transformation within banks. FinTech companies enhance transaction speed, reduce operational costs, and improve the accessibility and quality of financial services [1].

Technologies such as artificial intelligence (AI), blockchain, big data analytics, the Internet of Things (IoT), and cloud computing have revolutionized the delivery of financial services and opened new pathways for innovation in the banking industry [2], [3]. The core objective of FinTech is to provide transparent, efficient, and automated services that expand access to financial resources and promote inclusion across diverse customer segments.

Recent industry analyses predict that digital finance could add more than USD 3.7 trillion to global economic output by 2025 [10], with global FinTech investments surpassing USD 120 billion annually. The 2023 KPMG Pulse of FinTech Report further confirms the sector's robust growth, particularly in blockchain-based banking services [10].

While FinTech firms were once viewed as competitors to traditional banks, current evidence suggests a complementary

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relationship that strengthens the efficiency and innovation capacity of the financial ecosystem [6], [11]. Consequently, policymakers in both developed and developing economies are increasingly prioritizing the integration of FinTech to enhance monetary effectiveness and financial stability.

In Iran, where the banking sector remains the most dominant financial intermediary, the transition toward FinTech and digital assets presents both substantial opportunities and significant challenges. This study aims to explore data-driven FinTech expansion in Iran's banking sector, emphasizing the emerging role of non-fungible tokens (NFTs) as a tool for financial innovation and inclusion.

II. PROBLEM STATEMENT

The future of Iran's banking industry and the effectiveness of its monetary policies increasingly depend on the successful adoption of FinTech innovations. While global investment in FinTech rose from only USD 800 million in 2008 to over USD 67 billion in 2019 [7], Iran's financial institutions have yet to fully harness these opportunities.

Recent empirical evidence demonstrates that FinTech development significantly affects the liquidity, credit, and market risk measures of Iranian banks (Azari et al. [8]). NFTs, due to their characteristics of digital scarcity, verifiable ownership, and tradeability, offer unique potential for developing asset-backed financing tools, improving liquidity, and diversifying financial portfolios [9], [13].

However, challenges such as legal ambiguity, price volatility, and cyber risks have hindered NFT adoption in Iran. The absence of a localized regulatory and technological framework further limits the integration of NFT-based financial solutions. Therefore, there is an urgent need to design a predictive, data-driven model to identify behavioral factors influencing NFT adoption and to guide the strategic implementation of FinTech solutions in the Iranian banking context.

This research addresses that gap by analyzing user behavior data from Iranian cryptocurrency exchanges (2020–2025) to construct a quantitative model that predicts and enhances NFT adoption as a driver for smart banking development.

III. LITERATURE REVIEW

A. *Theoretical Background*

FinTech represents one of the most transformative developments in the modern digital economy. Its fundamental goal is to deliver faster, cheaper, and more transparent financial services through technology-driven innovation [4], [5]. By integrating blockchain, AI, machine learning, IoT, and cloud computing, FinTech firms now provide diverse services in payments, lending, risk management, and investment.

From a macroeconomic perspective, FinTech reduces transaction costs, increases transparency, enhances operational efficiency, and broadens access to financial resources [8], [32]. However, its adoption brings new challenges, including cybersecurity threats, digital fraud, and regulatory uncertainty [20], [34].

NFTs have recently emerged as a significant element within the FinTech ecosystem. Initially associated with digital art and collectibles, NFTs now serve as financial assets capable of representing ownership rights, collateralizing loans, and creating new financial instruments [35], [41]. The convergence of FinTech, NFTs, and decentralized finance (DeFi) presents new opportunities for innovation but also raises concerns regarding legal frameworks, valuation stability, and data privacy.

B. *Prior Studies*

1) Domestic Studies

Iranian research on FinTech has primarily focused on structural and institutional issues within the banking system. Qazi-Dezfouli [4] conceptualized FinTech as an intersection of financial, legal, and technological dimensions. Ghaemi et al. [5] identified startups as key players in modernizing Iran's banking services, while Madanlou Jouybari et al. [6] emphasized the role of FinTech startups in reducing traditional banking intermediation.

Mohaqer et al. [7] highlighted the dependence of FinTech progress on macroeconomic readiness and interinstitutional cooperation. Recent empirical research, such as that by Mohammadi et al. [8], demonstrated that FinTech development reduces banking risks in Iranian financial institutions. Similarly, Aminipour et al. [8] found that blockchain adoption improves transparency and liquidity control.

Jafari (2024) analyzed the Central Bank's efforts toward national cryptocurrency initiatives, while Asgari et al. (2024) stressed the need for strategic leadership in promoting smart contracts. Importantly, Haghi Nojehdeh et al. [27], [28] introduced process-mining and AI-based modeling frameworks to enhance FinTech operations in Iranian banks, providing methodological precedents that the present study extends.

2) International Studies

International research presents a broad and evolving perspective on FinTech innovation. Abubakar [9] and Milian et al. [23] classified FinTech challenges into business models, data governance, and regulatory adaptation. Svensson et al. [25] examined FinTech–bank collaborations that strengthen legitimacy and competitiveness. Priem [24] explored distributed ledger risks, and Teresiene et al. [21] analyzed the synergy between banking institutions and FinTech platforms.

Recent studies have increasingly explored NFT–FinTech integration. Henrique et al. [14] showed that blockchain-based systems can improve transparency and predictive modeling, while Wu et al. [17] applied fractal and wavelet analyses to NFT price series and identified nonlinear dynamics and abnormal trading patterns that point to potential market-manipulation risks. [19] detected abnormal trading and market-manipulation risk in NFT markets, Xiong & Luo [20] reviewed the global regulatory landscapes for crypto-assets and highlighted persistent legal uncertainty.

The latest empirical and methodological contributions include Jayasuriya and Sims [29], who developed a valuation framework for NFTs; Klein et al. [30], who examined return dynamics of secondary Ethereum-based NFT markets; and Bai et al. [31], who investigated how content characteristics influence customer purchase behavior. In the domain of system security and risk, Das et al. [33] analyzed vulnerabilities within the NFT ecosystem, while Ma et al. [34] provided a systematic review of security challenges related to non-fungible tokens. Furthermore, Fridgen et al. [32] analyzed pricing dynamics and herding behavior in NFT markets. Lastly, Kim et al. [35] proposed a multi-attention recommender system model specialized for NFT markets.

Together, these studies underpin the empirical foundation of our FinTech–NFT modeling approach.

Collectively, these studies provide both theoretical grounding and empirical evidence that justify a data-driven predictive modeling approach tailored to Iran's banking sector.

Synthesis and Research Gap

The review of existing literature indicates that domestic studies on FinTech in Iran have largely concentrated on institutional, regulatory, and structural perspectives, while international research has primarily focused on technological innovations, global risks, and market opportunities. However, despite the rapid expansion of FinTech and the growing significance of digital assets, a substantial research gap remains: the specific role of non-fungible tokens (NFTs) in shaping monetary and banking policies in Iran has not been adequately addressed.

This gap is particularly critical given the increasing convergence of FinTech, NFTs, and decentralized finance (DeFi), which are now recognized as key pillars of the digital economy. Addressing this issue is not only theoretically relevant but also of high practical importance for policymakers, financial institutions, and regulators in Iran.

The present study contributes to filling this void by developing a data-driven, simulation-oriented model based on data mining of Iranian cryptocurrency exchange users. Unlike prior research that has remained descriptive or conceptual, this work employs quantitative modeling and predictive analysis to identify behavioral patterns and adoption drivers of NFTs in Iran's financial ecosystem. By doing so, it provides an empirically grounded framework that can guide the Central Bank and financial institutions in policy design, risk management, and the strategic integration of FinTech and NFTs into the national banking system.

IV. Research Methodology

A research methodology provides the structural foundation for conducting a scientific investigation, ensuring that the process follows systematic, validated, and replicable procedures. In this study, an experimental–quantitative framework based on data-mining techniques is adopted to identify behavioral patterns and key determinants influencing NFT adoption among Iranian cryptocurrency exchange users.

The methodology consists of three core components:
(1) data collection and preprocessing,
(2) predictive modeling framework, and
(3) implementation of selected algorithms.

A. *Statistical Population*

Data were collected from verified Iranian cryptocurrency exchanges under confidentiality and data-sharing agreements covering the period 2020-2025. All datasets were anonymized prior to analysis to comply with ethical and privacy guidelines.

The final dataset includes 800 anonymized user profiles, consisting of:

• Demographic attributes: gender, age, user type (investor/trader)

• Transactional features: price, trading volume, time, volatility

• Behavioral indicators: NFT purchase frequency, token preferences, holding duration

Standard preprocessing procedures, including normalization, outlier removal, and mean-based missing-value imputation, were applied. The final dataset was divided into 70% training and 30% testing subsets for predictive analysis.

B. *Sampling Method*

The statistical population consists of active participants in Iran's cryptocurrency ecosystem-investors, traders, financial analysts, and blockchain developers. A stratified random sampling strategy was used to ensure proportional representation across demographic and behavioral categories.

The sample size of 800 users was determined based on data availability and statistical adequacy for predictive model development. As illustrated in Fig. 1, the gender distribution of the sample shows that male users constitute the majority of cryptocurrency exchange participants. Fig. 2 presents the NFT purchase behavior of users, indicating that a considerable proportion of participants have prior experience with NFT transactions. Furthermore, Fig. 3 demonstrates the cross-distribution of gender and NFT purchase decisions, highlighting observable differences in adoption behavior between male and female users.

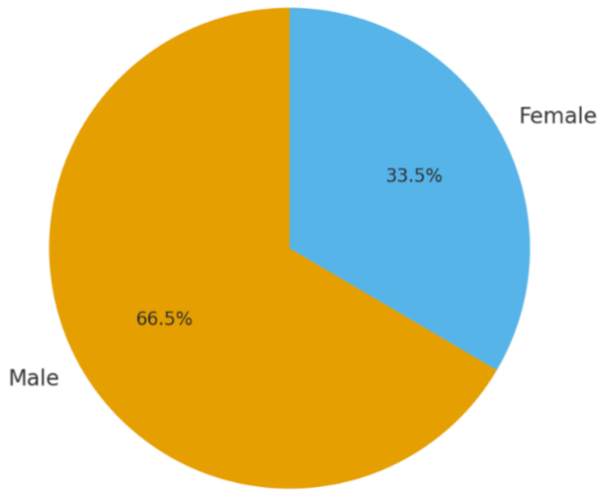

Fig 1. Sample size by gender(531 males, 267 females)

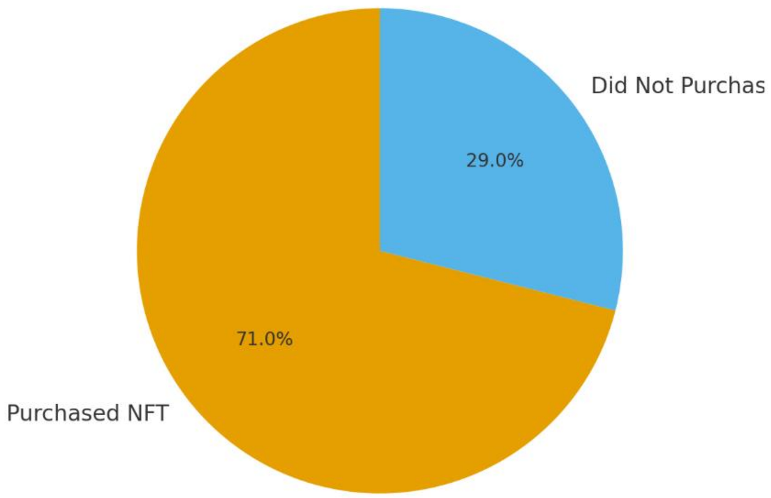

Fig 2. NFT purchase behavior (503 buyers, 205 non-buyers)

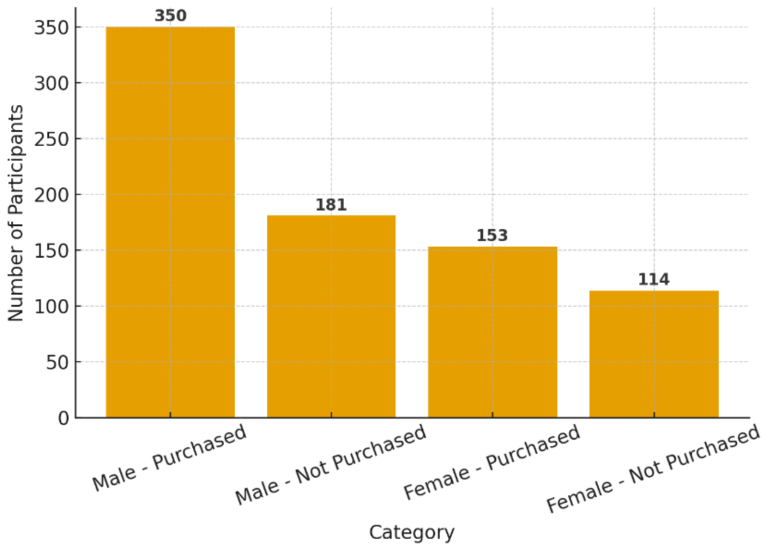

Fig 3. Cross-distribution of gender and NFT purchase decision

C. *Predictive Modeling Framework*

Predictive modeling was performed to identify behavioral determinants of NFT adoption. Several data-mining algorithms were tested, and four models were selected due to their predictive accuracy and computational efficiency:

- Decision Tree (J48)
- Naïve Bayes
- Rough Set Model
- Artificial Neural Network (ANN)

Decision-tree and rough-set approaches are widely used for classification and pattern-extraction tasks due to their interpretability and robustness [37].

All models were implemented using WEKA 3.9 and Rosetta 1.4.5, following a 10-fold cross-validation protocol.

For the ANN, parameter tuning included:

– 100 hidden neurons,

– learning rate = 0.3,

– momentum = 0.2.

Algorithms that did not contribute to the final analytical process were excluded to maintain methodological clarity and focus.

V. DATA ANALYSIS

This section presents the data analysis procedures and findings derived from the implemented data-mining algorithms. The goal is to extract meaningful patterns that explain the behavioral determinants of NFT adoption within Iran’s FinTech ecosystem. All analyses were performed using WEKA 3.9 and Rosetta 1.4.5. The preprocessed dataset was divided into training (70%) and testing (30%) subsets to evaluate model performance and generalizability.

A. *Evaluation Metrics*

To ensure consistent comparison across models, standard machine-learning evaluation metrics were used:

- **Accuracy**

Accuracy = (TP+TN) / (TP + FP + TN + FN)

- Sensitivity (Recall)

Recall=TP / (TP + FN)

- **Precision (PPV)**
- Precision (PPV) = TP / (TP + FP)2020–2025F1-Score

F1 Score = 2 × ((Precision*Recall) / (Precision+Recall))

- **Error Rate**

Error Rate=FP+FN / (TP+TN+FP+FN)

- **Negative Predictive Value (NPV)**

NPV=TN / (TN + FN)

- **Specificity**

Specificity=TN / (TN + FP)

Confusion Matrix Used in Calculations

TABLE I
Confusion Matrix for NFT Adoption Classification

	Predicted Negative	Predicted Positive
Actual Positive	16	784
Actual Negative	0	179

The confusion matrix used for calculating the evaluation metrics is presented in Table I.

Although specificity is low due to limited negative cases, high accuracy, recall, precision, and F1-score collectively indicate robust model performance.

B. Pattern Discovery Using Rough Set Model

The Rough Set model extracted transparent rule sets based on demographic and behavioral attributes. It revealed strong associations involving age group, gender, financial literacy, and prior market experience.

- Achieved highest accuracy: 0.98
- Identified financial literacy and market experience as the most influential determinants
- Produced interpretable rule structures suitable for FinTech policy design

C. Pattern Discovery Using Genetic Algorithm (GA)

A Genetic Algorithm was applied to optimize and refine the large rule base produced by the Rough Set model.

- Over 2,000 initial rules generated
- High-confidence optimized rules emphasized:
  - financial literacy
  - risk tolerance
  - previous trading experience

Users with a university education, moderate risk tolerance, and prior exposure to digital markets showed the highest NFT adoption likelihood.

D. Pattern Discovery Using Decision Tree (J48)

The J48 decision tree provided a clear hierarchical rule structure:

- Financial literacy was the strongest predictor
- Followed by the monthly trading volume and the age group

Results showed:

- 486 financially literate users purchased NFTs,
- while most users lacking literacy did not.

Accuracy achieved: 0.977

E. Pattern Discovery Using Naïve Bayes

Naïve Bayes achieved an accuracy of 0.977, consistent with the decision tree.

Findings demonstrated that:

- Experienced male investors aged 30–45
- With strong financial literacy
- And moderate risk perception

had the highest predicted probability of NFT adoption.

F. Pattern Discovery Using Artificial Neural Networks (ANN)

The ANN model captured nonlinear interactions among behavioral variables.

Network structure:

- 1 input layer
- 2 hidden layers
- 1 output layer

Training parameters:

- learning rate = 0.3
- momentum = 0.2

Accuracy: 0.938

Although lower than rule-based models, ANN identified complex relationships, particularly interactions involving financial literacy, transaction frequency, and income.

TABLE II

Comparative Performance of Data-Mining Algorithms

Algorithm	Accuracy	Key Predictors Identified
Rough Set Model	**0.980**	Financial literacy, trading experience, and age
Decision Tree (J48)	**0.977**	Financial literacy, transaction volume, risk tolerance
Naïve Bayes	**0.977**	Financial literacy, prior experience, and income
Neural Network (ANN)	**0.938**	Nonlinear behavioral and demographic interactions

Table II summarizes the comparative performance of all implemented algorithms in terms of predictive accuracy and key behavioral determinants.

The Rough Set model offered the best balance of accuracy and interpretability.

G. Summary of Findings

Across all models, four variables consistently emerged as the strongest predictors of NFT adoption:

- Financial literacy
- Risk tolerance
- Prior market experience
- Transaction volume

These findings support the use of data-driven strategies for designing NFT-based financial services and for guiding digital transformation initiatives in Iran's banking sector.

IV. CONCLUSION

This study applied four advanced data-mining algorithms-Decision Tree (J48), Naïve Bayes, Neural Networks, and the Rough Set model-to analyze behavioral data from 800 users of Iranian cryptocurrency exchanges. The aim was to identify key demographic and behavioral determinants of NFT adoption and develop a predictive framework to support FinTech expansion in Iran's banking sector.

Comparative results showed that the Rough Set model achieved the highest predictive accuracy (0.98), outperforming the Decision Tree (0.977), Naïve Bayes (0.977), and Neural Network (0.938). These findings highlight the importance of appropriate data preprocessing, model selection, and interpretability-oriented analytical methods for behavioral prediction in digital asset markets.

The overall predictive accuracy of the applied models is reported in Table III.

TABLE III

Predictive Accuracy of the Applied Models

Algorithm	Accuracy
Rough Set Model	**0.980**
Decision Tree (J48)	0.977
Naïve Bayes	0.977
Neural Networks	0.938

The results confirm that rule-based models, particularly the Rough Set approach, offer an effective balance between predictive accuracy and interpretability, making them suitable for banking policymakers and financial analysts who require transparent and data-driven decision-support tools.

A. Discussion

The models consistently identified financial literacy, risk tolerance, previous market experience, and transaction volume as the most influential factors affecting NFT purchase decisions.

The Rough Set model provided the clearest and most interpretable rules, enabling policymakers to understand how demographic and behavioral variables combine to drive adoption. While neural networks captured nonlinear interactions, their limited interpretability reduces their direct applicability in regulatory or banking environments where transparency is essential.

Overall, the findings demonstrate that data-mining methods are powerful tools for analyzing emerging digital-finance behaviors and can assist banks in designing targeted, customer-centric FinTech services, particularly in the rapidly evolving domains of NFTs and decentralized finance (DeFi).

B. Comparative Insights with Prior Research

The findings align with and extend recent studies in the fields of FinTech, user behavior, and predictive analytics:

1. Machine Learning in Finance

Prior studies, such as those by Kim (2003) and Henrique et al. (2019), demonstrated the strong predictive capabilities of AI-based algorithms. The present study supports these results while emphasizing the added interpretability of Rough Set rules in policy settings.

2. Behavioral Segmentation

Research by Sujatha et al. (2023) showed that segmenting users by financial literacy improves personalization. This study confirms similar segmentation potential using rule-based methods.

3. FinTech Innovation and Adoption

Results are consistent with Mohammadi et al. (2023) and Ali Haghi Nojehdeh et al. (2023), who found that data-driven approaches enhance FinTech development and behavioral prediction.

4. Hybrid Modeling

Echoing Subbarao et al. (2020), future frameworks may benefit from combining interpretable rule-based approaches with nonlinear neural models to improve performance.

5. Behavioral and Regulatory Context

Recent studies (e.g., Waliullah et al., 2025; Chandrasekaran, 2025) emphasize risk perception and regulatory clarity as key determinants of digital asset adoption—a pattern also observed in the Iranian context.

C. Policy Implications

The findings provide several practical insights for Iranian banking policymakers and FinTech regulators:

- Enhancing Financial Literacy

Education programs should be prioritized to increase awareness, trust, and responsible participation in digital asset markets.

- Supporting Smart Banking Initiatives

Data-mining models can help identify customer groups with high NFT adoption potential, enabling targeted product development.

- Strengthening Risk-Management Systems

Rule-based models, such as Rough Set, can inform risk assessments by highlighting behavioral indicators of high-risk or high-value customers.

- Developing Regulatory Infrastructure

Clear legal frameworks for NFTs and digital assets will support secure and transparent FinTech expansion.

D. Recommendations for Future Research

Future studies can extend the present work in several directions:

1. Hybrid Model Development

Integrate Rough Set models with advanced neural architectures to balance interpretability and nonlinear accuracy.

2. Sentiment Analysis

Examine social-media sentiment and psychological factors affecting NFT investment behavior.

3. Cross-Domain Application

Test the predictive framework in other FinTech areas such as decentralized lending, insur-tech, or digital payment systems.

4. Longitudinal Studies

Use multi-year datasets to analyze evolving behavioral and market dynamics over time.

E. Final Remarks

This study demonstrates that AI-driven and data-mining models can play a transformative role in supporting

FinTech development in emerging economies. By prioritizing financial literacy, risk assessment, and data-driven decision-making, Iranian banking institutions can accelerate the transition toward smart banking and a sustainable digital financial ecosystem.

F. Ethical and Privacy Compliance

All user data were fully anonymized prior to analysis and handled in accordance with national data-protection regulations and generally accepted ethical research standards. No identifiable or sensitive personal information was collected at any stage of the study.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

AUTHORS' CONTRIBUTIONS

The first author primarily contributed to the conceptualization, data analysis, and development of the core research content. The corresponding author was responsible for overall supervision, research framework design, and coordination of the study. The third and fourth authors contributed through academic guidance, methodological support, and critical review of the manuscript. All authors read and approved the final version of the manuscript.

STATEMENT ON THE USE OF GENERATIVE AI

The authors confirm that generative artificial intelligence tools were used solely for language editing and improving the clarity of the manuscript. All content was carefully reviewed and validated by the authors, who take full responsibility for the accuracy, integrity, and originality of the work.

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