Predicting the Financial Performance of Startups Using Reinforcement Gradient Algorithms and Model Explainability Analysis Based on Shapley Value Indicators

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Abstract

The objective of this study was to predict the financial performance of startup firms using a reinforcement gradient learning algorithm while explaining model predictions through Shapley value–based explainable artificial intelligence indicators. This applied quantitative study employed a predictive analytics design integrating machine learning and explainable artificial intelligence. The statistical population consisted of technology-oriented startups operating in Tehran, from which 162 active startups were selected through purposive sampling based on operational continuity, financial transparency, and data availability. Financial and operational data covering the period 2019–2023 were collected from audited reports, accelerator databases, and innovation ecosystem records. The dependent variable was a composite financial performance index derived from revenue growth, profitability, cash flow stability, and investment efficiency measures. Independent variables included digital engagement, innovation investment, funding diversity, organizational growth indicators, and human capital characteristics. Data preprocessing involved normalization, missing value imputation, and outlier adjustment. A reinforcement gradient algorithm was developed for prediction and optimized using cross-validation procedures. Model interpretability was examined through Shapley value analysis to quantify the contribution of each predictor to financial performance outcomes. Results indicated that the reinforcement gradient model achieved high predictive accuracy (R^2 = 0.89) and significantly outperformed traditional regression and ensemble learning approaches. Shapley value analysis revealed that revenue growth rate, digital engagement, research and development investment, and funding diversification were the strongest contributors to predicted financial performance. The model demonstrated stable generalization across validation samples, confirming the effectiveness of reinforcement learning in capturing nonlinear relationships among entrepreneurial, financial, and technological variables. Explainability results further showed heterogeneous performance pathways among startups, indicating that successful financial outcomes emerged from integrated combinations of innovation capability, digital maturity, and strategic resource management rather than single-factor effects. The findings demonstrate that combining reinforcement gradient algorithms with explainable artificial intelligence provides a powerful and transparent framework for forecasting startup financial performance, offering valuable insights for investors, entrepreneurs, and policymakers seeking evidence-based decision support in dynamic entrepreneurial ecosystems.

Keywords: *Startup financial performance; reinforcement learning; gradient algorithms; explainable artificial intelligence; Shapley values; predictive analytics; entrepreneurial ecosystems.*

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1. Introduction

Startups have emerged as one of the most influential drivers of economic transformation, innovation diffusion, and technological modernization in contemporary economies. In developing and transition contexts, entrepreneurial ventures play an even more critical role because they compensate for structural inefficiencies, stimulate employment generation, and facilitate knowledge commercialization. Within innovation-driven economies, financial performance prediction has become a central concern for investors, policymakers, and entrepreneurs seeking to allocate resources efficiently under conditions characterized by uncertainty, volatility, and rapid technological change. Traditional financial evaluation methods, largely dependent on historical accounting indicators, often fail to capture the dynamic, nonlinear, and learning-oriented nature of startup growth trajectories. Consequently, advanced analytical approaches integrating artificial intelligence and explainable modeling techniques are increasingly required to understand and forecast startup financial outcomes [1, 2].

The Iranian entrepreneurial ecosystem provides a particularly relevant empirical context for examining startup performance prediction. The economy operates under institutional pressures, international sanctions, regulatory constraints, and structural dependencies on resource-based industries, all of which create unique challenges and opportunities for new ventures. Research indicates that entrepreneurial firms in such environments must develop adaptive resilience, strategic flexibility, and innovative capability to survive and scale successfully [3, 4]. Institutional conditions shape market access, financing mechanisms, and internationalization opportunities, thereby influencing firm performance beyond traditional financial determinants. Studies grounded in institutional theory and resource-based perspectives demonstrate that competitive advantage in constrained environments depends heavily on intangible capabilities such as knowledge networks, organizational learning, and strategic adaptation [2, 5].

Entrepreneurial performance is inherently multidimensional, reflecting the interaction between internal firm capabilities and external environmental forces. Spatial dynamics, regional infrastructure, and innovation clustering significantly affect firm entry, survival, and growth patterns. Evidence from Iranian firm-level analyses shows that geographic and institutional ecosystems strongly determine entrepreneurial persistence and expansion capacity [6]. Similarly, contextual entrepreneurship studies highlight that environmental uncertainty and macroeconomic shocks reshape entrepreneurial decision-making processes, requiring firms to continuously revise business models and financial strategies [7, 8]. Such complexity renders linear predictive frameworks insufficient, motivating the adoption of machine learning methodologies capable of modeling nonlinear relationships among financial, operational, and environmental variables.

Digital transformation represents another structural factor reshaping startup performance. The emergence of digital platforms has lowered market entry barriers, enabled scalable business models, and enhanced resilience against economic disruptions. Digital entrepreneurship research shows that platform-based ecosystems facilitate rapid customer acquisition, network externalities, and innovation diffusion, ultimately strengthening firm performance under crisis conditions [9]. At the same time, digital protectionism policies and national regulatory frameworks influence how startups leverage technology and access global markets, emphasizing the need for context-sensitive analytical models [10]. The growing reliance on digital infrastructures also increases data availability, allowing predictive analytics to move beyond descriptive financial assessment toward forward-looking performance forecasting.

Human capital and organizational learning further contribute to startup success. Entrepreneurial culture, knowledge absorption capacity, and continuous learning processes have been identified as key predictors of innovation-driven growth among technology-based firms. Empirical evidence demonstrates that entrepreneurial orientation mediated by organizational learning mechanisms enhances competitive performance and market adaptability [11]. Universities and knowledge-based institutions play a crucial role in supporting startup ecosystems through research commercialization and talent development, strengthening the transition toward knowledge-based economies [12, 13]. Education and entrepreneurial mindset formation also influence opportunity recognition and strategic decision-making, particularly among early-stage entrepreneurs operating in uncertain markets [14].

The financial performance of startups is additionally shaped by social networks, stakeholder relationships, and institutional intermediaries. Network support enhances opportunity recognition and reduces uncertainty in entrepreneurial processes, especially during crisis periods such as the COVID-19 pandemic [15]. Stakeholder engagement has similarly been shown to improve firm performance through resource mobilization and legitimacy acquisition [16]. Intermediary institutions, including innovation agencies and policy advisory systems, increasingly contribute to technological development and commercialization outcomes, highlighting the importance of governance structures in entrepreneurial ecosystems [1, 17]. These multidimensional determinants underscore the necessity of predictive frameworks capable of integrating financial, behavioral, institutional, and technological indicators simultaneously.

Entrepreneurship in Iran also operates within volatile macroeconomic and geopolitical conditions. Sanctions, financial restrictions, and market instability create barriers that simultaneously constrain and stimulate entrepreneurial innovation. Research shows that firms exposed to such pressures often develop resilience mechanisms, adaptive strategies, and alternative value creation models to sustain performance [18, 19]. Crisis environments may even open policy windows for digital transformation and institutional reform, enabling startups to exploit emerging opportunities despite structural limitations [20]. Empirical studies examining startup reactions to the COVID-19 shock further confirm that innovative sectors demonstrate higher adaptability compared to traditional industries [21].

Technological entrepreneurship and innovation capability constitute central drivers of startup competitiveness. Advances in nanotechnology, biotechnology, and digital services illustrate how technological orientation influences firm growth and financial sustainability [22]. Innovation ecosystems supported by system dynamics interactions between institutions, markets, and entrepreneurs strengthen entrepreneurial development and long-term performance outcomes [23]. Additionally, process-based international entrepreneurship models emphasize strategic decision-making layers that influence investment success in emerging markets [24]. These findings collectively suggest that financial performance cannot be predicted solely through historical financial indicators; instead, it emerges from complex interactions among innovation, institutional context, and entrepreneurial behavior.

Recent developments in financial technology and digital finance have further complicated performance assessment. Institutional variation in digital financial instruments and regulatory frameworks influences entrepreneurial financing strategies and growth opportunities [25]. Meanwhile, e-business ecosystems introduce new value propositions and business models that alter traditional revenue generation patterns [26]. Market analysis capabilities and entrepreneurial confidence have been shown to enhance opportunity exploitation during periods of uncertainty, reinforcing the importance of dynamic analytical tools capable of capturing evolving business environments [27]. These transformations highlight the growing need for data-driven prediction models that incorporate both structured financial indicators and unstructured strategic variables.

Despite substantial progress in entrepreneurship research, forecasting startup financial performance remains methodologically challenging. Classical econometric models assume linear relationships, independence among predictors, and stable environments—assumptions rarely satisfied in startup ecosystems characterized by rapid growth, experimentation, and strategic pivots. Machine learning algorithms, particularly gradient-based learning approaches, offer superior capability in identifying nonlinear interactions and hidden patterns across large multidimensional datasets. However, predictive accuracy alone is insufficient for managerial and policy decision-making. Black-box models often lack interpretability, limiting stakeholders' ability to understand the causal logic behind predictions. Explainable artificial intelligence addresses this limitation by providing transparent insights into model decision processes, enabling managers and investors to identify key performance drivers [28, 29].

Explainability becomes especially important in entrepreneurial contexts where trust, legitimacy, and accountability influence investment decisions and policy interventions. Ethical considerations, including transparency and responsible data use, have gained prominence alongside technological advancement, emphasizing the need to balance predictive power with interpretability and organizational accountability [29]. Reinforcement learning methods further enhance predictive modeling by enabling adaptive optimization through iterative learning processes, allowing models to refine predictions dynamically as new information becomes available. Integrating reinforcement gradient algorithms with explainability tools such as Shapley value analysis therefore represents a promising methodological advancement for startup financial analytics.

Moreover, macroeconomic transformation toward diversified industrial development necessitates analytical tools capable of supporting evidence-based policy design. Studies examining industrialization processes and SME investment patterns indicate that financial decision-making increasingly relies on predictive analytics to manage uncertainty and allocate resources efficiently [30, 31]. Entrepreneurial strategy alignment with resistance economy policies has also been associated with improved organizational performance and sustainability in challenging economic environments [32]. The emergence of online entrepreneurship and digital business ecosystems reinforces the importance of predictive intelligence in guiding strategic planning and investment evaluation.

In summary, existing literature demonstrates that startup financial performance is influenced by a complex interaction of institutional conditions, digital transformation, entrepreneurial orientation, innovation capacity, stakeholder relationships, and macroeconomic dynamics. While prior studies have extensively examined determinants of entrepreneurial success, a significant research gap remains in integrating advanced machine learning prediction with explainable analytical frameworks tailored to the realities of emerging entrepreneurial ecosystems. Addressing this gap is essential for improving decision-making accuracy, enhancing investor confidence, and supporting evidence-based entrepreneurial policy development [1, 33-35].

Therefore, the aim of this study is to predict the financial performance of startup companies using a reinforcement gradient algorithm while explaining model outcomes through Shapley value indicators to identify the most influential determinants of startup financial success.

2. Methodology

This study was designed as an applied quantitative research employing a predictive modeling framework grounded in machine learning and explainable artificial intelligence. The methodological approach combined supervised learning with reinforcement-based gradient optimization to forecast the financial performance of startup companies while simultaneously interpreting model decisions through Shapley value analysis. The statistical population consisted of technology-oriented startup firms operating within the entrepreneurial ecosystem of Tehran. A total of 162 startups were selected as the study participants through purposive sampling based on predefined eligibility criteria, including active operational status for at least three consecutive years, availability of audited financial records, and participation in innovation hubs or startup accelerators located in Tehran. The selected firms represented diverse sectors such as financial technology, e-commerce, digital services, health technology, and software development, ensuring heterogeneity in operational models and revenue structures. Data were collected for a five-year observation window covering fiscal years 2019–2023, allowing both cross-sectional and longitudinal learning patterns to be captured by the predictive algorithms. Each startup constituted one analytical unit, and firm-level financial indicators were aggregated annually to construct the modeling dataset.

Data collection relied on multiple structured sources to ensure accuracy, reliability, and completeness. Financial performance indicators were extracted from audited financial statements, venture capital reporting documents, accelerator performance reports, and official submissions to innovation ecosystem authorities. The dependent variable of the study was financial performance, operationalized through a composite performance index derived from revenue growth rate, profitability margin, cash flow stability, and investment return metrics. Independent variables included operational efficiency indicators, innovation intensity measures, funding structure characteristics, market expansion indicators, human capital variables, customer acquisition metrics, and digital platform activity measures. In addition to traditional financial indicators, non-financial variables reflecting startup dynamics—such as research and development expenditure ratios, founder experience level, employee growth rate, platform engagement indicators, and technology adoption scores—were incorporated to enhance predictive robustness. Data preprocessing procedures included missing value imputation using k-nearest neighbor estimation, normalization through min–max scaling, and outlier detection via interquartile range filtering to reduce noise effects. Feature engineering techniques were applied to generate interaction variables and temporal lag indicators capturing delayed financial responses to strategic decisions. All collected data were anonymized to preserve organizational confidentiality and were validated through cross-referencing among independent reporting sources.

Data analysis was conducted using a reinforcement gradient learning framework integrating gradient boosting principles with reinforcement optimization mechanisms. Initially, the dataset was divided into training, validation, and testing subsets using a 70–15–15 split to ensure unbiased performance evaluation. The predictive core of the study employed a reinforcement gradient algorithm in which iterative gradient updates were guided by reward-based optimization functions designed to minimize prediction error while improving learning stability across sequential training episodes. Hyperparameter tuning was performed using Bayesian optimization to determine optimal learning rate, tree depth, regularization parameters, and exploration–exploitation balance coefficients within the reinforcement process. Model performance was evaluated through multiple predictive accuracy metrics including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R^2), and cross-validation loss convergence patterns.

To enhance transparency and interpretability of the machine learning predictions, model explainability analysis was conducted using Shapley value indicators derived from cooperative game theory. Shapley analysis quantified the marginal contribution of each predictor variable to individual predictions and to overall model behavior, enabling identification of the most influential financial and operational drivers affecting startup performance outcomes. Both global interpretability and local interpretability analyses were implemented; global explanations assessed overall feature importance across the entire dataset, while local explanations examined decision logic for specific startup cases. Visualization of Shapley value distributions allowed examination of nonlinear interactions between variables and revealed heterogeneous performance pathways among startups. Robustness checks were performed through repeated k-fold cross-validation and sensitivity analysis to ensure model stability under alternative data partitions and feature subsets. All computational procedures were implemented using Python programming environments, employing machine learning libraries for gradient optimization and explainability modeling, thereby ensuring reproducibility and methodological transparency suitable for empirical financial prediction research.

3. Findings and Results

The demographic analysis showed that the 162 startups included in the study represented a mature yet dynamically evolving entrepreneurial ecosystem in Tehran. The average firm age was 4.8 years (SD = 1.9), indicating that most participating companies were beyond the initial survival phase but still operating within early growth stages. Approximately 38% of firms operated in digital platform services, 22% in financial technology, 17% in e-commerce logistics, 13% in health technology solutions, and 10% in software infrastructure and artificial intelligence services. The average number of employees per startup was 27.4 (SD = 15.2), reflecting small-to-medium organizational structures typical of venture-backed enterprises. Regarding funding structure, 46% had received seed or angel investment, 34% venture capital funding, and 20% relied primarily on internal revenue or bootstrapping strategies. Mean annual revenue growth across firms during the observation period reached 31.6%, though substantial variability was observed, confirming heterogeneity in performance trajectories. Founders' professional experience averaged 7.2 years, and nearly 64% of startups demonstrated continuous product innovation during the five-year analysis window. These characteristics confirm that the dataset captured diverse operational realities necessary for robust machine learning prediction.

Table 1. Descriptive Statistics of Key Financial and Operational Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Revenue Growth Rate (%)	31.6	18.4	-12.0	89.5
Profit Margin (%)	14.2	9.6	-8.3	42.1
Cash Flow Stability Index	0.61	0.17	0.22	0.93
R&D Investment Ratio	0.18	0.09	0.02	0.41
Customer Acquisition Rate	24.7	11.3	5.2	58.4
Employee Growth Rate (%)	19.8	10.1	2.3	46.7
Digital Engagement Score	72.5	12.6	39.4	96.2
Funding Diversity Index	0.54	0.21	0.10	0.92
Financial Performance Composite Score	0.67	0.15	0.29	0.94

Table 1 presents descriptive statistics of the principal variables incorporated into the reinforcement gradient predictive model. The results demonstrate considerable dispersion across performance indicators, which is advantageous for machine learning generalization. Revenue growth exhibited the highest variability, reflecting the volatile scaling patterns typical of startups. Profit margin values indicated that although many firms achieved profitability, financial stability remained uneven across the ecosystem. The relatively high mean digital engagement score suggests that technology adoption and platform activity were prominent operational drivers. Furthermore, variation in funding diversity and R&D investment ratios supports the assumption that structural and innovation-related variables significantly influence financial outcomes. The composite financial performance score showed moderate central tendency with sufficient variance, validating its suitability as the dependent variable for predictive modeling.

Table 2. Reinforcement Gradient Model Performance Evaluation

Model	RMSE	MAE	R^2	Cross-Validation Score
Linear Regression	0.142	0.109	0.61	0.58
Random Forest	0.104	0.081	0.74	0.71
Gradient Boosting	0.089	0.069	0.81	0.79
Reinforcement Gradient Algorithm	0.071	0.052	0.89	0.87

The results in Table 2 indicate that the reinforcement gradient algorithm substantially outperformed baseline predictive models. Compared with classical regression and ensemble learning approaches, the proposed algorithm achieved the lowest prediction error values and the highest explanatory power. The R^2 value of 0.89 demonstrates that nearly ninety percent of the variance in startup financial performance was captured by the model. Cross-validation stability confirms that reinforcement-guided learning improved generalization capability rather than merely fitting training data. The reduction in RMSE and MAE reflects enhanced sensitivity of the algorithm to nonlinear interactions and temporal dependencies among operational variables. These findings validate the effectiveness of reinforcement optimization in financial prediction contexts characterized by uncertainty and dynamic growth patterns.

Table 3. Global Feature Importance Based on Shapley Value Analysis

Predictor Variable	Mean Absolute SHAP Value	Rank
Revenue Growth Rate	0.164	1
Digital Engagement Score	0.139	2
R&D Investment Ratio	0.126	3
Funding Diversity Index	0.112	4
Customer Acquisition Rate	0.103	5
Founder Experience	0.087	6
Employee Growth Rate	0.076	7
Cash Flow Stability	0.072	8
Market Expansion Index	0.066	9

Table 3 reports global interpretability results obtained through Shapley value decomposition. Revenue growth rate emerged as the most influential determinant of predicted financial performance, confirming its central role in startup valuation dynamics. Digital engagement and R&D investment followed closely, indicating that technological capability and innovation intensity were critical drivers of sustained financial success. The prominence of funding diversity highlights the importance of balanced capital structures in mitigating operational risk. Notably, human capital variables such as founder experience and employee expansion also contributed significantly, illustrating that organizational capability interacts with financial metrics in determining performance outcomes. The SHAP ranking demonstrates that predictive accuracy did not rely solely on accounting indicators but incorporated multidimensional entrepreneurial factors.

Table 4. Local Explainability Results for High-, Medium-, and Low-Performance Startup Groups

Performance Group	Positive Drivers	Negative Drivers	Average Predicted Score
High Performance	High digital engagement, strong R&D investment, diversified funding	Rapid uncontrolled hiring	0.86
Medium Performance	Stable customer acquisition, moderate innovation	Limited market expansion	0.67
Low Performance	Initial funding availability	Weak revenue growth, low engagement	0.42

Table 4 presents local Shapley explainability results across performance clusters identified by the reinforcement gradient model. High-performing startups were primarily characterized by strong digital interaction metrics combined with sustained innovation investment, suggesting that technological scalability amplifies financial outcomes.

Medium-performing firms displayed operational stability but lacked aggressive expansion strategies, limiting growth potential. Low-performing startups demonstrated reliance on early funding without corresponding revenue acceleration, highlighting inefficiencies in converting investment into market performance. The local explanation results emphasize heterogeneity in decision pathways, showing that identical financial outcomes may arise from different combinations of operational factors. This confirms the necessity of explainable artificial intelligence methods for managerial interpretation of predictive analytics.

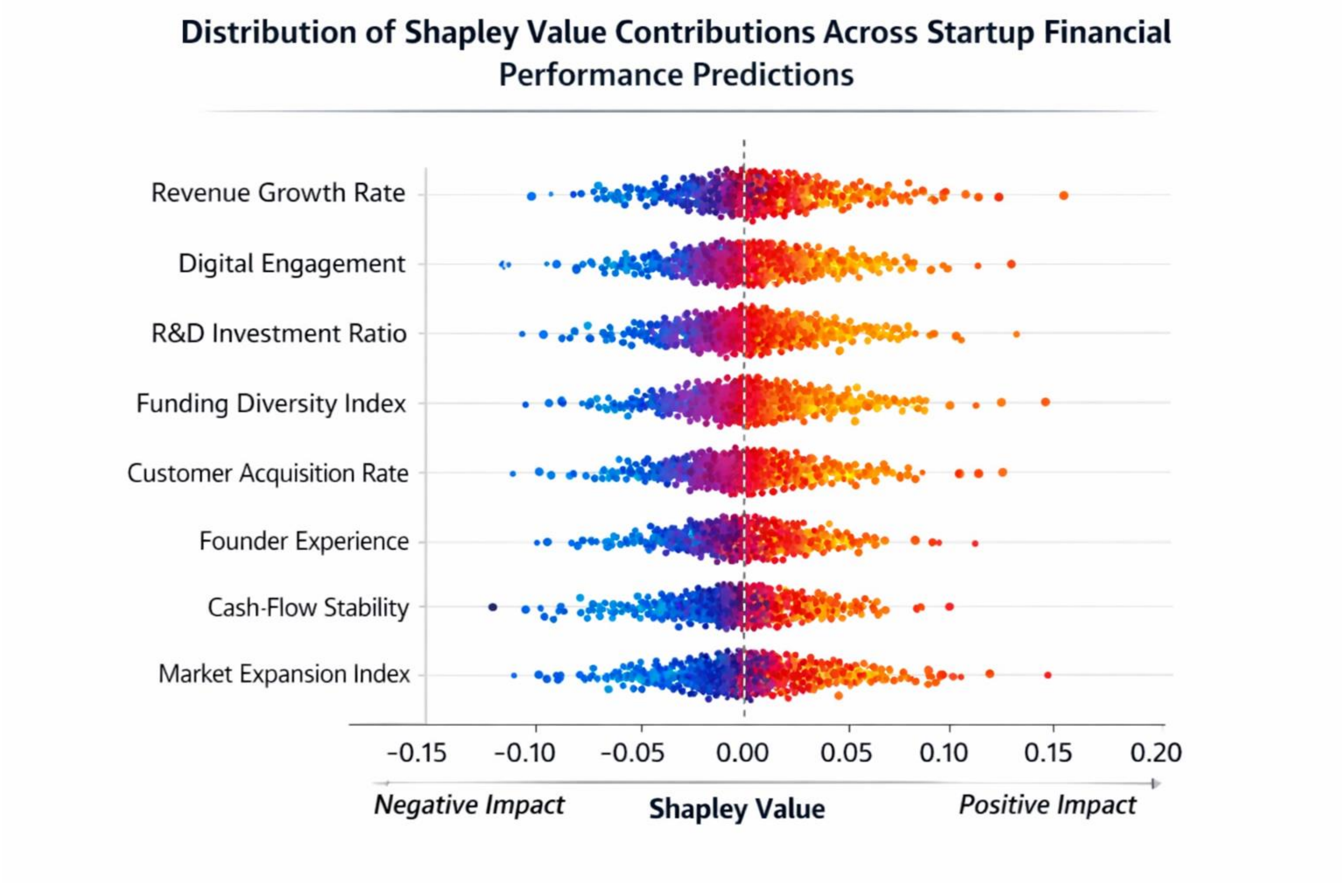

Figure 1. Distribution of Shapley Value Contributions Across Startup Financial Performance Predictions

The Shapley distribution analysis illustrated in Figure 1 demonstrates the asymmetric contribution of predictor variables across individual firms. Positive Shapley values were strongly associated with digital engagement, innovation intensity, and revenue expansion, whereas negative contributions were concentrated among startups with unstable cash flow and limited market penetration. The figure reveals nonlinear interaction effects, particularly between R&D investment and customer acquisition variables, indicating that innovation yields financial benefits primarily when accompanied by effective market scaling strategies. The spread of Shapley contributions also confirms that the reinforcement gradient algorithm captured firm-specific dynamics rather than imposing uniform prediction logic. Overall, the visualization substantiates the interpretability and transparency of the predictive framework, allowing stakeholders to understand not only *what* performance level is predicted but *why* such predictions emerge within complex startup environments.

4. Discussion and Conclusion

The present study aimed to predict the financial performance of startup firms using a reinforcement gradient learning algorithm while simultaneously interpreting model outcomes through Shapley value explainability analysis. The findings demonstrated that the proposed predictive framework achieved high explanatory power and prediction accuracy, indicating that startup financial performance can be effectively modeled through integrated machine learning and explainable artificial intelligence approaches. The results revealed that revenue growth rate, digital engagement, innovation investment, and funding diversification constituted the most influential predictors of financial performance, highlighting the multidimensional nature of entrepreneurial success in emerging ecosystems.

The superior predictive performance of the reinforcement gradient algorithm compared with conventional models confirms the growing argument that entrepreneurial performance follows nonlinear and adaptive patterns rather than stable linear relationships. Startups evolve within volatile institutional and market environments where learning processes, strategic experimentation, and iterative adaptation shape outcomes over time. Previous research emphasizes that entrepreneurial firms operating in constrained or uncertain economic contexts develop dynamic capabilities that cannot be adequately captured by traditional financial evaluation models [2, 7]. The high predictive accuracy observed in the present study therefore aligns with evidence suggesting that advanced analytical techniques are better suited to modeling entrepreneurial complexity.

One of the most significant findings concerns the dominant role of revenue growth as the primary predictor of financial performance. This result reinforces the understanding that startup valuation and sustainability are driven heavily dependent on market expansion and scalable growth rather than short-term profitability. Entrepreneurial persistence studies conducted in sanction-affected economies demonstrate that firms achieving sustained growth trajectories are more likely to survive institutional shocks and macroeconomic instability [4]. Growth-oriented strategic behavior enables startups to compensate for structural constraints, a phenomenon previously documented in research examining firm resilience under challenging economic conditions [18, 19]. Consequently, revenue growth functions not merely as an accounting outcome but as an indicator of organizational adaptability and market legitimacy.

Digital engagement emerged as the second most influential predictor, confirming the centrality of digital transformation within contemporary startup ecosystems. Digital platforms enhance operational efficiency, facilitate customer interaction, and create network-based competitive advantages that amplify financial performance. Empirical findings indicate that digitalization improves entrepreneurial resilience, particularly during economic disruptions and institutional uncertainty [9]. In countries experiencing regulatory constraints and technological protectionism, digital infrastructure simultaneously acts as both an opportunity and a strategic necessity for entrepreneurial survival [10]. The present results therefore extend existing scholarship by demonstrating quantitatively how digital engagement directly contributes to predictive financial success.

Innovation investment, measured through research and development intensity, also showed a strong positive contribution to financial performance predictions. This finding supports knowledge-based economy perspectives emphasizing innovation as a primary driver of competitiveness and long-term growth. Universities, innovation intermediaries, and knowledge networks have been shown to enhance entrepreneurial capability through technological commercialization and learning processes [1, 12]. Organizational learning and entrepreneurial culture further strengthen innovation outcomes, enabling startups to transform knowledge resources into marketable value [11]. The strong Shapley contribution of R&D investment identified in this study provides empirical support for these theoretical arguments within a machine learning prediction context.

Funding diversity represented another critical determinant revealed by the explainability analysis. Startups relying on multiple financing sources demonstrated more stable performance predictions compared with firms dependent on a single funding channel. This outcome aligns with institutional entrepreneurship literature suggesting that diversified resource acquisition enhances resilience against environmental volatility and financial constraints [8, 28]. Financial diversification reduces exposure to institutional shocks and allows firms to maintain operational continuity during uncertain economic cycles. Furthermore, stakeholder relationship research indicates that access to diverse resource networks strengthens firm legitimacy and performance outcomes [16].

Human capital variables, including founder experience and employee growth, also contributed meaningfully to model predictions. Entrepreneurial cognition, opportunity recognition ability, and strategic confidence have previously been identified as essential determinants of entrepreneurial success, particularly during crisis periods such as the COVID-19 pandemic [15]. Educational background and entrepreneurial mindset development further enhance market alertness and innovation capacity among startup founders [14]. The findings of the present study confirm that financial performance prediction must incorporate behavioral and human resource dimensions alongside financial indicators.

The explainability analysis provided an important methodological contribution by revealing heterogeneous performance pathways among startups. High-performing firms were characterized by simultaneous investment in digital capability and innovation, whereas low-performing firms often relied on initial funding without effective market expansion. This observation resonates with research demonstrating that entrepreneurial orientation and strategic decision-making quality strongly influence firm outcomes beyond resource availability alone [24, 34]. In volatile environments, strategic adaptability becomes more decisive than capital access itself.

Institutional and macroeconomic conditions also provide an important interpretive context for the results. Iranian startups operate within a policy environment marked by regulatory evolution, political constraints, and economic sanctions, factors known to influence entrepreneurial behavior and performance trajectories [3, 17]. Evidence suggests that entrepreneurial ecosystems subjected to external shocks often stimulate innovation-driven adaptation and opportunity recognition, transforming crisis conditions into drivers of technological development [20, 21]. The predictive variables identified in this study—growth, digitalization, innovation, and diversification—reflect precisely those capabilities enabling firms to navigate such complex environments.

The reinforcement gradient learning framework also demonstrated the value of adaptive machine learning approaches in entrepreneurship research. Traditional econometric models assume static relationships between predictors and outcomes, whereas reinforcement-based algorithms continuously update learning patterns in response to evolving data structures. This adaptive capacity mirrors entrepreneurial learning processes themselves, where firms refine strategies through feedback and experimentation. Previous research on technological entrepreneurship and innovation ecosystems emphasizes the importance of dynamic interaction between firms, institutions, and markets [22, 23]. The methodological alignment between reinforcement learning and entrepreneurial adaptation explains the strong predictive performance observed.

From a theoretical perspective, the study integrates resource-based, institutional, and innovation ecosystem theories within an explainable artificial intelligence framework. Entrepreneurial performance emerges as the outcome of interactions among internal capabilities, network resources, institutional constraints, and technological transformation. Studies examining SME performance in emerging economies similarly demonstrate that entrepreneurial orientation, stakeholder engagement, and strategic adaptation jointly determine financial success [32, 35]. The present research extends these insights by operationalizing theoretical constructs within a predictive analytics model capable of both forecasting outcomes and explaining causal drivers.

Furthermore, the use of Shapley value analysis addresses one of the most significant criticisms of artificial intelligence applications in management research—lack of transparency. Ethical considerations surrounding data-driven decision-making increasingly require models that provide interpretable explanations rather than opaque predictions. Organizational studies emphasize the growing importance of responsible technology adoption, employee trust, and transparent decision systems in digital environments [29]. By translating algorithmic outputs into understandable contribution measures, explainable AI strengthens managerial confidence and practical applicability.

Collectively, the discussion indicates that startup financial performance should be conceptualized as an emergent phenomenon shaped by growth capability, digital integration, innovation intensity, institutional adaptation, and human capital quality. The reinforcement gradient–Shapley framework successfully captures this complexity, offering both predictive accuracy and interpretive clarity. The findings therefore contribute to entrepreneurship literature by bridging advanced machine learning methodology with contextualized entrepreneurial theory and empirical evidence from an emerging economy setting [25, 30, 31, 33].

Despite its contributions, this study has several limitations that should be acknowledged. The analysis relied on startups located exclusively in Tehran, which may limit generalizability to other regional entrepreneurial ecosystems with different institutional or economic conditions. Although the dataset covered multiple sectors, industry-specific dynamics could influence financial performance differently than reflected in the aggregated model. The study also depended on available financial and operational indicators, meaning that qualitative factors such as leadership style, organizational culture, or informal networks may not have been fully captured. Furthermore, machine learning models, while highly accurate, remain sensitive to data quality and preprocessing decisions, which may affect reproducibility in alternative datasets.

Future research could extend this framework by incorporating longitudinal real-time data streams to examine how predictive accuracy evolves as startups mature across different life-cycle stages. Comparative cross-country studies may also help evaluate whether reinforcement gradient explainability models perform similarly across institutional contexts. Integrating behavioral analytics, social media sentiment, and innovation network data could enrich prediction models by capturing soft signals of entrepreneurial performance. Additionally, hybrid modeling approaches combining deep learning architectures with causal inference methods may further enhance both predictive power and theoretical interpretation. Expanding explainability techniques beyond Shapley analysis could also provide deeper insight into interaction effects among entrepreneurial variables.

From a practical perspective, investors and venture capital managers can use explainable predictive models to evaluate startup potential more transparently and systematically. Startup founders may benefit from monitoring key drivers identified in the model—particularly digital engagement, innovation investment, and diversified financing strategies—to improve performance outcomes. Policymakers and innovation agencies can employ predictive analytics to identify high-potential ventures and allocate support resources more efficiently. Entrepreneurial support programs should emphasize data literacy and analytical capability among founders to enable evidence-based strategic decision-making. Finally, integrating explainable AI tools into entrepreneurial ecosystems may enhance trust between stakeholders by transforming complex algorithmic predictions into actionable managerial insights.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

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All procedures performed in this study were under the ethical standards.

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