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Providing Strategies to Improve Investments of Iran's Social Security Organization with a Focus on the Role of Technology

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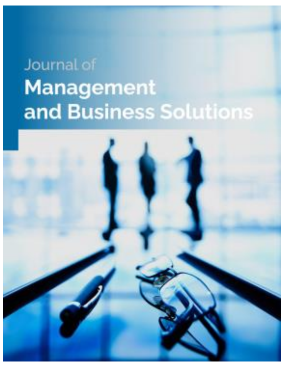
ABSTRACT

This study aims to conduct a foresight analysis of the investments of Iran's Social Security Organization with an emphasis on the role of technology. The research is applied in purpose, qualitative in nature, and adopts a descriptive–prescriptive approach. The study population consisted of experts in the fields of foresight, investment, and emerging technologies. Using a judgmental sampling method, ten interviews were conducted in two sessions over the course of one month in 2025. The research process followed a three-stage model including the identification of driving forces, layered causal analysis, and scenario development. Initially, 29 driving forces were identified, of which 28 were finalized using a binomial test. Subsequently, the indicators were analyzed across four layers, and the TOPSIS method revealed that the "extent of use of data-driven technologies" and the "managerial decision-making style" were the most influential driving forces. Based on these two factors, four scenarios were developed: the "Transformation Pioneer" scenario, in which the synergy of risk-taking and data orientation leads to a shift toward knowledge-based investments; the "Modern Bureaucrat" scenario, in which technology is used merely as a monitoring tool and investment is limited to preserving asset value; the "Intuitive Surge" scenario, where risk-taking without data results in fragmented decisions; and the "Isolated Conservative" scenario, which represents the worst case, where the absence of both factors leads to capital erosion. The findings emphasize the importance of linking leadership culture with analytical capabilities to achieve the desirable "Transformation Pioneer" scenario. This study can serve as a reference document, facilitating future research and enhancing the resilience of the Social Security Organization in the face of technological transformations.

Keywords: Social Security Organization investments, role of technology, foresight.

Introduction

Investment decision-making has become increasingly complex in contemporary economic environments characterized by volatility, rapid technological change, and heightened uncertainty. Organizations are no longer able to rely solely on traditional financial indicators or static capital allocation models; instead, they must integrate advanced analytical tools, digital technologies, and governance mechanisms to enhance investment efficiency and resilience. Recent studies emphasize that irrational behavioral biases, such as anchoring effects, information



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asymmetry, and cognitive limitations, continue to shape financial investment decisions, often leading to suboptimal outcomes if not systematically addressed (1). As a result, modern investment frameworks increasingly combine behavioral finance insights with data-driven and technology-enabled approaches to mitigate risk and improve strategic alignment.

One of the most influential developments in this context is the growing role of digital transformation and artificial intelligence in investment analysis and forecasting. AI-powered financial forecasting tools have demonstrated significant potential in improving risk management, portfolio optimization, and overall corporate profitability across industries by enabling predictive analytics and real-time decision support (2). Similarly, advances in machine learning have facilitated sophisticated investment strategies in capital markets, cryptocurrencies, and quantitative stock selection, enhancing the accuracy and adaptability of investment decisions under dynamic conditions (3, 4). These technological capabilities are particularly relevant for large institutional investors, where the scale and complexity of assets require advanced analytical infrastructures.

At the firm level, investment efficiency is closely linked to internal governance structures, managerial characteristics, and organizational culture. Research indicates that deviations from optimal resource allocation strategies significantly increase investment inefficiency, especially in environments characterized by weak corporate governance, high information asymmetry, and intense product market competition (5). CEO characteristics and managerial styles also play a critical role in shaping investment behavior, as executives' attitudes toward technology, risk, and accounting conservatism directly influence information investment and strategic choices (6). Consequently, investment outcomes are not solely a function of available capital but are deeply embedded in decision-making processes and leadership orientations.

From a broader perspective, social and institutional factors further condition investment behavior and outcomes. Social capital has been shown to enhance firm-level investment efficiency by facilitating trust, information sharing, and cooperative behavior among stakeholders (7). At the household and societal level, social security systems and health capital significantly influence investment behavior by shaping risk tolerance and long-term financial planning (8). These findings highlight the interconnectedness between social structures, institutional arrangements, and investment dynamics, particularly in emerging and developing economies.

The integration of technology into financial oversight and auditing functions has also transformed investment governance. Deep learning and anomaly detection techniques are increasingly applied in internal auditing to identify irregularities in financial accounting data, thereby reducing operational risk and enhancing the reliability of investment-related information (9). In parallel, improvements in financial reporting readability and transparency have been found to positively affect corporate investment decisions by reducing uncertainty and improving stakeholders' understanding of firms' financial positions (10, 11). These developments underscore the importance of information quality and analytical capability in supporting sound investment strategies.

At the macroeconomic and policy level, investment decisions are shaped by regulatory frameworks, national development strategies, and exposure to global economic shocks. Studies on foreign direct investment and development strategies reveal that coherent policy environments and innovation-oriented frameworks are essential for promoting sustainable and green investment outcomes (12, 13). In emerging economies, strategic tax reforms, diversification policies, and institutional reforms are critical for enhancing economic resilience and attracting both domestic and foreign investment (14, 15). However, persistent macroeconomic instability and external shocks continue to pose significant challenges to long-term investment planning.

The role of sustainability and green finance has gained prominence in recent years, further reshaping investment priorities. Sustainable investment strategies, particularly in sectors such as renewable energy, agriculture, and infrastructure, increasingly rely on digital tools and analytics to balance financial performance with environmental and social objectives (16, 17). Comparative analyses of investment practices across countries highlight the importance of integrating AI-driven green finance mechanisms to support sustainable development goals while maintaining competitiveness (18). These trends reflect a shift toward more holistic investment frameworks that incorporate ESG considerations alongside traditional financial metrics.

Risk analysis and management remain central to investment decision-making, especially in entrepreneurial and high-uncertainty contexts. Effective risk management strategies require not only quantitative models but also adaptive organizational capabilities to respond to rapidly changing conditions (19). Post-crisis studies, including those examining the COVID-19 period, demonstrate that constrained budgets and disrupted supply chains necessitate resilient investment strategies supported by data-driven insights and flexible governance structures (20, 21). These findings are particularly relevant for pension funds and large institutional investors operating under long-term obligations and financial constraints (22).

Another critical dimension of contemporary investment systems is the role of inter-organizational collaboration and knowledge exchange. Industry–university–research alliances have been shown to influence technological innovation investment channels, shaping firms' strategic behavior and long-term competitiveness (23). Similarly, financial analytics frameworks developed for strategic decision-making in capital-intensive sectors, such as telecommunications and satellite projects, illustrate how collaborative and data-intensive approaches can enhance opportunity assessment and risk control (24). These collaborative mechanisms are essential for leveraging external expertise and accelerating technological adoption in investment processes.

In transitional and resource-dependent economies, the strategic positioning of investment hubs and technology clusters plays a decisive role in attracting capital and fostering innovation. Analyses of regional investment and technology prospects emphasize that effective integration of technological infrastructure, institutional support, and international cooperation is necessary to transform such regions into competitive investment destinations (25). At the same time, the development of investment knowledge itself is influenced by both genetic and social capital, suggesting that human and social dimensions are critical complements to technological advancement (26).

Despite the growing body of literature on technology, governance, and investment behavior, gaps remain in understanding how these factors interact within complex institutional settings, particularly in large social and financial organizations. Prior studies often examine individual components—such as technology adoption, managerial behavior, or policy frameworks—in isolation, overlooking their systemic interdependencies. Furthermore, while international evidence provides valuable insights, contextualized analyses are needed to capture the unique structural, cultural, and economic conditions shaping investment decisions in specific organizational and national contexts (16, 27, 28). Addressing these gaps is essential for developing actionable strategies that align technological capabilities with governance reforms and investment objectives.

Against this background, the present study seeks to contribute to the literature by providing an integrated analysis of investment decision-making that combines technological, organizational, and strategic perspectives. By drawing on insights from digital transformation, behavioral finance, governance theory, and sustainability-oriented investment research, this study aims to offer a comprehensive framework for understanding and improving investment performance in complex institutional environments, with a particular focus on the role of technology and managerial decision-making culture (1, 8, 29).

Accordingly, the aim of this study is to analyze the determinants of investment decision-making and efficiency through an integrated technology-driven and governance-oriented perspective, and to identify strategic pathways for improving investment outcomes in complex organizational settings.

Methods and Materials

This study was conducted with the aim of foresight analysis of the investments of Iran's Social Security Organization with a focus on the role of technology. In terms of nature, it is qualitative, applied, and based on an integration of exploratory and normative approaches. In the exploratory phase, influential factors and plausible scenarios were identified, and in the normative phase, technology-oriented pathways and policies for achieving a desirable future were formulated. Data analysis was carried out using Causal Layered Analysis (CLA) and the Six Pillars framework of foresight, and the research time horizon was set as the year 2030.

The structure of the study was organized based on the Saunders research onion model, and the data were analyzed qualitatively. The panel of experts consisted of 10 senior managers and specialists from the Social Security Organization, as well as academic faculty members with expertise in investment, foresight, and technology. These experts were selected through judgmental sampling based on the principle of theoretical saturation.

This research was conducted with a short- to medium-term horizon. In the short term, the current status of the role of technology in the investments of the Social Security Organization is described; in the medium term, the systemic and structural causes influencing this status are analyzed; and in the long-term horizon, the dominant discourses and worldviews shaping the organization's approach to financial technology are examined in order to clarify future orientations and the level of the organization's digital readiness:

1. In the field of investments of Iran's Social Security Organization with a focus on the role of technology, what is the observable and surface-level condition (litany level); what are the fundamental systemic causes underlying this condition; how is the dominant discourse or worldview in this field defined; and what is the prevailing metaphor or myth that frames this context?
2. What are the forward-looking scenarios for the investments of Iran's Social Security Organization with a focus on the role of technology?
3. What strategies can guide the organization toward the optimal scenario in order to improve the investments of Iran's Social Security Organization with a focus on the role of technology?

Findings and Results

In the first step, based on a review of the literature, information related to the indicators influencing the investments of Iran's Social Security Organization with a focus on the role of technology was collected.

In this study, various databases covering the period 2000–2025 were reviewed. The main objective of this step was to extract key information from scholarly articles. A total of 24 codes and criteria were initially extracted. Following interviews with experts, five additional factors were added, resulting in a total of 29 factors, which are presented in Table 1.

Table 1. Indicators Influencing the Future of Investments of Iran's Social Security Organization with a Focus on the Role of Technology

No.	Indicator	Sources
1	Level of development of the financial industry in Iran	P1
2	Diversity of Iranian fintechs	P2
3	Growth of financing and investment fintechs in Iran	P3,P4
4	National regulatory policies on technology	P3
5	Development of digital technologies in the country	P4
6	Reforms in the insurance system	P5
7	Changes in global financial markets	Interview
8	International economic crises	Interview
9	Government financial support	P6
10	Government policies in the field of social security	P7
11	Government debts to the Social Security Organization	P7, P8
12	Exchange rate volatility	P9
13	Inflation rate	P10, P11
14	National economic growth rate	P12
15	Development of regtechs in the country	P13
16	Level of cooperation between financial institutions and fintechs	P14
17	Information systems of the Social Security Organization	P14
18	Demographic composition of the country	P4
19	Level of cooperation between the Social Security Organization and universities	P15
20	Level of cooperation between the Social Security Organization and technology startups	P16, P17
21	Level of development of social security technologies (SinTech) in the country	Interview
22	Revenue-generation policies of the Social Security Organization	P4
23	Governance and management style of the Social Security Organization	P4
24	Extent of using international experiences in the Social Security Organization	Interview
25	Unemployment rate	P18, P19
26	Use of technology and financial consultants (innovative financing and investment instruments) in the Social Security Organization	P20, P21
27	Managerial decision-making style in the Social Security Organization	P4
28	Extent of use of data-driven technologies in the Social Security Organization	P22
29	National information technology infrastructure	Interview

At this stage, in order to eliminate factors with lower relevance to the research topic, an expert evaluation questionnaire was designed. After completion of the questionnaire, the significance levels of the factors were calculated using SPSS version 26 and the binomial test. The binomial test is a nonparametric test, and its use was justified by the non-normal distribution of the research data. Based on the results of the binomial test, factors with significance levels greater than 5% were evaluated, and the results are presented in Table 2.

Table 2. Screening of Driving Forces Using the Binomial Test

No.	Indicators	Statistical Hypotheses	Test Probability	Significance Level	Test Result
1	Level of development of the financial industry in Iran	≥3 / <3	0.50	0.021	Accepted
2	Diversity of Iranian fintechs	≥3 / <3	0.50	0.021	Accepted
3	Growth of financing and investment fintechs in Iran	≥3 / <3	0.50	0.002	Accepted
4	National regulatory policies on technology	≥3 / <3	0.50	0.002	Accepted
5	Development of digital technologies in the country	≥3 / <3	0.50	0.021	Accepted
6	Reforms in the insurance system	≥3 / <3	0.50	0.002	Accepted
7	Changes in global financial markets	≥3 / <3	0.50	0.002	Accepted
8	International economic crises	≥3 / <3	0.50	0.002	Accepted
9	Government financial support	≥3 / <3	0.50	0.002	Accepted
10	Government policies in the field of social security	≥3 / <3	0.50	0.021	Accepted
11	Government debts to the Social Security Organization	≥3 / <3	0.50	0.002	Accepted
12	Exchange rate volatility	≥3 / <3	0.50	0.021	Accepted
13	Inflation rate	≥3 / <3	0.50	0.002	Accepted
14	National economic growth rate	≥3 / <3	0.50	0.021	Accepted
15	Development of regtechs in the country	≥3 / <3	0.50	0.344	Rejected

16	Level of cooperation between financial institutions and fintechs	≥3 / <3	0.50	0.021	Accepted
17	Information systems of the Social Security Organization	≥3 / <3	0.50	0.002	Accepted
18	Demographic composition of the country	≥3 / <3	0.50	0.021	Accepted
19	Level of cooperation between the Social Security Organization and universities	≥3 / <3	0.50	0.002	Accepted
20	Level of cooperation between the Social Security Organization and technology startups	≥3 / <3	0.50	0.021	Accepted
21	Level of development of social security technologies (SinTech) in the country	≥3 / <3	0.50	0.021	Accepted
22	Revenue-generation policies of the Social Security Organization	≥3 / <3	0.50	0.002	Accepted
23	Governance and management style of the Social Security Organization	≥3 / <3	0.50	0.002	Accepted
24	Extent of using international experiences in the Social Security Organization	≥3 / <3	0.50	0.021	Accepted
25	Unemployment rate	≥3 / <3	0.50	0.002	Accepted
26	Use of technology and financial consultants (innovative financing and investment instruments) in the Social Security Organization	≥3 / <3	0.50	0.002	Accepted
27	Managerial decision-making style in the Social Security Organization	≥3 / <3	0.50	0.021	Accepted
28	Extent of use of data-driven technologies in the Social Security Organization	≥3 / <3	0.50	0.002	Accepted
29	National information technology infrastructure	≥3 / <3	0.50	0.002	Accepted

As observed, among the 29 factors extracted from the research literature and expert interviews, only the factor related to the development of regtechs in the country was excluded, and 28 final factors were selected. In the subsequent stage, data were collected through semi-structured interviews with a sample of 10 participants using the snowball sampling method, and the process continued until theoretical saturation was achieved. The data were examined across different levels of Causal Layered Analysis (CLA). At the first level, the future of the Social Security Organization's investments with a focus on technology was addressed, and at the second level, a deeper exploration was conducted through organized perspectives. The worldview layer examined deeper assumptions influencing the future of investments, and the myth layer was assessed as the deepest level of analysis. In the final two stages, in order to align the layered analysis with scenario planning, the identified elements were categorized based on policy, economic, social, and related analyses. Table 3 presents the Causal Layered Analysis of factors affecting the investments of Iran's Social Security Organization with a focus on the role of technology.

Table 3. Causal Layered Analysis of Factors Affecting the Future of Investments of Iran's Social Security Organization with a Focus on the Role of Technology

Layer	Main Theme	Subthemes
Litany	Global and environmental forces	International economic crises
		Changes in global financial markets
	Domestic macroeconomic forces	Inflation rate
		Exchange rate volatility
		National economic growth rate
		Unemployment rate
		Demographic composition of the country
Systemic	Government macro-level policies	Government policies in the field of social security
		Government financial support
		Government debts to the Social Security Organization
		Reforms in the insurance system
	Technological and regulatory infrastructures	National technology regulatory policies
		Development of digital technologies in the country

		National information technology infrastructure
Worldview	Governance and internal capabilities	Information systems of the Social Security Organization
		Revenue-generation policies
		Organizational management style
	Ecosystem interactions and external orientation	Development of the financial industry
		Diversity of fintechs
		Growth of financing fintechs
		Cooperation between institutions and fintechs
		Cooperation between the organization and universities
		Use of international experiences
Myths/Metaphors	Misalignment with technological culture (technology as a tool rather than a paradigm shaper)	Extent of use of technology and financial consultants
		Extent of use of data-driven technologies
	Traditional decision-making structure (dominance of hierarchy over efficiency)	Managerial decision-making style
	Gap between the ecosystem and the organization (“we-are-different” syndrome)	Cooperation with technology startups
		Level of SinTech development

After identifying the factors affecting the investments of Iran’s Social Security Organization with a focus on the role of technology, scenario planning was conducted using the Global Business Network (GBN) approach. Table 4 presents the uncertainties that were taken into account.

Table 4. Uncertainties of Factors Affecting the Investments of Iran’s Social Security Organization with a Focus on the Role of Technology

No.	Uncertainties
1	Development of the financial industry
2	Diversity of fintechs
3	Growth of financing fintechs
4	Cooperation between institutions and fintechs
5	Cooperation between the organization and universities
6	Information systems of the Social Security Organization
7	Revenue-generation policies
8	Organizational management style
9	Use of international experiences
10	Extent of use of technology and financial consultants
11	Extent of use of data-driven technologies
12	Managerial decision-making style
13	Cooperation with technology startups
14	Level of SinTech development

In the next step, the results of the second stage were evaluated using the TOPSIS method. In this evaluation, the options were the identified uncertainties, and the criteria were the importance and probability of occurrence of each uncertainty. To rank the driving forces using the TOPSIS approach, a questionnaire capturing expert opinions was distributed to 10 specialists. Accordingly, the first step in this technique involved constructing the decision matrix.

Table 5. Decision Matrix for Ranking the Driving Forces

Criteria	c1	c2	c3	c4	c5	c6
A1	6	4	7	6	1	1
A2	3	4	6	4	1	3
A3	6	5	4	5	1	1
A4	3	5	1	7	5	5
A5	1	3	3	4	3	3
A6	6	3	1	2	1	2
A7	2	5	2	4	2	7
A8	1	3	5	4	3	4
A9	4	2	3	6	4	1
A10	1	3	5	7	5	3
A11	7	9	9	7	7	9
A12	9	7	7	2	2	6
A13	1	5	3	6	3	5
A14	3	1	4	3	4	4

In Table 5, A1 refers to the first driving force under study, for which the degree of importance relative to other options (driving forces) is to be determined. Normalization, or scale-free transformation, constitutes the second step in solving all matrix-based multi-criteria decision-making techniques.

Table 6. Normalized Decision Matrix of the Driving Forces

Criteria	c1	c2	c3	c4	c5	c6
A1	0.113	0.068	0.117	0.090	0.024	0.019
A2	0.057	0.068	0.100	0.060	0.024	0.056
A3	0.113	0.085	0.067	0.075	0.024	0.019
A4	0.057	0.085	0.017	0.104	0.119	0.093
A5	0.019	0.051	0.050	0.060	0.071	0.056
A6	0.113	0.051	0.017	0.030	0.024	0.037
A7	0.038	0.085	0.033	0.060	0.048	0.130
A8	0.019	0.051	0.083	0.060	0.071	0.074
A9	0.075	0.034	0.050	0.090	0.095	0.019
A10	0.019	0.051	0.083	0.104	0.119	0.056
A11	0.132	0.153	0.150	0.104	0.167	0.167
A12	0.170	0.119	0.117	0.030	0.048	0.111
A13	0.019	0.085	0.050	0.090	0.071	0.093
A14	0.057	0.017	0.067	0.045	0.095	0.074

In the third step of the TOPSIS method, the normalized decision matrix must be weighted. For this purpose, the weight of each criterion is multiplied by all entries under the same criterion. Based on the previous sections, all criteria were assumed to have equal weights (the weight of each criterion equals 0.167). Accordingly, the results are presented in Table 7.

Table 7. Weighted Normalized Decision Matrix

Criteria	c1	c2	c3	c4	c5	c6
A1	0.0189	0.0113	0.0195	0.0150	0.0040	0.0031
A2	0.0095	0.0113	0.0167	0.0100	0.0040	0.0093
A3	0.0189	0.0142	0.0111	0.0125	0.0040	0.0031
A4	0.0095	0.0142	0.0028	0.0174	0.0199	0.0155
A5	0.0032	0.0085	0.0084	0.0100	0.0119	0.0093
A6	0.0189	0.0085	0.0028	0.0050	0.0040	0.0062
A7	0.0063	0.0142	0.0056	0.0100	0.0080	0.0216
A8	0.0032	0.0085	0.0139	0.0100	0.0119	0.0124
A9	0.0126	0.0057	0.0084	0.0150	0.0159	0.0031
A10	0.0032	0.0085	0.0139	0.0174	0.0199	0.0093
A11	0.0221	0.0255	0.0251	0.0174	0.0278	0.0278

A12	0.0284	0.0198	0.0195	0.0050	0.0080	0.0186
A13	0.0032	0.0142	0.0084	0.0150	0.0119	0.0155
A14	0.0095	0.0028	0.0111	0.0075	0.0159	0.0124
PIS	0.0284	0.0255	0.0251	0.0174	0.0278	0.0278
NIS	0.0032	0.0028	0.0028	0.0050	0.0040	0.0031

At this stage, the type of criteria must be specified. Criteria can be either benefit (positive) or cost (negative). Benefit criteria are those whose increase leads to system improvement; for these, the ideal solution equals the maximum value in the criterion column, and the anti-ideal solution equals the minimum value. For cost criteria, the reverse applies. Since all criteria in this study are benefit-type (i.e., higher values are preferable), the maximum value is considered the ideal solution and the minimum value the anti-ideal solution. In the next step, the distances from the positive and negative ideals are examined. At this stage, the relative closeness of each option to the ideal solution is calculated.

Table 8. Distances of Options from the Ideal and Anti-Ideal Solutions

	d_i^+	d_i^-
d+1	0.0305	0.0264
d+2	0.0357	0.0182
d+3	0.0323	0.0224
d+4	0.0325	0.0241
d+5	0.0393	0.0123
d+6	0.0405	0.0167
d+7	0.0381	0.0140
d+8	0.0371	0.0157
d+9	0.0333	0.0192
d+10	0.0337	0.0238
d+11	0.0063	0.0463
d+12	0.0248	0.0351
d+13	0.0363	0.0181
d+14	0.0364	0.0161

The final step involves calculating the ideal solution. At this stage, the relative closeness of each option to the ideal solution is computed. Accordingly, the results are presented in Table 9.

Table 9. Ideal Solution for the Examined Driving Forces

Option	Final Weight	Rank
CL 1	0.4635	3
CL 2	0.3373	9
CL 3	0.4090	6
CL 4	0.4259	4
CL 5	0.2388	14
CL 6	0.2924	12
CL 7	0.2688	13
CL 8	0.2972	11
CL 9	0.3653	7
CL 10	0.4134	5
CL 11	0.8795	1
CL 12	0.5859	2
CL 13	0.3327	8
CL 14	0.3066	10

Based on the final ranking of options relative to the weighted criteria, the driving forces “extent of use of data-driven technologies” and “managerial decision-making style,” with weights of 0.879 and 0.585 respectively, rank first and second, whereas “organizational cooperation with universities,” with a weight of 0.238, ranks fourteenth.

The high weight of data-driven technologies indicates the critical importance of the organization's analytical capability for risk management and opportunity identification, and any scenario in which this driving force is weak entails a high likelihood of failure and adverse outcomes. Moreover, although managerial decision-making style has a lower weight, it reflects the culture and willingness required for effective technology utilization, emphasizing that technology without an appropriate culture will not achieve the desired efficiency.

Subsequently, based on the collective judgment of a five-member team of specialists familiar with foresight processes, the following scenarios were developed.

Scenario One: Transformation Pioneer

This scenario represents the ideal state, in which data-driven technology and an innovative, risk-tolerant organizational culture are simultaneously strengthened. The organization leverages advanced analytical infrastructures, machine learning models, and an integrated data lake, enabling it to forecast cash flows and systemic risks and to manage the investment portfolio dynamically. The investment strategy is aggressive and knowledge-based, with technology functioning as an active competitive advantage. The primary risk is excessive reliance on models and the neglect of non-modelable variables.

Scenario Two: Modern Bureaucrat

This scenario represents the most likely medium-term condition. Advanced technology exists, but a conservative and hierarchical organizational culture prevents the strategic use of data. Technology is employed mainly for control, monitoring, and improving internal efficiency, while innovative and long-term decisions are limited or delayed. The investment strategy is confined to preserving the value of traditional assets, resulting in missed opportunities for rapid growth.

Scenario Three: Intuitive Surge

In this scenario, a risk-tolerant and innovative culture exists, but technological capability is weak. Managerial decisions are largely based on intuition and enthusiasm and lack robust analytical support. The outcome is fragmented and loss-prone investments, and the sustainable realization of this culture without strong analytical data is unlikely.

Scenario Four: Isolated Conservative

This weakest scenario combines low technology with a conservative culture. Investments are undertaken solely to preserve the nominal value of assets, with no effort toward growth or entry into emerging markets. Technology is limited to basic operational systems, and the organization faces a serious long-term threat to its survival.

To achieve the desirable "Transformation Pioneer" scenario, the organization must simultaneously cultivate a risk-tolerant and innovative culture and establish strong analytical and data-driven infrastructures. Given the higher weight of technology (0.879) relative to culture (0.585), the "Modern Bureaucrat" scenario represents the most likely short- and medium-term trajectory. The role of financial technology along this path is realized through three main channels—data analytics, risk management, and operational transparency and efficiency—yet its full realization requires overcoming cultural barriers.

In the next step, a SWOT analysis was employed to analyze the situation and propose strategies for steering toward the third scenario. The results of the SWOT analysis, along with the proposed strategies, are illustrated in Figures 1 and 2.

Weaknesses	Strengths
The dominance of a traditional decision-making style and resistance of senior managers to data-driven decisions. Fragmented and siloed data, along with a lack of systemic integration across organizational units. Low levels of data literacy among middle and senior management. Outdated IT infrastructures and dependence on legacy systems that lack big data processing capabilities.	The organization possesses a massive volume of proprietary data (insurance, healthcare, and financial data). There is a relative availability of information technology infrastructure and technical experts in central units. The financial capacity of investment holding companies (Shasta) provides potential funding for digital transformation. There is internal motivation to automate processes in order to reduce human error.
Threats	**Opportunities**
Severe and unpredictable economic volatility in Iran, which may reduce the accuracy of data-driven forecasting models. Persistent cybersecurity and security threats to sensitive and confidential policyholder data. The emigration of technology and data analytics talent, making it difficult to maintain and develop intelligent systems. Restrictive administrative regulations and heavy bureaucracy in public organizations, hindering the rapid implementation of digital transformation projects.	The rapid development of the domestic fintech and startup ecosystem, enabling strategic collaborations. Access to open-source and cloud-based artificial intelligence and machine learning tools at competitive costs. Social and media pressure for greater financial transparency, creating opportunities for implementing transparency-enhancing technologies (e.g., blockchain). The existence of successful international pension fund models that utilize technology for asset–liability management (ALM).

Figure 1. SWOT Matrix of Strategic Objectives and Vision

Weaknesses	Strengths
Predominance of intuitive and informal decision-making. Resistance to analytically grounded risk-taking. Weak and time-consuming accountability mechanisms. Conflicts of interest and politicization.	Accumulated historical experience of senior managers. Availability of experienced financial analysts and specialists. Formal and hierarchical organizational structure. A tendency toward conservatism.
Threats	Opportunities
Frequent managerial turnover. Governmental laws and regulatory constraints. Pressure from political stakeholders. Financial crises affecting the fund.	The growing importance of corporate governance. Managerial training and development initiatives. The need for agility in responding to inflationary pressures. The use of external consultants.

Figure 2 SWOT Matrix of Managerial Decision-Making Style

Based on the SWOT analyses, and focusing on the two variables “extent of use of data-driven technologies” and “managerial decision-making style,” two categories of macro-level and operational strategies can be formulated to improve the technological status of investments in the Social Security Organization (Shasta) and to move toward the “Transformation Pioneer” position.

Macro-level strategies are designed to change long-term orientations and optimize the use of organizational data. The data–market synergy strategy facilitates investment in fintech, insurtech, and regtech by leveraging the organization’s large-scale and proprietary datasets. Proposed actions include establishing a specialized fintech accelerator to develop indigenous technologies and formulating an integrated data architecture framework to create a centralized data lake and enable large-scale analytics. The analytical and transparent governance strategy aims to reform traditional and politically influenced decision-making styles and includes the localization of data-based incentive models and the development of a blockchain-based transparency system to enhance public trust and prevent discretionary decision-making.

Operational strategies focus on short- and medium-term actions to strengthen internal capabilities and reduce vulnerability. Developing technical and human capacity includes establishing a data academy to enhance managers' data literacy and implementing recruitment and retention models for technology specialists. Infrastructure upgrading and agility are pursued through migration to a hybrid cloud infrastructure and the development of real-time risk analytics tools, enabling rapid responses to market volatility. Decision-making standardization, through mandatory analytical documentation and reduced bureaucracy in technology projects, provides the foundation for effective data utilization and enhanced organizational agility.

Overall, by integrating data-driven technology, transforming decision-making styles, and strengthening organizational infrastructures, these strategies pave the way for Shasta to move toward intelligent, transparent, and agile investment practices.

Discussion and Conclusion

The findings of the present study provide strong empirical support for the central role of technology-driven analytics and managerial decision-making culture in shaping investment efficiency and strategic outcomes within complex organizational settings. The results indicate that data-driven technologies constitute the most influential driver of effective investment decision-making, surpassing traditional structural and policy-related factors. This outcome is consistent with prior research emphasizing that advanced analytics, artificial intelligence, and machine learning substantially enhance forecasting accuracy, risk management, and portfolio optimization by transforming raw data into actionable insights (2-4). The prominence of this driver underscores the transition from intuition-based and experience-driven investment models toward evidence-based, algorithm-supported decision frameworks.

The high ranking of data-driven technologies also aligns with studies demonstrating that digital transformation fundamentally reshapes investment cycles and capital allocation behavior, particularly in large and resource-intensive organizations. Hao et al. argue that digital transformation predicts not only investment volume but also timing and cyclicality by improving information flows and managerial responsiveness (29). Similarly, Zhong highlights that behavioral biases in investment decisions can be mitigated when managers rely on structured analytical systems rather than cognitive shortcuts, such as anchoring or overconfidence (1). The present study extends these findings by showing that without robust data infrastructures, even well-capitalized organizations face a heightened probability of strategic failure and inefficient investments.

The second most influential factor identified in this study is managerial decision-making style, which reflects the cultural and behavioral dimension of investment governance. Although its weight is lower than that of data-driven technologies, its strategic importance lies in enabling—or constraining—the effective use of technological tools. This result corroborates earlier evidence suggesting that executive characteristics, leadership orientation, and openness to analytical risk-taking significantly affect investment outcomes (5, 6). Organizations characterized by conservative, hierarchical, and politically influenced decision-making structures tend to underutilize analytical insights, leading to delayed responses and missed investment opportunities. Conversely, adaptive and analytically oriented leadership cultures facilitate the translation of technological capabilities into strategic value.

The interaction between these two drivers—technology and managerial culture—emerges as a critical explanatory mechanism in the study's scenario analysis. The "Transformation Pioneer" scenario illustrates how the convergence of advanced data analytics and an innovative, risk-tolerant culture enables dynamic portfolio management, proactive risk mitigation, and knowledge-based investment strategies. This scenario resonates with research on AI-driven green finance and sustainable investment, which shows that technological sophistication alone is insufficient unless supported by governance mechanisms and strategic intent (17, 18). The findings thus reinforce the argument that technology acts as a strategic amplifier rather than an autonomous determinant of investment success.

In contrast, the “Modern Bureaucrat” scenario—identified as the most probable short- to medium-term trajectory—reflects a partial and constrained adoption of technology. In this configuration, digital tools are primarily employed for monitoring, control, and incremental efficiency improvements, while strategic and long-term investment decisions remain conservative. This outcome is consistent with studies indicating that organizations often adopt new technologies superficially, using them to reinforce existing bureaucratic structures rather than to enable transformational change (27, 28). The persistence of such a scenario highlights the inertia embedded in formal hierarchies and the challenges of cultural change in large institutional environments.

The lower-ranked drivers, such as cooperation with universities and external knowledge institutions, suggest that while collaborative networks are valuable, their impact on investment outcomes is indirect and contingent upon internal absorptive capacity. Previous studies on industry–university–research alliances emphasize that collaboration enhances innovation investment only when organizations possess sufficient internal capabilities to integrate and exploit external knowledge (23). Similarly, Ochuba et al. note that financial analytics and strategic decision frameworks are most effective when embedded within coherent organizational processes rather than treated as external add-ons (24). The present findings imply that collaboration without strong internal data governance and decision-making discipline yields limited strategic returns.

The SWOT-based strategic analysis further contextualizes these results by revealing structural strengths, weaknesses, opportunities, and threats associated with data-driven investment transformation. The presence of large volumes of proprietary data and financial capacity provides a strong foundation for analytical investment strategies, consistent with evidence that social and informational capital enhance investment efficiency (7). However, weaknesses such as fragmented data systems, low data literacy among senior managers, and outdated IT infrastructures mirror challenges identified in emerging economies, where technological potential is often constrained by institutional rigidity and skills gaps (14, 15). These internal constraints amplify exposure to external threats, including macroeconomic volatility and cybersecurity risks, which have been shown to undermine predictive models and investor confidence (19, 22).

The study’s results also contribute to the broader literature on risk management and resilience. By demonstrating that data-driven technologies enhance not only forecasting accuracy but also organizational agility, the findings align with resilience-oriented investment research emphasizing adaptive strategies under budgetary and environmental constraints (20). Moreover, the emphasis on transparency-enhancing technologies, such as blockchain, corresponds with evidence that improved financial reporting readability and transparency positively influence investment decisions and stakeholder trust (10, 11). Thus, technology-driven transparency emerges as both a risk mitigation tool and a governance mechanism.

Overall, the findings underscore that effective investment strategies in complex organizations require a systemic alignment of technological infrastructure, managerial culture, and governance frameworks. Technology-driven analytics provide the analytical backbone for informed decision-making, but their strategic impact depends on leadership willingness to embrace data-based reasoning and reform traditional decision processes. This integrated perspective advances existing research by empirically validating the interdependence between technological and behavioral drivers of investment performance and by offering a structured scenario-based explanation of potential developmental pathways (1, 8, 29).

Despite its contributions, this study has several limitations. First, the qualitative and expert-based nature of the analysis may limit the generalizability of the findings to other organizational or national contexts. Second, the reliance on perceived importance and probability assessments introduces subjective bias, which may influence the ranking of drivers and scenarios. Third, the study focuses primarily on internal organizational factors and does not empirically model external macroeconomic shocks or geopolitical risks in depth.

Future research could adopt mixed-method or quantitative approaches to validate the identified drivers and scenarios across different industries and institutional settings. Longitudinal studies would be particularly valuable in examining how shifts in managerial culture and technological capability affect investment performance over time. Additionally, future studies could integrate macroeconomic modeling and stress-testing techniques to assess the robustness of data-driven investment strategies under extreme uncertainty.

From a practical perspective, organizations should prioritize the development of integrated data infrastructures alongside targeted programs for enhancing managerial data literacy. Reforming decision-making processes to mandate analytical justification can reduce reliance on intuition and political considerations. Finally, incremental pilot projects in data-driven investment management can serve as learning platforms, enabling organizations to build confidence, reduce resistance to change, and gradually transition toward more intelligent, transparent, and agile investment practices.

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Authors' Contributions

All authors equally contributed to this study.

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The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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