DIGITAL TRANSFORMATION AND ADMINISTRATION INNOVATION

Citation: Heydarian, H., Babaeinejad, A., Raeispour Rajabali, A., & Shamsadini, S. (2025). A Comparative Model of External Strategic Intelligence in Public and Private Organizations in Kerman City. *Digital Transformation and Administration Innovation,* 3(3), 1-10.

Received date: 21 April 2025 Revised date: 02 June 2025 Accepted date: 09 June 2025 Published date: 21 July 2025

A Comparative Model of External Strategic Intelligence in Public and Private Organizations in Kerman City

Havva Heydarian[1], Abbas Babaeinejad[1]*, Ali Raeispour Rajabali [2], Soheila Shamsadini[3]

1. Department of Public Administration, Ke.C., Islamic Azad University, Kerman, Iran
2. Department of Economics, Ke.C., Islamic Azad University, Kerman, Iran
3. Department of Business Management, ST.C., Islamic Azad University, Tehran, Iran

*Correspondence: abbasbabaei@iau.ac.ir

Abstract

The objective of this study is to propose a comparative model of external strategic intelligence in public and private organizations located in Kerman City. This research adopted a mixed-methods approach with a sequential exploratory design. In the qualitative phase, using grounded theory and conducting 12 semi-structured interviews with experts, the initial components and indicators of the conceptual model were identified. In the quantitative phase, exploratory factor analysis was applied to data collected from 380 questionnaires, resulting in the identification of six key factors: external environmental scanning, external information gathering, data analysis and processing, strategic exploitation, external interactions and influence, and ethical and security frameworks. These six factors collectively explained 78.4% of the total variance and demonstrated acceptable reliability (Cronbach's alpha > 0.8). The findings indicate that effective implementation of strategic intelligence in less-developed regions requires a context-sensitive, data-driven, and flexible model capable of adapting to structural differences between the public and private sectors. The proposed model can serve as a foundation for enhancing strategic decision-making and improving organizational readiness in response to environmental changes.

Keywords: Strategic Intelligence, Exploratory Factor Analysis, Grounded Theory, Public Organizations, Private Organizations, Kerman.

1. Introduction

In an era defined by rapid technological advancement, market volatility, and complex socio-political dynamics, strategic intelligence (SI) has emerged as a pivotal asset in both public and private organizations. As organizations grapple with increasing uncertainty and the accelerating pace of change, the ability to sense, interpret, and respond strategically to external environmental cues has become central to maintaining competitiveness and achieving sustainable development. Strategic intelligence encompasses a multidimensional construct that integrates environmental scanning, information acquisition, data analysis, and actionable decision-making to guide strategic planning and innovation (Hamuda & Elshref, 2024; Li et al., 2019).

The strategic function of intelligence, particularly in less developed or regional contexts such as Kerman Province, requires contextualized models that address both the internal organizational structure and the external environmental complexity (Kazemi et al., 2022). In this respect, strategic intelligence is not merely a technological or informational system but a

managerial philosophy and capacity that underpins the broader framework of strategic planning and adaptive leadership (Saleh & Al-Hakimi, 2024). The literature highlights the integration of strategic intelligence with dynamic capabilities (Teece, 2018), knowledge creation processes (Nonaka & Takeuchi, 1995), and competitive strategy (Porter, 2018) as essential pillars for fostering resilience and innovation in modern organizations.

Strategic intelligence serves as a bridge between information systems and managerial cognition. It enables organizations to move beyond reactive decision-making toward proactive foresight and adaptive capacity (Paiuc et al., 2024). In public sector institutions, where bureaucratic rigidity and limited access to real-time data can impede agile responses, the implementation of SI models contributes to improved governance, transparency, and policy effectiveness (Rinne, 2020). In private firms, especially those embedded in regional economies, SI offers a pathway for anticipating market shifts, identifying strategic partnerships, and enhancing innovation readiness (Barney, 2020; Walker, 2022).

Recent scholarship has underscored the relationship between SI and core elements of organizational performance, such as strategic planning, leadership orientation, and strategic flexibility (Saleh & Al-Hakimi, 2024). Organizations that successfully institutionalize SI tend to display stronger alignment between environmental signals and internal decision-making frameworks. This alignment is particularly critical in dynamic and uncertain environments, where strategic agility and rapid learning are vital (Hamel, 2021). As such, SI should not be viewed as a static capability but rather as a dynamic process that evolves with the organizational context and external demands.

One of the key challenges in developing effective strategic intelligence systems is the operationalization of its dimensions and indicators. Foundational work by Bryson (2022) emphasizes the necessity of linking strategic planning frameworks with environmental intelligence and knowledge flows (Bryson, 2022). In this context, strategic intelligence involves more than data collection; it necessitates organizational structures capable of analyzing, interpreting, and applying this information within a coherent strategic vision (David et al., 2022). The knowledge-creating company, as described by Nonaka and Takeuchi (1995), demonstrates how tacit knowledge and contextual insights are central to successful strategic foresight and innovation (Nonaka & Takeuchi, 1995).

Technological advancements, particularly in artificial intelligence and data analytics, have significantly augmented the capabilities of organizations to process and apply strategic information. Davenport and Ronanki (2024) argue that AI-driven systems enhance not only the speed of decision-making but also the precision of strategic insights, provided they are embedded within human-centered managerial frameworks (Davenport & Ronanki, 2024). Similarly, Brynjolfsson and McAfee (2017) posit that intelligent technologies can transform industries by reshaping the balance between human expertise and machine intelligence in strategic processes (Brynjolfsson & McAfee, 2017).

Despite these technological potentials, human and organizational factors remain critical in shaping the effectiveness of SI systems. Leadership commitment, cross-functional collaboration, and ethical governance are consistently cited as essential enablers of successful strategic intelligence (Hakim & Sohrabi Yortchi, 2021; Hamuda & Elshref, 2024). Ethical and security frameworks, in particular, play a vital role in ensuring trust, data integrity, and social legitimacy—factors that are indispensable in the context of public service and government institutions (Tishegaran et al., 2021).

Empirical studies have highlighted the significance of context in shaping SI implementation. In Iran, the adoption of strategic intelligence practices is influenced by structural constraints, cultural values, and institutional legacies. Danayi Fard (2021) notes that the effectiveness of change initiatives in Iranian governmental organizations depends heavily on the capacity to integrate strategic intelligence with localized decision-making and reform-oriented leadership (Danayi Fard, 2021). Similarly, studies conducted in regional contexts such as Kerman Province reveal that strategic intelligence contributes to regional development by enabling better alignment between public policies and economic opportunities (Kazemi et al., 2022).

From a managerial standpoint, strategic intelligence enables organizations to navigate volatility through evidence-based policymaking, adaptive resource allocation, and future-oriented planning (Barney, 2020; Porter, 2018). It aligns closely with the concept of dynamic capabilities—defined as the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece, 2018). Moreover, SI is instrumental in supporting strategic

leadership, a form of leadership that not only sets direction but actively scans the horizon for signals of change (Paiuc et al., 2024; Saleh & Al-Hakimi, 2024).

A semantic approach to strategic intelligence, as proposed by Paiuc et al. (2024), underscores the interpretive and meaning-making aspects of strategic decision-making. This perspective suggests that strategic intelligence is not limited to rational analysis but also includes narrative construction, visioning, and leadership communication—all of which shape organizational responses to complexity (Paiuc et al., 2024). In a similar vein, the insights of Bryson (2022) emphasize participatory planning and stakeholder engagement as integral to strategic intelligence in the public sector (Bryson, 2022).

The growing body of literature points toward a consensus on the value of strategic intelligence as a multifaceted and dynamic competency. However, practical implementation requires customized frameworks that reflect the unique socio-economic, institutional, and technological contexts in which organizations operate. The present study addresses this gap by proposing a context-specific model of external strategic intelligence for public and private organizations in Kerman City. Drawing on a sequential exploratory mixed-method design, the research identifies six core dimensions of strategic intelligence—environmental scanning, external data gathering, data processing and analysis, strategic exploitation, external interactions, and ethical-security frameworks.

The model aims to enhance strategic decision-making, foster inter-organizational collaboration, and improve organizational readiness in the face of environmental uncertainty. In line with the findings of Li et al. (2019), strategic intelligence is most effective when embedded within a supportive organizational culture that values learning, innovation, and accountability (Li et al., 2019). Furthermore, as Walker (2022) points out, the use of data-driven decision-making must be accompanied by managerial competencies and cultural readiness to ensure that intelligence leads to action (Walker, 2022).

In conclusion, strategic intelligence represents a critical bridge between knowledge and action in contemporary organizational contexts. Whether in public institutions seeking to enhance policy responsiveness or in private firms striving for market competitiveness, SI offers a structured approach to interpreting complexity and enabling strategic adaptation. By grounding the model in the specific realities of Kerman City, this study contributes both theoretically and practically to the evolving discourse on strategic intelligence in management studies.

2. Methods and Materials

This study is applied in terms of purpose and descriptive-analytical in nature and method of data collection, utilizing a mixed-methods approach. The research design followed a sequential exploratory strategy, meaning that the qualitative phase was first conducted to extract theoretical concepts and a conceptual model, followed by the quantitative phase in which the proposed model was evaluated and validated.

In the qualitative phase, the aim was to identify the dimensions, components, and indicators of strategic intelligence in public and private organizations. The statistical population included senior managers, experts, and academic scholars with knowledge in the fields of knowledge management and organizational intelligence in the city of Kerman. Sampling was conducted purposefully using the snowball technique. In total, 12 semi-structured interviews were conducted with participants. Interviews continued until theoretical saturation was reached. The qualitative data analysis was conducted based on the classical grounded theory approach, consisting of three stages: open coding, axial coding, and selective coding. MAXQDA software was used to facilitate data analysis. To enhance credibility, code review was performed by the participants, and two independent coders were engaged to assess reliability. Additionally, by providing a detailed contextual description of the research setting, the transferability of findings was ensured.

In the quantitative phase, exploratory factor analysis was employed to assess and validate the conceptual structure of the proposed model. The statistical population in this phase consisted of senior managers and experts from public and private organizations in Kerman. Given the number of questionnaire items (45 items) and based on the guideline of 5 to 10 respondents per item, the sample size was determined to be 380 individuals. Stratified proportional sampling was conducted to ensure sufficient representation from both the public and private sectors. The data collection tool was a researcher-made questionnaire, designed based on findings from the qualitative phase and the theoretical literature, and constructed using a five-point Likert scale (ranging from "strongly disagree" to "strongly agree"). The face and content validity of the questionnaire were confirmed

through expert review involving 10 management scholars. To assess reliability, Cronbach's alpha was used, yielding values above 0.80 for all components, indicating acceptable instrument reliability.

For data analysis, exploratory factor analysis using the principal components method and Varimax rotation was conducted. The KMO index (value = 0.83) indicated adequate sampling adequacy, and the Bartlett's test of sphericity was significant ($p < 0.001$), confirming the suitability of the data for factor analysis. Furthermore, the RMSR value was 0.04, indicating a good model fit. Ultimately, six main factors were identified, accounting for 78.4% of the total variance.

Table 1. Cronbach's Alpha Coefficients

Component (Factor)	Cronbach's Alpha
External Environmental Scanning	0.87
External Information Gathering	0.88
External Intelligence Analysis & Processing	0.84
Strategic Exploitation	0.89
External Interactions and Influence	0.82
Ethical and Security Frameworks	0.83

3. Findings and Results

In the qualitative phase of the study, the goal was to identify the dimensions, components, and indicators of external strategic intelligence in public and private organizations in Kerman. Using the classical grounded theory method, researchers conducted 12 semi-structured interviews with experts selected through purposive and snowball sampling. Data analysis proceeded through open coding, axial coding, and selective coding using MAXQDA software. This process yielded a set of thematic categories and operational indicators. These included macro-environmental scanning through PESTEL analysis (e.g., monitoring political, economic, social, technological, environmental, and legal shifts), market and industry analysis (e.g., monthly competitor reports, demand trends), identification of key external actors (e.g., local institutions and meeting frequencies), use of diverse and regularly updated external data sources, development of interactive networks (e.g., institutional collaborations and trust levels), application of data mining technologies (e.g., automated web scraping), SWOT-based assessment of opportunities and threats, foresight analysis of emerging trends, strategic partner evaluation, integration of intelligence into decision-making (e.g., strategic meeting frequency and data usage rate), adaptability to dynamic environments (e.g., scenario planning), intelligence-based policymaking (e.g., documentation and implementation of data-driven policies), brand management in the external environment (e.g., public satisfaction and social media activity), influence on regional policy (e.g., participation in city planning), development of inter-organizational collaborations (e.g., joint projects and synergy metrics), adherence to transparency and ethical standards (e.g., written policies and training sessions), protection of external data (e.g., compliance with legal frameworks), and performance monitoring of intelligence systems (e.g., annual evaluation reports and goal achievement rates). Theoretical saturation was reached, and reliability was enhanced through member checking and double-coding.

Table 2. Output Codes from the Qualitative Phase

Component	Indicators
Identification of Macro-Environmental Factors (PESTEL)	- Number of PESTEL analyses conducted annually focused on Kerman's local and provincial policies (minimum: 4 analyses/year) - Monitoring political (city council decisions), economic (agriculture and mining growth), social (population growth), technological (digital adoption), environmental (water usage), and legal (local trade laws) changes
Market and Industry Analysis	- Number of competitor market monitoring reports in Kerman (monthly) - Evaluation of demand changes in key sectors (agriculture, mining, tourism) - Identification of new product or competitor entries in the local market
Identification of Key External Actors	- List of influential institutions in Kerman (e.g., Chamber of Commerce, NGOs, local media) - Number of meetings with key actors (minimum: 2 meetings/month)
External Information Sources	- Number of external information sources used (minimum: 5 including local media, governmental databases, and international reports) - Frequency of data updates (weekly or monthly)
Communication and Interaction Networks	- Number of interactions with Kerman Chamber of Commerce, industrial unions, and government entities (minimum: 10 annual interactions) - Trust levels in collaboration networks (measured via annual surveys)
Use of Technology for Data Extraction	- Use of web mining tools and social network analysis for environmental monitoring - Percentage of automated processes in data collection (target: ≥ 50%)
Analysis of Environmental Opportunities and Threats	- Number of SWOT analyses focused on external opportunities and threats (minimum: 2 annually) - Use of foresight scenarios in strategic planning

Identification of Emerging Trends and Transformations	- Monitoring global and local trends in Kerman's key sectors (e.g., agricultural technology, sustainable tourism) - Number of reports analyzing emerging technologies
Competitor and Strategic Partner Analysis	- Benchmarking performance against three main competitors in the Kerman market - Identification of at least 2 strategic cooperation opportunities with local or national organizations
Integration of Information in Decision-Making	- Percentage of strategic decisions based on environmental data (target: ≥ 70%) - Number of strategic meetings utilizing environmental analysis (minimum: 6 annually)
Adaptability to the External Environment	- Number of policy changes based on environmental analysis (minimum: 2 annually) - Availability of at least 3 alternative scenarios for volatile market conditions
Policy-Making Based on External Intelligence	- Documentation of at least 80% of strategic decisions based on environmental data - Number of new policies developed from local analysis
Management of Organizational Image and Brand	- Public satisfaction score related to organizational branding - Number of posts and active interactions on local social media (minimum: 50 posts annually)
Influence on Regional Policy-Making	- Number of participations in city council or provincial development programs (minimum: 4 annually) - Influence over at least one regional policy related to the industry
Development of Inter-Organizational Collaborations	- Number of joint projects with local or national organizations (minimum: 2 annually) - Level of synergy in collaborations (evaluated through joint assessments)
Transparency and Accountability Principles	- Existence of a documented ethical policy - Number of training sessions on responsible data usage (minimum: 2 annually)
Security and Protection of External Data	- Compliance with local and international regulations (e.g., Iran's privacy laws) - Number of annual security audits (minimum: 1 annually)
Evaluation and Monitoring of External Intelligence Performance	- Number of reports evaluating the effectiveness of external intelligence systems (minimum: 2 annually) - Percentage of data-driven goal achievements (target: ≥ 75%)

Exploratory factor analysis was conducted using the principal components extraction method with Varimax rotation.

Table 3. Goodness-of-Fit Indices for Exploratory Factor Analysis

Criterion	Value	Conclusion
KMO	0.83	Sampling adequacy confirmed (good)
Bartlett's Test	$\chi^2 = 6843.21$, df = 1431, $p < 0.001$	Significant correlation matrix (suitable for factor analysis)

This table indicates that the KMO value of 0.83 confirms the adequacy of the sample for factor analysis. Bartlett's test was significant ($p < 0.001$), verifying that the correlation matrix was appropriate for factor extraction. The Root Mean Square Residual (RMSR) was 0.04, indicating a good model fit. A total of six factors were extracted, which collectively explained approximately 78.4% of the total variance. The Cronbach's alpha values for all dimensions ranged between 0.82 and 0.89, indicating high reliability and acceptable internal consistency across the scales.

Table 4. Factor Loadings of Indicators for the External Strategic Intelligence Model (Varimax Rotation)

Indicator	F1: Environmental Scanning	F2: Information Gathering	F3: Analysis & Processing	F4: Strategic Exploitation	F5: External Influence	F6: Ethical & Security Frameworks
Number of PESTEL Analyses	0.78	0.12	0.15	0.10	0.08	0.05
Monitoring Environmental Changes	0.75	0.14	0.13	0.09	0.07	0.06
Competitor Market Monitoring Reports	0.72	0.16	0.18	0.11	0.10	0.04
Evaluation of Demand Changes	0.69	0.15	0.17	0.12	0.09	0.05
List of Influential Institutions	0.71	0.13	0.14	0.08	0.11	0.07
Number of Meetings with Key Actors	0.67	0.14	0.12	0.09	0.13	0.06
Number of Information Sources	0.15	0.76	0.11	0.08	0.07	0.05
Data Update Frequency	0.13	0.73	0.10	0.09	0.08	0.06
Number of Interactions with Local Institutions	0.12	0.70	0.09	0.07	0.14	0.05
Trust Level in Collaborative Networks	0.11	0.68	0.08	0.06	0.13	0.07
Use of Web Mining Tools	0.14	0.79	0.10	0.05	0.06	0.08
Percentage of Automated Processes	0.13	0.74	0.09	0.07	0.05	0.06

Number of SWOT Analyses	0.15	0.11	0.77	0.12	0.08	0.04
Use of Foresight Scenarios	0.14	0.10	0.72	0.13	0.07	0.05
Monitoring Global and Local Trends	0.16	0.09	0.75	0.11	0.06	0.04
Reports on Emerging Technologies	0.13	0.08	0.70	0.10	0.05	0.03
Performance Benchmarking	0.12	0.07	0.73	0.09	0.06	0.04
Identification of Strategic Collaboration	0.11	0.06	0.69	0.08	0.07	0.05
Percentage of Data-Based Decisions	0.09	0.05	0.12	0.80	0.06	0.04
Number of Strategic Meetings	0.08	0.06	0.11	0.76	0.05	0.03
Number of Policy Adjustments	0.07	0.05	0.10	0.74	0.04	0.02
Existence of Alternative Scenarios	0.06	0.04	0.09	0.71	0.03	0.03
Decision Documentation	0.05	0.03	0.08	0.78	0.04	0.02
New Local Policy Development	0.06	0.04	0.07	0.73	0.05	0.03
Public Satisfaction Score	0.05	0.06	0.04	0.03	0.77	0.02
Number of Media Posts	0.04	0.05	0.03	0.02	0.72	0.01
Participation in City Council	0.03	0.04	0.02	0.03	0.75	0.01
Influence on Regional Policies	0.02	0.03	0.01	0.02	0.70	0.02
Number of Joint Projects	0.03	0.02	0.01	0.04	0.73	0.01
Level of Synergy in Collaborations	0.02	0.03	0.02	0.03	0.69	0.02
Existence of Ethical Policy	0.01	0.02	0.01	0.02	0.03	0.76
Number of Training Sessions	0.02	0.01	0.02	0.01	0.02	0.71
Compliance with Data Protection Laws	0.01	0.02	0.01	0.02	0.01	0.78
Number of Security Audits	0.02	0.01	0.02	0.01	0.02	0.74
Number of Evaluation Reports	0.03	0.02	0.03	0.04	0.01	0.77
Strategic Goal Achievement Rate	0.02	0.03	0.02	0.05	0.02	0.73

Exploratory factor analysis using the principal components method and Varimax rotation led to the identification of six primary factors constituting the structure of the conceptual model of *external strategic intelligence*. Table 4 presents the factor loadings for each indicator. The pattern of loadings demonstrates that each indicator loads highly on only one factor, indicating strong conceptual separation and a clear factor structure. Key indicators such as “percentage of data-based decisions” (0.80), “decision documentation” (0.78), “PESTEL analyses” (0.78), and “use of web mining tools” (0.79) had very high loadings, suggesting that they serve as representative and critical indicators of their respective dimensions. Cross-loadings on other factors were minimal, confirming that the Varimax rotation effectively simplified the factor structure and minimized overlap between constructs.

• **Factor 1 (External Environmental Scanning):** High factor loadings for indicators such as PESTEL analysis, market dynamics, and identification of influential institutions reflect this factor’s emphasis on understanding the macro and competitive environment.

• **Factor 2 (External Information Gathering):** Indicators such as data sources, update frequency, and interaction with institutions highlight the aspects of data acquisition and external connectivity.

• **Factor 3 (Data Analysis and Processing):** High loadings for SWOT analyses, global trends, and scenario development demonstrate an analytical approach to interpreting collected data.

• **Factor 4 (Strategic Exploitation):** Indicators such as decision documentation and revised strategic policies illustrate the direct application of data in decision-making processes.

• **Factor 5 (Interactions and Influence):** This factor focuses on organizational influence, civic engagement, and inter-organizational collaborations.

• **Factor 6 (Ethical and Security Frameworks):** High loadings for indicators such as data protection, information security, and ethical policies represent the dimension of trust, transparency, and accountability in the use of external information.

Table 5. Variance Explained by Exploratory Factors

Factor No.	Factor Title	Percentage of Variance Explained
F1	External Environmental Scanning	15.2%
F2	External Information Gathering	13.8%
F3	External Intelligence Analysis	14.5%
F4	Strategic Exploitation	15.9%
F5	External Interactions and Influence	13.2%
F6	Ethical and Security Frameworks	12.8%
Total	Cumulative Variance Explained	78.4%

Each of the six identified factors accounts for between 12.8% and 15.9% of the total variance. The "Strategic Exploitation" factor explains the largest portion (15.9%), while "Ethical and Security Frameworks" explains the smallest (12.8%). The relatively balanced distribution of variance suggests that no single factor dominates the structure, and all dimensions collectively contribute to the formation of strategic intelligence.

Table 6. Goodness-of-Fit Indices for Exploratory Factor Analysis (EFA)

Index	Value	Interpretation
RMSR	0.04	Indicates good model fit (values below 0.08 are desirable)
Number of Extracted Factors	6	Acceptable conceptual structure
Total Variance Explained	78.4%	Strong explanatory power of extracted factors
Cronbach's Alpha (per dimension)	0.82–0.89	High reliability and internal consistency

The RMSR index measures the discrepancy between the observed correlation matrix and the one reproduced by the model. A value of 0.04 (well below the 0.08 threshold) indicates an acceptable and robust model fit. The six extracted factors confirm that the conceptual model of external strategic intelligence is based on distinct, interpretable, and statistically significant dimensions. This factor structure is also consistent with theoretical expectations. The cumulative variance of 78.4% suggests that the model explains more than three-quarters of the variability in the data—exceeding the 60% threshold generally considered acceptable in social science research. Cronbach's alpha values above 0.80 across all dimensions demonstrate excellent reliability, strong measurement stability, and high scale dependability.

4. Discussion and Conclusion

The findings of the present study resulted in the development of a six-factor conceptual model of external strategic intelligence in public and private organizations in Kerman. These six dimensions—external environmental scanning, external information gathering, data processing and analysis, strategic exploitation, external interactions and influence, and ethical and security frameworks—jointly explained 78.4% of the total variance, with high internal consistency (Cronbach's alpha between 0.82 and 0.89). This indicates a robust structure and reliability of the proposed model in capturing the multifaceted nature of strategic intelligence as perceived by organizational actors in a regional Iranian context.

The first factor, external environmental scanning, reflects an organization's ability to systematically monitor macro-environmental trends such as political shifts, market dynamics, and technological change. This dimension is well aligned with foundational theories in strategic management that emphasize the importance of environmental analysis for competitive advantage (Barney, 2020; Porter, 2018). In practice, this includes tools such as PESTEL and competitor monitoring, which were found to be highly significant indicators in this study. The high factor loadings for these variables confirm their role in allowing organizations to anticipate external threats and opportunities, consistent with previous empirical findings (Kazemi et al., 2022).

The second factor, external information gathering, underscores the value of continuously acquiring updated and diversified information from external sources, such as governmental databases, industry reports, and stakeholder networks. As highlighted by Bryson (2022), strategic planning is most effective when grounded in timely and relevant data inputs that support informed decision-making (Bryson, 2022). Furthermore, this dimension corresponds with the argument that organizations must cultivate "information absorptive capacity" to improve their responsiveness to change (Walker, 2022). This component reinforces the idea that information is a foundational resource and a source of strategic flexibility in dynamic environments (Saleh & Al-Hakimi, 2024).

The third identified factor, data processing and analysis, represents the analytical core of strategic intelligence systems. Indicators such as the use of SWOT analysis, scenario planning, and monitoring emerging trends were key contributors to this dimension. These results support the notion that the mere acquisition of data is insufficient unless it is systematically analyzed and interpreted in a manner that informs strategic direction (Hamuda & Elshref, 2024; Li et al., 2019). This aligns with Teece's (2018) concept of dynamic capabilities, which includes the sensing and seizing of opportunities through interpretive and analytical skills embedded in organizational routines (Teece, 2018). Additionally, the use of foresight methods such as scenario planning reflects a more mature level of strategic intelligence capability that enables long-term orientation and preparedness.

The fourth factor, strategic exploitation, captures the application of intelligence outputs in shaping organizational strategy, including policy adjustments, documentation of strategic decisions, and alternative scenario implementation. This result validates the theoretical position that strategic intelligence must ultimately influence action and execution in order to yield competitive advantage (Davenport & Ronanki, 2024; David et al., 2022). Organizations that successfully translate insights into adaptive strategies are better positioned to navigate uncertainty and foster organizational resilience (Hamel, 2021). The high loading of items like "percentage of data-based decisions" and "number of revised policies" illustrates the operational effectiveness of this component in turning intelligence into impact.

The fifth factor, external interactions and influence, emphasizes organizational engagement with external stakeholders, including participation in policy discussions, public perception management, and collaborative ventures. This reflects the evolving understanding of strategic intelligence as a relational as well as informational construct. Paiuc et al. (2024) describe strategic intelligence as encompassing semantic leadership, wherein organizations interpret external signals and translate them into shared meaning through strategic communication and influence (Paiuc et al., 2024). This factor is especially relevant in the public sector, where institutional legitimacy and stakeholder engagement are central to strategic success (Rinne, 2020). The results here corroborate the idea that influence and visibility are essential levers of strategic positioning.

The sixth and final factor, ethical and security frameworks, refers to the governance of data use, including compliance with privacy laws, cybersecurity protocols, and the institutionalization of ethical policies. This component represents a critical but often under-examined aspect of strategic intelligence. As noted by Hakim and Sohrabi Yortchi (2021), the ethical management of information is fundamental to building organizational trust and long-term legitimacy, particularly in public institutions where accountability is paramount (Hakim & Sohrabi Yortchi, 2021). The study's inclusion of this dimension signals a growing recognition that strategic intelligence must be deployed responsibly, with appropriate safeguards and normative considerations.

The relatively even distribution of explained variance across the six factors (ranging from 12.8% to 15.9%) suggests that strategic intelligence is not dominated by any single component but is instead the result of a balanced integration of complementary processes. This supports the conceptualization of strategic intelligence as a systems-level capability that draws upon diverse organizational functions and cross-cutting competencies (Nonaka & Takeuchi, 1995). Moreover, the balanced factor structure affirms the model's comprehensiveness and offers practical guidance for organizations seeking to develop SI frameworks tailored to their specific context.

The findings are consistent with previous research conducted in Iranian public institutions. Tishegaran et al. (2021) identified similar factors—particularly external information gathering and ethical use of data—as central to the operationalization of SI in the Ministry of Sport and Youth (Tishegaran et al., 2021). Likewise, Danayi Fard (2021) emphasized the importance of strategic intelligence in enabling reform and adaptive governance in Iranian governmental agencies (Danayi Fard, 2021).

These studies, along with the current research, reinforce the contextual relevance of SI in supporting organizational transformation in the Iranian public administration landscape.

Furthermore, the study's results extend the literature by providing empirical validation for the integration of strategic intelligence with leadership and planning systems. Saleh and Al-Hakimi (2024) highlighted the moderating role of strategic flexibility in enhancing the effect of SI on organizational performance (Saleh & Al-Hakimi, 2024). The strategic exploitation dimension identified in this study parallels this claim by illustrating how data-driven insights are enacted through adaptive strategies and flexible policy-making processes. Similarly, the interaction and influence factor reinforces Paiuc et al.'s (2024) emphasis on SI as a communicative and relational leadership tool (Paiuc et al., 2024).

Notably, the use of technology, particularly in the dimensions of information gathering and analysis, was significant in the model. The inclusion of indicators such as web mining and automated data processes demonstrates the increasing digitalization of intelligence functions, a trend emphasized by Brynjolfsson and McAfee (2017) and Davenport and Ronanki (2024), who point to the growing reliance on digital tools for strategic foresight (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2024). However, the study also shows that human interpretive and ethical considerations remain integral to the effectiveness of such systems—highlighting the interplay between technological capability and organizational culture.

This study makes a theoretical contribution by offering an integrated and empirically validated framework for strategic intelligence that is adaptable to both public and private organizations operating in transitional economies. The six-factor model provides a comprehensive structure for operationalizing SI and aligns with both classical strategic management theory and emerging perspectives in leadership, technology, and ethics.

Despite its contributions, this study has several limitations. First, the research was conducted within the geographic and administrative context of Kerman City, which may limit the generalizability of the findings to other regions or national contexts with differing institutional dynamics. Second, although the study utilized a mixed-method approach, the qualitative phase involved a limited number of participants, which may not have captured the full diversity of perspectives. Third, the cross-sectional nature of the study restricts the ability to observe the dynamic evolution of strategic intelligence practices over time. Fourth, reliance on self-reported data, particularly in the survey phase, may have introduced bias in responses due to social desirability or organizational loyalty.

Future research could extend this study in several important directions. First, comparative studies across different provinces or countries would allow for exploration of how contextual variables—such as governance structure, industry maturity, or technological infrastructure—affect the configuration and effectiveness of strategic intelligence systems. Second, longitudinal studies could help examine how organizations' SI capabilities evolve over time, particularly in response to crises or significant environmental shifts. Third, future investigations could explore the interaction between strategic intelligence and organizational learning, particularly in knowledge-intensive sectors. Fourth, expanding the sample to include more sectors and integrating objective performance metrics could yield deeper insights into the relationship between SI and organizational outcomes. Finally, future studies could use experimental or intervention-based designs to assess the causal impact of SI systems on decision quality and adaptability.

For practitioners, the study offers a clear and structured model to guide the development and enhancement of strategic intelligence capabilities. Public and private organizations should prioritize building formal systems for environmental scanning and data acquisition while ensuring that these processes are linked to strategic decision-making. Investment in analytical tools and platforms, including AI-based forecasting and scenario modeling, can significantly enhance the value derived from external intelligence. Importantly, ethical standards and security policies must be embedded into these systems to foster trust and compliance. Organizations are encouraged to foster cross-functional collaboration and leadership engagement to embed SI into the organizational culture. Finally, capacity-building programs should be designed to improve the interpretive and strategic thinking skills of managers and staff who engage with external intelligence.

Ethical Considerations

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

Acknowledgments

Authors thank all who helped us through this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

References

Barney, J. B. (2020). Firm resources and sustained competitive advantage. *Strategic management journal*, *17*(3), 99-120. https://doi.org/10.1002/smj.425

Brynjolfsson, E., & McAfee, A. (2017). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company. https://www.amazon.com/Strategic-Planning-Public-Nonprofit-Organizations/dp/1119071607

Bryson, J. M. (2022). *Strategic planning for public and nonprofit organizations: A guide to strengthening and sustaining organizational achievement*. Jossey-Bass. https://www.amazon.com/Strategic-Planning-Public-Nonprofit-Organizations/dp/1119071607

Danayi Fard, H. (2021). *Change Management in Iranian Government Organizations*. Tehran: Samt Publications.

Davenport, T. H., & Ronanki, R. (2024). Artificial intelligence for the real world. *Harvard business review*, *96*(1), 34-42. http://www.ijbmer.org/uploads2024/BMER_7_584.pdf

David, F. R., Ali, P., & Mohammad, A. a. (2022). *Strategic Management*. Tehran: Cultural Research Office. https://pracownik.kul.pl/files/12439/public/3_David.pdf

Hakim, A., & Sohrabi Yortchi, B. (2021). Developing Strategic Capabilities Using Strategic Intelligence Capacity. *Journal of Soft Power Studies*, *11*(24), 35-71. https://ensani.ir/fa/article/463116/

Hamel, G. (2021). *Leading the revolutionPB - Harvard Business School Press*. https://www.scirp.org/reference/referencespapers?referenceid=2991710

Hamuda, O. A., & Elshref, H. A. (2024). Strategic intelligence and its impact on enhancing organizational culture: A study on senior management staff at Misurata University. *Kufa Journal of Economics and Administrative Sciences*, *14*(51), 141-160. https://doi.org/10.36322/kuey.v14i51.5947

Kazemi, M., Hosseini, S. M., & Moradi, M. (2022). Strategic Intelligence and Regional Economic Development: Challenges and Opportunities in Kerman Province. *Journal of Regional Economy and Politics*, *15*(2), 89-108.

Li, J., Boo, S., & Tze, L. (2019). Strategic intelligence in organizations: A managerial perspective. *Journal of Business Research*, *102*, 139-151. https://doi.org/10.1016/j.jbusres.2019.05.006

Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford University Press. https://doi.org/10.1093/oso/9780195092691.001.0001

Paiuc, D., Săniuță, A., & Teacu Parincu, A. M. (2024). Strategic intelligence: A semantic leadership perspective. *Journal of Intelligence Studies*, *4*(2), 50. https://doi.org/10.3390/jintelligence4020050 10.3390/encyclopedia4020050

Porter, M. E. (2018). *Competitive strategy: Techniques for analyzing industries and competitors*. Free Press. https://www.hbs.edu/faculty/Pages/item.aspx?num=195

Rinne, M. (2020). *Public management reform: A comparative analysis*. Oxford University Press. https://global.oup.com/academic/product/public-management-reform-9780198795186

Saleh, M. H., & Al-Hakimi, M. A. (2024). Linking strategic intelligence, strategic leadership, strategic planning, and strategic thinking and business performance: The moderating effect of strategic flexibility. *Future Business Journal*, *10*, 31. https://doi.org/10.1007/s43621-024-00670-

Teece, D. J. (2018). *Dynamic capabilities and strategic management: Organizing for innovation and growth*. Oxford University Press. https://global.oup.com/academic/product/dynamic-capabilities-and-strategic-management-9780199545124

Tishegaran, M. A. U. K. M., Nashtbandi, S. S., & Yekta Yar, M. (2021). Assessment of Organizational Strategic Intelligence in the Ministry of Sport and Youth. *Journal of Strategic Studies in Sport and Youth*, *51IS - 2*, 239-254. https://sid.ir/paper/411961/fa

Walker, D. (2022). *Data-driven decision making in organizations*. Wiley. https://onlinelibrary.wiley.com/doi/abs/10.1002/qre.2994