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A Context-Specific Framework for Managing Digital Transformation with Artificial Intelligence in Data-Driven Decision-Making: A Delphi Gap Analysis of Executive Agencies in Bushehr Province

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ABSTRACT

This study develops a context-specific framework for managing digital transformation in Iran's administrative system, with an emphasis on artificial intelligence (AI) in data-driven decision-making, and examines the gap between the perceived necessity of digital-transformation requirements and their implementation feasibility in the executive agencies of Bushehr Province. The study is applied in purpose and descriptive–exploratory in design. Twenty-eight indicators in ten dimensions, derived from the literature, were evaluated in a two-round modified Delphi survey by 25 experts in public administration, information technology and administrative transformation, each on two five-point scales: necessity and implementation feasibility. All 28 indicators were rated as necessary (mean necessity 4.00–4.72) in the first round; feasibility means ranged from 3.76 to 4.12 after the second round. Feasibility was lower than necessity for every indicator (gaps from −0.08 to −0.84). Paired Wilcoxon signed-rank tests showed that the gap was significant for 24 indicators at the 5% level and for 7 after Holm correction. The largest gaps concerned the use of intelligent tools to shorten responses to citizens (−0.84), the share of strategic decisions supported by AI (−0.76), and decision-support systems, integrated data infrastructure, AI maturity and cost reduction (−0.68 each), followed by managers' commitment, employees' data literacy and an evidence-based decision culture (−0.64). Based on these findings, a four-layer conceptual–operational framework (infrastructure, processes, human resources and governance) is proposed, together with practical recommendations for the province. Because the evidence comes from a small expert panel, the framework is a well-founded proposal to be tested empirically rather than a validated causal model.

1. INTRODUCTION

Contemporary governance systems are currently transitioning from fourth-generation technocratic models toward new horizons of smart and human-centered governance in the fifth era [1]. In this strategic shift, the focus is no

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longer limited to automation and connectivity; rather, it increasingly centers on intelligent human–artificial intelligence interaction, value-based governance, and the enhancement of organizational resilience [2].

In this context, emerging technologies have become among the most critical drivers of transformation in managerial structures [3]. Alongside this transformation, governments worldwide have increasingly leveraged capabilities such as big data, cloud computing, and, particularly, artificial intelligence (AI) to move toward models commonly referred to as smart governance or data-driven government [4].

Within this paradigm, managerial decision-making is increasingly based not on individual experience, speculation, and intuitive judgment, but on the rigorous analysis of objective data and the application of intelligent algorithms [5, 6]. AI, in this regard, can fundamentally enhance the quality, speed, and accuracy of administrative decisions by identifying hidden patterns and generating strategic forecasts [7].

In Iran, considerable efforts have also been undertaken in recent years to develop e-government and advance the realization of smart government [8]. The establishment of integrated service portals, the national information exchange gateway, and the development of specialized information systems represent important steps forward. Nevertheless, the current situation indicates that many of these initiatives have largely remained at the level of digitizing traditional processes and have not yet resulted in genuine digital transformation, which requires a fundamental shift in the decision-making paradigm [9]. At present, many executive agencies face the problem of fragmented and siloed information systems, while decision-making processes remain influenced by conservative practices and personal judgments [10].

Under such circumstances, Iran's administrative system faces a paradox of data accumulation accompanied by analytical fragmentation. Despite the massive generation of big data, decision-making processes continue to rely on entrenched administrative routines and inflexible patterns inherited from the past [11]. This profound gap between the technological capabilities of the contemporary era and implementation realities further highlights the need to reconsider digital transformation management models, with particular emphasis on AI as a decision-support and decision-enabling capability [12].

A key and distinctive premise of this study is that the fundamental problem facing Iran's administrative system is not necessarily a lack of data; rather, the central challenge lies in the ineffective and non-value-creating utilization of data. In fact, while vast amounts of governmental data are generated and stored in information databases, organizations continue to experience a condition of insight poverty amid data abundance [13]. The absence of analytical infrastructures, the lack of an integrated data governance system, and managerial skills gaps have prevented these valuable assets from being transformed into actionable managerial knowledge [14].

On the other hand, success in this endeavor requires the localization of global models in accordance with the specific requirements and institutional characteristics of Iran's administrative system. The country's administrative structure is characterized by features such as pronounced centralization, constraints arising from budgetary regulations, and a traditional organizational culture [15]. Therefore, merely replicating foreign models is likely to undermine the success of the transformation process [16].

Furthermore, the introduction of AI has generated emerging ethical and security considerations, including the protection of privacy, safeguarding national data security, and preventing algorithmic bias. Neglecting these considerations may undermine public trust [17, 18].

In light of the above, the central problem addressed by this study is to investigate the gap between the technological capabilities of the fifth era and the implementation realities of Iran's administrative system. Most previous studies have either focused on technical aspects or examined individual dimensions of digital transformation in isolation. Focusing on the executive agencies of Bushehr Province, this study seeks to explain how digital transformation management and the application of AI can facilitate the transition of the decision-making system from a traditional state toward an intelligent, data-driven state, while simultaneously addressing local and ethical requirements and enhancing the productivity and effectiveness of executive agencies.

1.1. Research objectives

1.1.1. Main objective

To develop a conceptual framework for digital transformation management in the executive agencies of Bushehr Province, with an emphasis on transitioning from insight poverty to intelligent, data-driven decision-making in the fifth era of governance.

1.1.2. Specific objectives

- To identify and explain the key components of AI-driven digital transformation in accordance with the requirements of contemporary administrative systems.
- To investigate and prioritize local challenges including structural, cultural, ethical, and legal dimensions in the process of realizing digital transformation.
- To examine the challenges of digital transformation in the executive agencies of Bushehr Province.
- To develop a context-specific conceptual framework for establishing an intelligent, data-driven decision-making system at the macro-management level of the province.

1.2. Definitions of key concepts

1.2.1. Digital transformation

Digital transformation is a fundamental and strategic process that, through the integration of information, computing, communication, and connectivity technologies, brings about significant changes in the characteristics of an institution and drives it toward redefining its value proposition, organizational identity, and business models [19]. At a broader level, this process strategically employs key resources and capabilities to create substantial improvements and innovation within an organization, industry, or society and to generate value for stakeholders [4, 20].

1.2.2. Futures studies

Futures studies is a systematic approach that, by identifying drivers and uncertainties, focuses not on predicting a single future but on mapping possible, probable, and desirable futures [21]. With the aim of designing a desirable future and reducing strategic surprises, this field enables actors to make more informed and proactive decisions in the present through methods such as scenario planning and trend analysis. In the present study, this concept serves an intermediary role by transforming raw digital transformation data into strategic insights [22, 23].

1.2.3. Data-driven decision-making

Data-driven decision-making represents a transition from an intuitive approach to an analytical and evidence-based approach. By reducing cognitive biases and progressing through the cycle of transforming data into insights and decisions, it can substantially improve the efficiency, accuracy, and transparency of organizational decisions [19, 24, 25]. However, success in this transition cannot be achieved merely through the acquisition of technological tools. It requires leadership commitment, investment in workforce capabilities, and, most importantly, the development of an organizational culture in which data is recognized as a valuable asset and a primary basis for decision-making [26, 27].

1.2.4. Administrative system

The administrative system is an interconnected set of structures, laws and regulations, processes, institutions, and human resources responsible for planning, organizing, directing, and delivering public services [28, 29]. As the executive arm of government, this system is responsible for providing public services, implementing laws, and realizing governmental objectives and policies within society [30, 31]. In other words, governmental political, economic, social, and cultural decisions and programs cannot be effectively implemented without the support of a functioning administrative system [29].

2. LITERATURE REVIEW

2.1. Iranian studies

In one domestic study, Kazemi et al. (2025) examined the future-oriented dimensions of smart public governance in their study entitled "Smart Public Governance Scenarios Based on Digital Transformation: Foresight of Government Human Capital Transformation." The findings indicated that realizing smart public governance requires rethinking government human capital, developing digital competencies, and strengthening organizational capabilities in accordance with the requirements of the digital era [32]. The study argues that without preparing human resources, developing knowledge infrastructures, and addressing emerging requirements of digital governance, the effective implementation of smart governance models in the public sector will face significant limitations.

Similarly, Ghaeminia et al. (2025), in a study entitled "Artificial Intelligence in the Context of Digital Transformation: A Pathological Reappraisal of Concepts and Applications," examined the conceptual relationship among artificial intelligence, smartification, automation, and digital transformation. The findings indicated that some of the existing challenges in this field stem from conceptual ambiguity and the conflation of different levels and stages of digital transformation [33]. The authors emphasize that accurately distinguishing among these concepts is a prerequisite for sound policymaking and the effective application of AI in organizations and governance institutions. From this perspective, rather than focusing primarily on implementation, the study emphasizes conceptual clarification and the enhancement of conceptual coherence in the domains of digital transformation and AI.

Marzdar (2025), in a study entitled "Artificial Intelligence in Iranian Public Administration: Opportunities, Challenges, and Strategic Approaches to Governance Innovation," examined the potential of AI to improve government services and operations. The results showed that AI can promote innovation in governance by increasing productivity, simplifying processes, reducing administrative burdens, and improving public service delivery. However, the study also highlighted challenges such as conceptual ambiguity, organizational barriers, ethical issues, and social consequences [34]. It recommends that AI adoption in Iran's public sector should be pursued strategically, with simultaneous consideration of organizational, ethical, and social dimensions.

At the provincial level, the study by Esmaeilpoor et al. (2018), entitled "Identifying Barriers to the Adoption of E-Commerce in Small and Medium-Sized Enterprises," can also be noted. Conducted as a case study of companies operating in the Bushehr Industrial Estate, the study demonstrated that the adoption of digital technologies at the organizational level is confronted with barriers including infrastructural limitations, managerial issues, insufficient organizational readiness, and environmental challenges [35]. Although this study focused on businesses and the private sector, its findings can, from a local contextual perspective, indicate the presence of certain general barriers to digital transformation in Bushehr Province and can therefore contribute to understanding the provincial context of the present study.

2.2. International studies

As a first step in reviewing the international literature, Zhu (2026) examined the future of public administration in the era of intelligence, focusing on the transformative role of artificial intelligence in governance systems. The findings indicate that AI not only has the potential to substantially enhance administrative capabilities and the quality of decision-making processes, but has also emerged as a novel phenomenon in regulation and public policymaking and is transforming established methodological practices in public administration [36]. From the perspective of this study, a successful transition toward digital transformation requires simultaneous attention to three fundamental components: the education and empowerment of human capital, innovation in methodological practices, and the adoption of an evidence-based policymaking approach, all of which are identified as essential prerequisites for this transition.

In a recent study, Calleo and Pilla (2025) introduced an AI-based real-time Delphi method and demonstrated that integrating AI models with the Delphi method can facilitate decision-making and futures studies [37]. The findings indicate that the use of AI not only accelerates convergence among expert perspectives but also contributes to generating more diverse and creative scenarios and improves the efficiency of data analysis under conditions of

limited expert availability. Accordingly, this method can serve as an innovative approach with considerable potential for strategic studies and forward-looking policymaking, particularly in data-driven decision-making contexts.

Wang (2025) investigated the potential of multi-agent AI systems in futures studies and strategic decision-making and proposed the concept of collaborative foresight as a framework for human–machine collaboration. The findings demonstrated that agentic AI, through processing large-scale datasets, identifying emerging signals, and generating diverse scenarios, can function as a virtual expert council and reduce human cognitive limitations [38]. However, the study emphasizes that this process should not lead to the elimination of human judgment. Rather, responsible foresight requires human-in-the-loop design, transparency, interpretability, and human oversight of algorithmic outputs.

Neiroukh et al. (2025) also examined the impact of AI capabilities on organizational performance, with an emphasis on decision-making processes. The findings showed that AI capabilities significantly enhance the speed and quality of decision-making and thereby improve organizational performance [39]. The results further indicated that decision-making processes, particularly decision-making speed, mediate the relationship between AI capabilities and organizational performance. The study emphasizes the importance of AI as an effective tool for strengthening data-driven decision-making and improving organizational outcomes.

Vatamanu and Tofan (2025), in a study entitled "Integrating Artificial Intelligence into Public Administration: Challenges and Vulnerabilities," examined the application of AI in public administration from the perspectives of government efficiency, sustainability, and resilience. Using factor analysis and ordinary least squares (OLS) regression, the study demonstrated that AI-based applications can contribute to improved governance, enhanced public service delivery, and economic growth [40]. However, the transition toward AI-augmented public administration is accompanied by challenges such as algorithmic bias, cybersecurity risks, workforce adaptation, and ethical concerns. The authors emphasize the need for robust governance structures, comprehensive security measures, and active citizen participation to manage these challenges.

The study by Sadiku-Dushi et al. (2026) demonstrated that AI technical capabilities can improve the quality of strategic decision-making and AI-enabled organizational performance. However, perceived fairness risk reduces trust in AI, while trust alone does not have a significant effect on decision-making quality [41]. The study emphasizes that the success of AI in strategic decision-making depends not only on technical capabilities but also on organizational conditions and sociotechnical considerations.

2.3. Synthesis and research gap

The review of domestic and international literature indicates that artificial intelligence and digital transformation can transform administrative systems through improved decision-making, strategic foresight, enhanced organizational performance, and innovation in public services. Domestic studies have primarily emphasized the institutional, cultural, managerial, and conceptual challenges associated with digital transformation and AI adoption, whereas international studies have focused more extensively on the mechanisms through which AI influences decision-making, organizational performance, and governance.

Nevertheless, within the context of Iran's administrative system, there remains a relative lack of comprehensive models that systematically integrate the relationships among digital transformation, futures studies, data-driven decision-making, and the administrative system. Accordingly, the present study seeks to address this gap by focusing specifically on the executive agencies of Bushehr Province.

3. CONCEPTUAL FRAMEWORK AND OPERATIONALIZATION OF THE VARIABLES

The present study is based on the premise that digital transformation management in the administrative system is not merely a matter of adopting modern tools and technologies. Rather, it is a multidimensional, continuous, and strategic process in which transformations in structures, processes, organizational culture, decision-making practices, and governance models occur simultaneously [42, 43]. Within this framework, digital transformation in executive agencies becomes meaningful and effective when technological adoption is accompanied by a

reconsideration of governance models, organizational capacity building through open bureaucracy, and the acquisition of specialized competencies [44, 45].

Accordingly, the present study considers digital transformation management as the central phenomenon and identifies several key dimensions for its explanation:

Futures Studies (Strategic Dimension): First, futures studies is conceptualized as a strategic dimension because digital transformation, without an understanding of environmental trends, anticipation of changes, scenario development, and preparedness for the future, may be reduced to fragmented and reactive initiatives [46]. Futures studies enables executive agencies to identify technological developments and emerging governance requirements before they fully materialize and to plan appropriate responses [47].

Data-Driven Decision-Making: The second dimension is data-driven decision-making, which is regarded as one of the fundamental pillars of digital transformation in public organizations [48]. In modern administrative systems, effective decision-making can no longer rely solely on experience, traditional practices, or individual perceptions; rather, it must be based on valid, analyzable, and timely data [6]. Accordingly, data quality, access to information, data integration, analytical capacity, and the utilization of analytical outputs constitute essential components of this dimension [4, 49]. As organizations progress toward data-driven operations, their capacity to formulate more accurate, faster, and more intelligent policies and decisions also increases [50].

Artificial Intelligence (Enabling Capability): In this context, artificial intelligence, as one of the key drivers of digital transformation, plays an enabling and reinforcing role [51]. AI can enhance the digital maturity of executive agencies by processing large volumes of data, discovering patterns, providing predictive analytics, supporting decision-making, and automating portions of administrative processes [4, 5]. In fact, the role of AI in this study is not viewed merely as an independent technology [52, 53]. Rather, it is conceptualized as an enabling capability serving data-driven decision-making, smart governance, and enhanced administrative efficiency. From this perspective, the greater the capacity to deploy AI within the administrative structure, the greater the potential for realizing more advanced dimensions of digital transformation [54].

Digital Transformation Culture: Another dimension of this framework is digital transformation culture. The experience of numerous transformation programs in the public sector demonstrates that failures in digital transformation often result not merely from technological deficiencies but also from weak cultural acceptance, resistance to change, low levels of learning orientation, limited employee participation, and the absence of an innovative mindset [45]. Therefore, effective digital transformation requires a culture characterized by learning, acceptance of innovation, trust in technology, readiness for change, and organizational participation. This dimension provides the necessary soft and human foundation for the success of other dimensions of transformation [55, 36].

Smart Governance: Furthermore, smart governance is considered another key dimension of the framework. Smart governance concerns how the administrative system utilizes data, emerging technologies, information transparency, and accountability mechanisms to improve the quality of policymaking, decision support, and public service delivery [56, 57]. In this study, smart governance is regarded both as an outcome of and as a reinforcing context for digital transformation. On the one hand, digital transformation creates the conditions necessary for realizing smart governance; on the other hand, the existence of smart governance mechanisms enhances the capacity to effectively guide transformation initiatives [58, 59].

Alongside these dimensions, attention to structural and cultural barriers is also essential. Within Iran's administrative system, particularly at the level of provincial executive agencies, digital transformation faces challenges such as centralization, inadequate infrastructure, data fragmentation, shortages of specialized skills, administrative resistance, lack of coordination among organizational units, and limitations in context-specific policymaking [60, 15].

Therefore, analyzing digital transformation without considering these barriers would result in an incomplete analysis. In this regard, contextualization and localization of models is also identified as a conceptual necessity in the present study [61], because imported digital transformation models may fail to achieve the required effectiveness if they do not account for the institutional, cultural, and implementation characteristics of Iran and Bushehr Province.

This conceptual framework demonstrates that digital transformation in the public sector is a multidimensional process requiring the coordination of structural, cultural, and institutional factors. In the proposed model, digital transformation management, incorporating dimensions such as AI infrastructure, data governance, agility, and futures studies, functions as a driving variable and influences the improvement of administrative system performance through AI-based data-driven decision-making.

Within this framework, futures studies provides strategic orientation; AI provides analytical capacity; data-driven decision-making provides executive rationality; and data governance provides the foundation for the secure utilization of data. At the same time, structural and cultural barriers including siloed information systems, weak analytical capabilities, resistance to change, and legal constraints affect the trajectory of this transformation. This framework constitutes the basis for designing the research measurement instrument within the modified Delphi methodology.

Table 1. Operationalization of the Research Variables Based on Dimensions and Indicators

Main Variable	Main Dimension	Indicator Code	Measurement Indicators	Sources
Digital Transformation Management Requirements (Independent Variable – X)	**1. AI Infrastructure and Technology**	X11	Deployment of advanced data analytics and data-mining tools within the organization	Fan [62]; de Almeida et al. [63]; Elkaabi et al. [64]
Digital Transformation Management Requirements (Independent Variable – X)	**1. AI Infrastructure and Technology**	X12	Operational use of predictive algorithms and machine learning	Fan [62]; de Almeida et al. [63]; Elkaabi et al. [64]
Digital Transformation Management Requirements (Independent Variable – X)	**1. AI Infrastructure and Technology**	X13	Deployment of intelligent decision support systems (DSS)	Fan [62]; de Almeida et al. [63]; Elkaabi et al. [64]
Digital Transformation Management Requirements (Independent Variable – X)	**2. Digital Agility and Responsiveness**	X21	Reduction in response time to citizen requests through intelligent tools	Trautendorfer & Eder [65]; Jonathan et al. [66]
Digital Transformation Management Requirements (Independent Variable – X)	**2. Digital Agility and Responsiveness**	X22	Proportion of administrative processes and government services automated through intelligent automation	Trautendorfer & Eder [65]; Jonathan et al. [66]
Digital Transformation Management Requirements (Independent Variable – X)	**2. Digital Agility and Responsiveness**	X23	Dynamic adaptability of organizational processes to changes in laws and regulations	Trautendorfer & Eder [65]; Jonathan et al. [66]
Digital Transformation Management Requirements (Independent Variable – X)	**3. Digital Culture and Literacy**	X31	Senior managers' willingness and commitment to using emerging technologies and data	Haryanti et al. [20]; Kunadt [22]
Digital Transformation Management Requirements (Independent Variable – X)	**3. Digital Culture and Literacy**	X32	Enhancement of employees' data literacy and digital skills	Haryanti et al. [20]; Kunadt [22]
Digital Transformation Management Requirements (Independent Variable – X)	**3. Digital Culture and Literacy**	X33	Holding formal decision-making meetings based on data analytics reports	Haryanti et al. [20]; Kunadt [22]
Digital Transformation Management Requirements (Independent Variable – X)	**4. Foresight and Environmental Readiness**	X41	Establishment of a systematic environmental scanning process to identify signals of change	Korhonen et al. [67]; Cretu [68]
Digital Transformation Management Requirements (Independent Variable – X)	**4. Foresight and Environmental Readiness**	X42	Development, review, and dynamic scenario planning concerning the future of the administrative system	Korhonen et al. [67]; Haryanti et al. [20]
Digital Transformation Management Requirements (Independent Variable – X)	**4. Foresight and Environmental Readiness**	X43	Alignment of ongoing programs and strategic thinking with forward-looking scenarios	Kunadt [22]; Trautendorfer & Eder [65]

AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**5. Data Integration and Governance**	M11	Establishment of an integrated infrastructure for data collection and sharing	Cretu [68]; Vissing et al. [69]; Rho [70]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**5. Data Integration and Governance**	M12	Enhancement of the quality, consistency, and security of organizational data	Cretu [68]; Vissing et al. [69]; Rho [70]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**5. Data Integration and Governance**	M13	Implementation of an integrated data governance charter and framework within the organization	Cretu [68]; Vissing et al. [69]; Rho [70]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**6. Intelligent Analytical Capacity**	M21	Proportion of strategic decisions supported by AI-based tools	Fan [62]; de Almeida et al. [63]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**6. Intelligent Analytical Capacity**	M22	Assessment of the maturity level of AI technologies and tools within the organization	Fan [62]; de Almeida et al. [63]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**6. Intelligent Analytical Capacity**	M23	Identification and analysis of hidden patterns in administrative data to support decision-making	Fan [62]; de Almeida et al. [63]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**7. Evidence-Based Decision-Making Culture**	M31	Preference for objective evidence derived from data analysis over discretionary and traditional decision-making	Cretu [68]; Jonathan et al. [66]
AI-Based Data-Driven Decision-Making (Mediating Variable – M)	**7. Evidence-Based Decision-Making Culture**	M32	Organizational flexibility in revising previous decisions based on new evidence	Cretu [68]; Jonathan et al. [66]
Administrative System Performance Improvement (Dependent Variable – Y)	**8. Operational Efficiency and Optimization**	Y11	Reengineering and elimination of redundant steps in service delivery processes	Elkaabi et al. [64]; Haryanti et al. [20]
Administrative System Performance Improvement (Dependent Variable – Y)	**8. Operational Efficiency and Optimization**	Y12	Maximization of electronic service delivery portals available to citizens	Elkaabi et al. [64]; Haryanti et al. [20]
Administrative System Performance Improvement (Dependent Variable – Y)	**8. Operational Efficiency and Optimization**	Y13	Reduction in administrative and operational costs relative to the volume of services delivered	Elkaabi et al. [64]; Haryanti et al. [20]
Administrative System Performance Improvement (Dependent Variable – Y)	**9. Public Transparency and Accountability**	Y21	Reduction in response time to administrative correspondence and public requests	Vissing et al. [69]; Rho [70]
Administrative System Performance Improvement (Dependent Variable – Y)	**9. Public Transparency and Accountability**	Y22	Establishment and development of systems providing citizens with open access to information	Vissing et al. [69]; Rho [70]
Administrative System Performance Improvement (Dependent Variable – Y)	**9. Public Transparency and Accountability**	Y23	Continuous measurement and improvement of stakeholder satisfaction with service outcomes	Vissing et al. [69]; Rho [70]
Administrative System Performance Improvement (Dependent Variable – Y)	**10. Structural Flexibility and Readiness**	Y31	Targeted allocation of budgets and investment in transformative technologies	Trautendorfer & Eder [65]; Kunadt [22]
Administrative System Performance Improvement (Dependent Variable – Y)	**10. Structural Flexibility and Readiness**	Y32	Establishment of dynamic structures and dedicated units responsible for digital transformation and AI	Trautendorfer & Eder [65]; Kunadt [22]

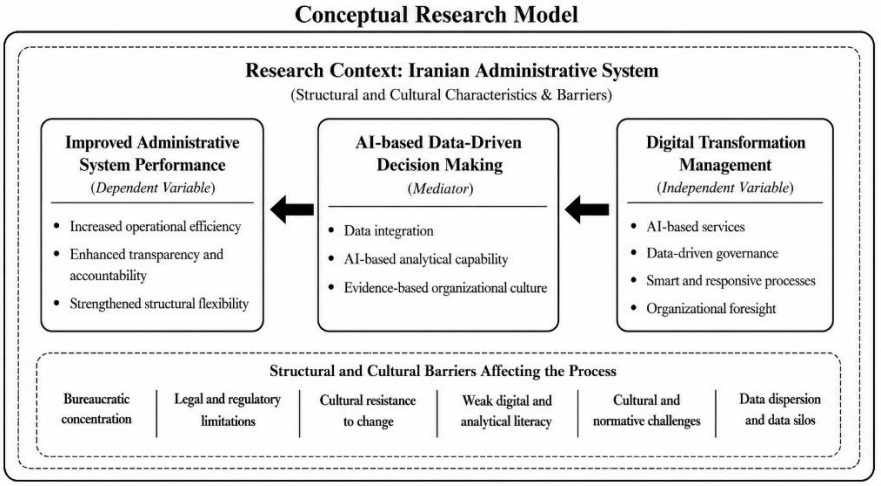


Fig. 1. Initial Conceptual Model of the Study

4. METHODOLOGY

The present study is applied in terms of its purpose and descriptive-exploratory in terms of its nature. It was conducted with the aim of developing and validating a context-specific framework for managing digital transformation in Iran's administrative system, with an emphasis on the application of artificial intelligence in data-driven decision-making. Given the complex and forward-looking nature of the subject, a modified Delphi method was employed. Accordingly, the initial indicators were extracted from the literature review, higher-level policy documents, and the variable operationalization table, and were then incorporated into a structured questionnaire for evaluation by experts in two rounds.

The study population consisted of managers and senior experts from executive agencies in Bushehr Province, as well as faculty members and specialists in the fields of public administration, digital transformation, and artificial intelligence. Purposive sampling combined with snowball sampling was employed, and 25 qualified experts were selected as members of the expert panel.

Data were collected using a structured questionnaire based on a five-point Likert scale, with the 28 indicators organized into ten dimensions under three main variables (Table 1). An open-ended section was also included to obtain additional comments and suggestions from the experts. The Delphi process was conducted in two rounds. In the first round, the importance of the indicators was assessed, while in the second round, the results and feedback from the previous round were provided to the experts to facilitate a higher degree of consensus.

Of the 32 experts invited, 25 completed the first round (78%) and all 25 completed the second round. Before the first round, face validity was checked by three faculty members, and content validity was assessed by the same 25 experts: each item was rated as essential, useful but not essential, or not necessary to compute Lawshe's content validity ratio (CVR; critical value 0.37 for 25 raters), and its relevance was rated on a four-point scale to compute the item-level content validity index (I-CVI; items rated 3 or 4) and the scale-level index (S-CVI/Ave). Reliability was assessed with Cronbach's alpha for each scale. Agreement among the experts on the relative order of the items was assessed with Kendall's coefficient of concordance (W, corrected for ties) and the equivalent Friedman test; consensus on each item was judged with the decision rules in Section 5.2. Because the necessity and feasibility ratings come from the same experts, the gap of each item was tested with the Wilcoxon signed-rank test on the paired ratings, with Holm correction for the 28 tests. Analyses were performed in Python (SciPy) at a significance level of 0.05. Finally, the framework for digital transformation management, with an emphasis on AI, was developed from the results of the two Delphi rounds.

5. FINDINGS

The primary purpose of this section is to analyze the data obtained from the implementation of the modified Delphi method in order to identify and prioritize the components of digital transformation management in the administrative system of Bushehr Province, with an emphasis on AI applications. Digital transformation in the public sector extends beyond the adoption of technological tools and requires structural, cultural, human, and policy alignment. In the present study, the indicators extracted from the theoretical literature and preliminary studies were classified into three main dimensions:

Digital Transformation and AI Requirements (X): Including technological infrastructure, laws and regulations, and human resources.

Data-Driven Decision-Making (M): Including data quality and integration, data analytics processes, and decision-making culture.

Performance of Executive Agencies (Y): Including productivity enhancement, transparency and accountability, and citizen satisfaction.

The monitoring and consensus-building process among the experts was conducted through two rounds of the modified Delphi method. The indicators were evaluated across two corresponding dimensions necessity and implementation feasibility in order to reveal the gap between the desired state (necessity) and the existing state (feasibility). The remainder of this section first presents the demographic characteristics of the expert target group, followed by a detailed analysis of the Delphi rounds and the corresponding gap analysis.

5.1. Characteristics of the expert panel

With regard to the statistical description of the individual and social characteristics of the expert target group, the study included 25 individuals consisting of senior managers, senior information technology and administrative transformation experts from executive agencies in Bushehr Province, as well as university faculty members in the fields of public administration and information technology. Table 2 presents the demographic characteristics of these experts.

Table 2. Demographic Characteristics of the Delphi Expert Target Group (N = 25)

Demographic Indicator	Category	Frequency	Percentage
Gender	Male	18	72%
	Female	7	28%
Educational Attainment	Master’s degree	11	44%
	Doctor of Philosophy (Ph.D.)	14	56%
Years of Service	10–15 years	5	20%
	16–20 years	12	48%
	More than 20 years	8	32%
Field of Activity	Executive agencies of Bushehr Province	17	68%
	Universities and research centers	8	32%

Analysis of the above table indicates that more than half of the participants held a doctoral degree, while 80% had more than 15 years of professional experience. This finding indicates the high level of expertise and practical experience of the expert target group within the local context of the administrative system of Bushehr Province.

Validity and reliability. All items exceeded the critical CVR value (CVR = 0.68–0.92; lowest for X23), the I-CVI ranged from 0.88 to 1.00 and the S-CVI/Ave was 0.96, so no item was removed on content-validity grounds. Cronbach’s alpha was 0.91 for the necessity scale and 0.92 and 0.92 for the feasibility scale in the first round and in the final ratings.

5.2. Delphi rounds and evaluation of the items

In the first round, a questionnaire comprising 28 items, measured using a five-point Likert scale, was administered to the 25 experts. Based on the study's decision-making rules, the following criteria were applied to both the necessity and feasibility dimensions:

- **Definitive acceptance of an item:** Mean score ≥ 3.75 and standard deviation ≤ 1
- **Reconsideration in the second round:** Mean score between 3.00 and 3.75 or standard deviation > 1
- **Item elimination:** Mean score < 3.00

Because feasibility describes the current capacity of the agencies rather than the merit of an indicator, the consensus rules above were used to judge whether the experts *agreed* on the level of feasibility, not to accept or reject indicators on that basis. Repeated rounds that push feasibility ratings towards a threshold risk inducing conformity; the second-round feasibility ratings should therefore be read as the panel's converged estimate of current feasibility.

Following the collection of responses in the first round, the results showed that, in the necessity dimension, all 28 items achieved the threshold for definitive acceptance. However, in the feasibility dimension, only 10 items were definitively accepted, while the remaining 18 items, due to either a feasibility mean score below 3.75 or disagreement among the expert group (standard deviation greater than 1), were carried forward to the second round to achieve final consensus.

The items accepted in both dimensions during the first round included the following codes:

Accepted Items (Round 1): X11, X12, X21, X41, M23, Y11, Y12, Y21, Y31, and Y32.

The items that were not accepted in the feasibility dimension during the first round were reassessed in the second round. At this stage, each expert was provided with the mean scores from the previous round, together with the frequency distribution of responses, allowing them to reconsider and revise their assessments. Table 3 presents the final evaluation results for all 28 research items following completion of the second round.

Table 3. Necessity and feasibility ratings of the 28 items (N = 25; SD = population standard deviation). Necessity met the acceptance rule for all items in round 1; feasibility was re-rated in round 2 for the 18 items that did not meet it.

Item	Necessity M (SD)	Feasibility, round 1 M (SD)	Feasibility, round 2 M (SD)	Feasibility accepted in
X11	4.56 (0.57)	4.12 (0.71)	–	Round 1
X12	4.40 (0.63)	4.08 (0.74)	–	Round 1
X13	4.48 (0.50)	3.56 (1.10)	3.80 (0.85)	Round 2
X21	4.72 (0.45)	3.88 (0.82)	–	Round 1
X22	4.36 (0.62)	3.48 (0.90)	3.84 (0.73)	Round 2
X23	4.00 (0.63)	3.56 (1.10)	3.92 (0.80)	Round 2
X31	4.52 (0.57)	3.44 (1.10)	3.88 (0.77)	Round 2
X32	4.44 (0.57)	3.44 (0.94)	3.80 (0.85)	Round 2
X33	4.32 (0.68)	3.48 (1.06)	3.76 (0.81)	Round 2
X41	4.60 (0.49)	4.04 (0.82)	–	Round 1
X42	4.24 (0.59)	3.48 (0.90)	3.80 (0.80)	Round 2
X43	4.36 (0.62)	3.52 (1.10)	3.88 (0.77)	Round 2
M11	4.48 (0.57)	3.48 (1.02)	3.80 (0.80)	Round 2
M12	4.40 (0.57)	3.52 (1.06)	3.84 (0.73)	Round 2
M13	4.40 (0.57)	3.56 (1.02)	3.84 (0.73)	Round 2
M21	4.56 (0.50)	3.48 (0.98)	3.80 (0.80)	Round 2
M22	4.44 (0.50)	3.36 (0.93)	3.76 (0.81)	Round 2
M23	4.28 (0.45)	4.12 (0.65)	–	Round 1
M31	4.52 (0.57)	3.56 (1.02)	3.88 (0.77)	Round 2
M32	4.28 (0.53)	3.48 (1.06)	3.76 (0.81)	Round 2
Y11	4.60 (0.49)	4.12 (0.71)	–	Round 1
Y12	4.44 (0.50)	4.04 (0.82)	–	Round 1
Y13	4.56 (0.57)	3.60 (0.94)	3.88 (0.77)	Round 2

Y21	4.52 (0.57)	4.08 (0.69)	–	Round 1
Y22	4.40 (0.57)	3.56 (0.98)	3.84 (0.73)	Round 2
Y23	4.28 (0.45)	3.56 (1.02)	3.80 (0.80)	Round 2
Y31	4.48 (0.50)	4.12 (0.71)	–	Round 1
Y32	4.36 (0.48)	4.08 (0.69)	–	Round 1

As shown in Table 3, at the end of the second round all 18 re-rated items reached the threshold for the feasibility dimension: their feasibility means rose from 3.36–3.60 (SD 0.90–1.10) in round 1 to 3.76–3.92 (SD ≤ 0.86). Therefore, all 28 items, with mean scores of at least 3.75 and standard deviations below 1, were retained in the final conceptual model. Several items have identical summary statistics (e.g. M12, M13 and Y22); with 25 integer ratings this is common, and the expert-level ratings show different response patterns. Kendall's W was low in both rounds (necessity: $W = 0.081$, $\chi^2(27) = 54.8$, $p = .001$; feasibility, round 1: $W = 0.116$, $\chi^2(27) = 78.6$, $p < .001$; final feasibility: $W = 0.042$, $\chi^2(27) = 28.6$, $p = .381$). Low W values are expected when almost all items are rated highly: the experts agreed that every item was necessary, but they did not order the items consistently. After the second round, the feasibility ratings converged to a common level, and the remaining differences in their order were not systematic. The order of items with similar gaps should therefore be interpreted with caution. In the Friedman test, X21 had the highest mean rank for necessity (18.38) and X23 the lowest (9.14).

To conduct the gap analysis, which is an effective tool for comparing the desired level of importance and necessity of a factor with its feasibility or practical implementability within an organizational context, the gap for each item was calculated using the following formula:

$$Gap = Mean_{Feasibility} - Mean_{Necessity} \quad (1)$$

Since the ideal gap value is zero, negative values indicate a discrepancy between perceived requirements and the organization's implementation constraints. Table 4 presents the gaps, ranked from the largest negative gap to the smallest, with the Holm-adjusted p-values of the Wilcoxon signed-rank test. Feasibility was significantly lower than necessity for 24 of the 28 items at the 5% level; the exceptions were X12, X23, M23 and Y32. After Holm correction, 7 gaps remained significant (X21, M11, M13, X13, M21, M31 and X33).

Table 4. Gap between feasibility and necessity (Gap = feasibility − necessity), ranked; tied gaps share a rank. p (Holm): Wilcoxon signed-rank test on the paired ratings, Holm-adjusted for 28 tests.

Rank	Item	Indicator (Table 1)	Necessity	Feasibility	Gap	p (Holm)
1	X21	Reduction in response time to citizen requests through intelligent tools	4.72	3.88	−0.84	.006
2	M21	Share of strategic decisions supported by AI tools	4.56	3.80	−0.76	.026
3	M11	Integrated infrastructure for data collection and sharing	4.48	3.80	−0.68	.011
3	M22	Maturity of AI technologies in the organization	4.44	3.76	−0.68	.061
3	X13	Intelligent decision-support systems	4.48	3.80	−0.68	.019
3	Y13	Reduction in administrative and operational costs	4.56	3.88	−0.68	.061
7	M31	Preference for evidence over discretion	4.52	3.88	−0.64	.026
7	X31	Senior managers' commitment to emerging technologies and data	4.52	3.88	−0.64	.061
7	X32	Employees' data literacy and digital skills	4.44	3.80	−0.64	.061
10	M12	Quality, consistency and security of data	4.40	3.84	−0.56	.061
10	M13	Integrated data-governance charter and framework	4.40	3.84	−0.56	.012
10	X33	Decision meetings based on data-analytics reports	4.32	3.76	−0.56	.040
10	X41	Systematic environmental scanning	4.60	4.04	−0.56	.074
10	Y22	Open-access information systems for citizens	4.40	3.84	−0.56	.061
15	M32	Flexibility in revising decisions on new evidence	4.28	3.76	−0.52	.075
15	X22	Share of processes and services automated	4.36	3.84	−0.52	.110
17	X43	Alignment of programmes with forward-looking scenarios	4.36	3.88	−0.48	.119
17	Y11	Re-engineering of service processes	4.60	4.12	−0.48	.070
17	Y23	Measurement of stakeholder satisfaction	4.28	3.80	−0.48	.070
20	X11	Advanced data analytics and data-mining tools	4.56	4.12	−0.44	.126
20	X42	Scenario planning for the administrative system	4.24	3.80	−0.44	.076

20	Y21	Reduction in response time to correspondence and requests	4.52	4.08	−0.44	.070
23	Y12	Availability of electronic service portals	4.44	4.04	−0.40	.226
24	Y31	Targeted budgets for transformative technologies	4.48	4.12	−0.36	.110
25	X12	Operational use of predictive algorithms and machine learning	4.40	4.08	−0.32	.358
26	Y32	Dedicated digital-transformation and AI units	4.36	4.08	−0.28	.358
27	M23	Detection of hidden patterns in administrative data	4.28	4.12	−0.16	.496
28	X23	Adaptability of processes to changes in laws and regulations	4.00	3.92	−0.08	.637

5.3. Analysis of the largest gaps

The gaps in Table 4 reveal a consistent pattern in the challenges of implementing digital transformation and AI in the administrative system of Bushehr Province. The interpretations below follow the definitions of the indicators in Table 1; the explanations of *why* the gaps arise come from the experts' open-ended comments and should be regarded as hypotheses for further study.

5.3.1. Intelligent service delivery and AI-supported decisions (largest gaps)

The largest gap concerned X21, the use of intelligent tools to reduce response times to citizen requests (−0.84): the experts rated it as the most necessary of all indicators (4.72) but judged its implementation feasibility to be only moderate (3.88). The second-largest gap concerned M21, the proportion of strategic decisions supported by AI-based tools (−0.76). Together, these two indicators show that the experts see the main deficit not in the availability of data but in turning data and AI into faster services and better decisions. According to the experts' comments, the implementation of AI and big-data analytics is limited by the lack of capable local data centres, computing resources and stable bandwidth, by budgetary constraints and by the centralised allocation of national resources in Tehran.

5.3.2. Decision-support systems, data infrastructure and cost efficiency

Four indicators shared the next-largest gap (−0.68): intelligent decision-support systems (X13), an integrated infrastructure for collecting and sharing data (M11), the maturity of AI technologies (M22) and the reduction of administrative and operational costs (Y13). The presence of M11 in this group supports the experts' observation that siloed operation of government organisations at the provincial level is a major obstacle: despite awareness of the need for unrestricted information flows, data sharing in practice faces legal and discretionary barriers. Regarding cost efficiency, the experts noted that a substantial share of smart-government contracts is awarded to entities outside the province because of procurement and tendering regulations, which limits the development of a local technology and AI ecosystem.

5.3.3. Managerial commitment, data literacy and decision culture

The gaps for senior managers' commitment to emerging technologies (X31), employees' data literacy and digital skills (X32) and the preference for evidence over discretionary decision-making (M31) were each −0.64. They indicate that the human and cultural prerequisites of AI-based management are not yet in place. The experts mentioned traditional resistance to new technologies and concerns about the elimination or reduction of administrative roles as major barriers to a data-driven decision culture.

The smallest gaps concerned the adaptability of processes to legal change (X23, −0.08) and the detection of hidden patterns in administrative data (M23, −0.16), for which the experts judged feasibility to be close to necessity.

5.4. Synthesis and contextualized conceptual model

In this section, the data obtained from the two-round modified Delphi analysis were subjected to scientific examination. All 28 proposed items across the domains of digital transformation requirements, data-driven decision-making, and executive-agency performance were ultimately approved following two rounds of consultation with 25 experts in management and technology.

The results of the gap analysis indicate that although there is broad consensus regarding the necessity of implementing artificial intelligence and digital transformation within the administrative system of Bushehr Province, their effective implementation requires addressing substantial gaps in hardware infrastructure, integration of databases, human-capital development, and improvement of the legal and budgetary environment at the provincial level.

The findings obtained at this stage provide the foundation for developing the final framework and formulating practical recommendations. Accordingly, and with the aim of integrating the findings derived from the Delphi analysis and gap analysis, a contextualized conceptual model of the study was developed. This model illustrates the structure and relationships among the key research variables within the administrative context of Bushehr Province and is presented in Figure 2.

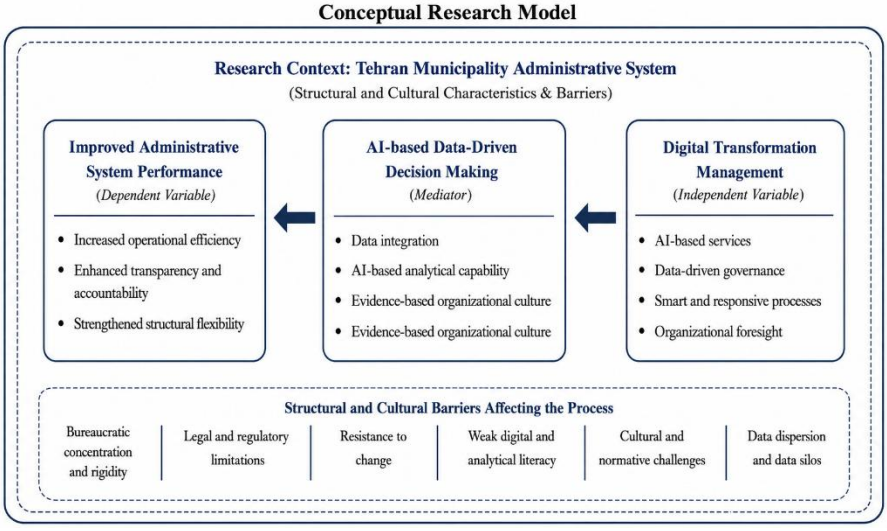


Fig. 2. Contextualized Conceptual Model of Digital Transformation Management in the Administrative System of Bushehr Province (Source: Research Findings)

As shown in Figure 2, the model consists of three core components. Digital transformation management, as the driving variable, contributes to the improvement of administrative system performance (the outcome variable) at the provincial level through the mediating mechanism of AI-based data-driven decision-making. In addition, the gaps and barriers identified through the experts' assessments such as data silos, inadequate digital skills, resistance to change, and administrative centralization are incorporated into the model as a supporting and constraining layer beneath the main structure. These structural and cultural challenges act as moderating factors, directly affecting the implementation process and effectiveness of the drivers. Controlling and mitigating these barriers constitutes a fundamental prerequisite for the successful digital transformation of executive agencies in Bushehr Province.

6. DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

The ultimate objective of applied research extends beyond describing and analyzing the existing situation to providing practical solutions, models, and recommendations derived from empirical findings to address real-world problems. The present study was conducted to develop a framework for managing digital transformation in the administrative system of Bushehr Province, with a particular focus on the role of artificial intelligence in data-driven decision-making and smart governance. In discussing the research findings, the data obtained from the two rounds of the expert Delphi process and the gap analysis between the two dimensions of necessity and feasibility were evaluated.

As the final stage of the study, this section first summarizes and explains the findings obtained from the analysis of the 28 items. Subsequently, a detailed discussion and interpretation of the findings is presented based on the key research variables, with particular emphasis on the structural, cultural, infrastructural, and regional barriers specific to Bushehr Province. The final framework for digital transformation management is then presented, followed by

practical and operational recommendations for government agencies in the province and suggestions for future research.

6.1. Summary of the findings

Analysis of the statistical data obtained from the perspectives of the experts including information technology managers, university faculty members, and senior experts from executive agencies in Bushehr Province revealed several important findings:

Necessity Dimension: The mean necessity scores of all 28 items were at least 4.00 on the five-point Likert scale. This finding demonstrates a strong consensus among the experts regarding the critical and undeniable importance of implementing digital transformation and artificial intelligence tools within the administrative system. Indicator X21 (reduction in response time to citizen requests through intelligent tools) received the highest necessity score, with a mean of 4.72.

Feasibility Dimension: The mean feasibility scores of the items ranged from 3.76 to 4.12. Comparison of these scores with those obtained for the necessity dimension indicates a clear gap. The lowest feasibility ratings (3.76) were given to data-based decision meetings (X33), the maturity of AI technologies (M22) and flexibility in revising decisions on new evidence (M32), followed by decision-support systems, employees' data literacy, scenario planning, integrated data infrastructure, AI-supported strategic decisions and stakeholder-satisfaction measurement (3.80).

Gap Analysis Results: The calculated gap analysis showed that the gap was negative for all 28 items. The largest negative gap was associated with item X21 (intelligent tools for faster responses to citizens; −0.84), followed by M21 (AI-supported strategic decisions; −0.76) and, jointly, X13, M11, M22 and Y13 (−0.68). The smallest gap was associated with X23 (adaptability of processes to legal change; −0.08). The gap itself was significant for 24 items (Wilcoxon test) and for 7 after Holm correction. Whether the differences between gaps are statistically meaningful cannot be judged from the means alone, because with 25 experts a difference of 0.1–0.2 between two gaps lies within sampling variation.

6.2. Interpretation

The findings of this study can be discussed and interpreted across the following three key dimensions:

6.2.1. Infrastructure and the analytical gap

The large gaps for intelligent service delivery (X21), AI-supported decisions (M21) and integrated data infrastructure (M11) point to the same underlying problem. Within the administrative system of Bushehr Province, the siloed nature of information systems and the lack of data sharing among different organizations including the provincial governorate, municipalities, customs offices and ports, government departments, and companies constitute a major obstacle to the development of data-driven decision-making.

An analytical gap occurs when decision-makers do not have access to processed, up-to-date, and aggregated data, while decisions continue to be made on the basis of intuition or traditional paper-based reports. Entering the Fifth Era of governance and utilizing artificial intelligence algorithms require high-quality data; the province's current situation remains considerably distant from this desired state.

6.2.2. Management and structural barriers

The traditional and hierarchical structure governing executive agencies in Bushehr Province lacks the flexibility required to transition toward smart governance. The absence of dedicated and sustainable budgets for research and development in artificial intelligence and digital transformation, together with cumbersome administrative regulations, has reduced the pace of adoption of emerging technologies.

The experts believe that AI capabilities cannot be fully activated unless the organizational structure shifts from centralized models toward agile and network-based models.

6.2.3. Cultural and local dimension

Due to its strategic border, port, and energy-hub position, particularly the South Pars Special Economic/Energy Zone, Bushehr Province possesses substantial economic potential. Nevertheless, its administrative system faces a degree of cultural inertia and resistance to change.

Fear of job displacement resulting from the automation of processes through artificial intelligence, insufficient technological skills among professional staff, and the lack of confidence among some traditional managers in the effectiveness of data-driven analytics represent major cultural challenges within this context. Digital transformation is not merely a technological transformation; before anything else, it is a transformation in mindset and organizational culture.

6.3. Proposed framework

Based on the integration of the Delphi findings and the priorities identified through the gap analysis, a context-specific digital transformation framework for the administrative system of Bushehr Province is developed across four main layers.

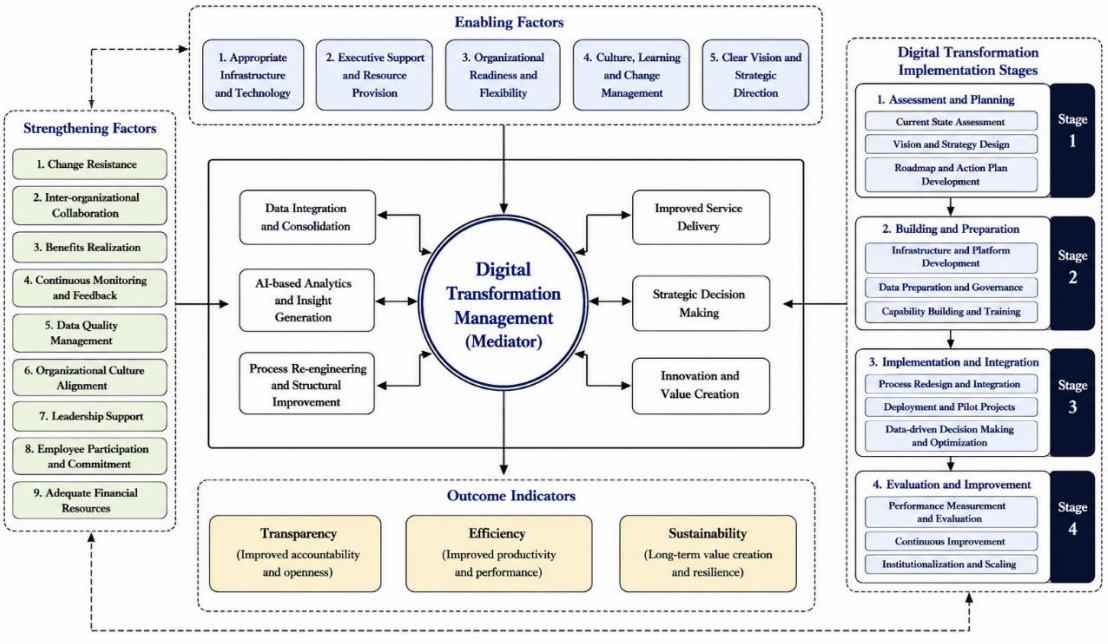


Fig. 3. Localized Conceptual–Operational Framework for Digital Transformation in the Administrative System of Bushehr Province

This figure presents the overarching framework for implementing digital transformation in the administrative system of Bushehr Province. In this framework, digital transformation management serves as the driving core and, under the influence of contextual and inhibiting factors, contributes to improvements in transparency, efficiency, and organizational flexibility through a four-layer implementation framework encompassing infrastructure, processes, human resources, and governance.

6.4. Practical recommendations

Based on the results obtained from the gap analysis of the items, the following operational recommendations are proposed to improve digital transformation management in Bushehr Province:

A. Macro-level and Infrastructural Recommendations (Addressing the Largest Gaps): Given the current fragmentation of service delivery systems and the time wasted in inter-organizational processes, it is essential to establish a provincial integrated smart service portal as a unified electronic gateway. By connecting key organizations such as customs authorities, ports, municipalities, government agencies, and companies, this portal

can contribute to information integration, facilitate business processes, and substantially improve stakeholder satisfaction.

B. Structural and Managerial Recommendations: Considering the current fragmentation of smart-government projects and the absence of a unified governance body, it is necessary to establish a specialized committee consisting of technology experts to oversee digital transformation across the executive agencies of Bushehr Province. Subsequently, a Chief Technology Officer (CTO) or senior technology manager with sufficient executive authority should be appointed for each government department. Such appointments would facilitate continuous monitoring of projects, inter-organizational coordination, and alignment with the comprehensive digital transformation roadmap.

C. Cultural and Educational Recommendations (Addressing Skill Gaps): One of the major barriers to digital transformation is organizational resistance arising from employees' concerns that their efforts may become ineffective or irrelevant. Therefore, incentive and motivational systems should be designed to recognize employees and experts who propose innovative solutions based on smart technologies and process improvement. In addition to receiving certificates of appreciation, such employees should benefit from special incentives, including financial rewards, career advancement opportunities, or institutional support for implementing their ideas. This approach can not only reduce organizational resistance but also provide an environment for developing and leveraging human capital in the digital transformation process.

Data availability

The questionnaire and the anonymised expert ratings of both rounds are provided as supplementary material.

Ethics

Participation was voluntary and anonymous; the purpose of the study was explained in the invitation, and completing the questionnaire was taken as informed consent. No personal data other than the demographic categories in Table 2 were collected.

Conflict of interest

The author declares no conflict of interest.

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Use of AI tools

An AI-based tool was used to improve the language of the manuscript; the author reviewed the text and takes full responsibility for it.

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