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Readiness Assessment for Big Data Analytics in Citizen Relationship Management: a Case Study of Tehran Governorate

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Abstract

This research examined how external organizational factors influence the acceptance and readiness assessment for integrating big data analytics into citizen relationship management (CRM) at Tehran Governorate. The study employed Davis's Technology Acceptance Model (TAM) in an applied, field-based design. Data were collected using a standardized questionnaire based on TAM, with a sample of 105 managers and experts from Tehran Governorate, and analyzed using Structural Equation Modeling (SEM) in SPSS and SmartPLS software. The questionnaire comprised five main dimensions, with validated reliability and validity. Results indicated that external factors (scalability, data storage and processing, data analysis capabilities, flexibility, and reliability), perceived ease of use, and perceived usefulness significantly impact the acceptance of big data analytics. Furthermore, organizational external components such as data storage and processing, flexibility, and reliability lead to satisfaction and intention to utilize big data analytics in managing citizen relations by creating perceived usefulness and confirming user expectations. These findings corroborated the previous research and demonstrated that strategic attention to training, expert recruitment, hardware development, infrastructure enhancement, and information security can facilitate effective adoption of big data analytics, thereby creating opportunities for research development in legal, economic, and other fields.

Keywords

Tehran governorate, Big data, Technology acceptance, Citizen, Citizen relationship management (CRM).

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Introduction

Countries establish conditions for determining citizenship and rules for its revocation. Citizens, once formally recognized by the state, gain civil, political, and social rights that are less salient for non-citizens. Basic rights include the right to possess a passport, exit and return, and live and work in the country. Some countries permit multiple nationalities, while others emphasize single citizenship (Allen et al., 2020). Corresponding to these rights and responsibilities, urban authorities have reciprocal obligations to citizens, particularly in receiving and addressing public complaints and citizen needs (Ju et al., 2018).

Governments worldwide have targeted improvement of communications with citizens and responsiveness to their requests and complaints. Public sector organizations, by involving citizens in governmental processes, pursue greater transparency. These efforts reflect the importance of effective interaction between government and citizens, with governments leveraging digital transformation to promote citizen participation, social engagement, shared resources, inclusive community consideration, protection of vulnerable groups, and enhanced safety (Chamoso et al., 2020). Such initiatives require societal support and effective communication among all involved groups. Facilitating the citizens' contact with organizations should be prioritized, employing modern tools such as big data analytics, artificial intelligence (AI), and communication programs (Chamoso et al., 2020; Lampropoulos et al., 2022). These technological tools offer significant potential for enhancing service quality and elevating levels of citizen satisfaction.

Citizens view government organizations as experts in various affairs. Whether an organization provides emergency information, facilitates understanding of newly approved laws or policies, or acts as a reliable research resource influences citizen participation and communication patterns (Allen et al., 2020). Increasing citizen knowledge constitutes the foundation for designing digital engagement strategies focused on citizen services. This communications strategy aligns with organizational goals and identifies audiences through digital channels and data analytics. Key avenues to improve citizen engagement through digital communications include identifying audience, branding, sending useful messages, increasing interaction, establishing close outreach, taking person-centered approaches, and conducting precise data analysis (Lampropoulos et al., 2022).

Given these considerations, organizations should effectively apply citizen relationship management (CRM) principles, because citizens within organizations such as provincial governorates are effectively the customers of these organizations. CRM refers to the concepts, tools, and strategies that enhance an organization's ability to understand current and potential customers (Anshari et al., 2018). These systems have been studied across many fields including business, healthcare, science, and other service industries. The widespread adoption of big data has prompted a new perspective in CRM (Anshari et al., 2019; Li et al., 2022).

It is important to distinguish CRM in governmental contexts from traditional business/commercial CRM. While both share foundational principles of managing relationships and leveraging data analytics, governmental CRM fundamentally differs in several key aspects. First, the objective of governmental CRM is public service delivery and democratic accountability rather than profit maximization. Second, citizens are not traditional "customers" who can choose alternatives freely; they are stakeholders with rights and civic responsibilities. Third, governmental CRM must prioritize transparency, data privacy, and equitable service access in ways that exceed commercial requirements. Fourth, success metrics differ. Governmental CRM measures citizen satisfaction, service efficiency, and democratic engagement rather than sales conversion or customer lifetime values. These distinctions necessitate adaptation of CRM principles when applied to public sector organizations such as provincial governorates.

Large volumes of data are exchanged through devices and various systems, collected by search engines and made usable, whether structured or unstructured (Xu et al., 2020). Data from multiple channels are analyzed by organizations to understand patterns and customer behavior. For managing large data volumes in large organizations, big data analytics is essential. It is projected that by 2025 the world will generate 175 zettabytes of data annually, making the traditional processing methods inadequate and necessitating big data analytics (Al-Ateeq et al., 2022). Through using big data, citizens' behaviors, preferences, and needs can be analyzed to improve their experience and increase their satisfaction.

CRM is essentially a process by which an organization manages its interactions with the public and uses data analysis to understand them (Kumar & Reinartz, 2018). Modern CRM systems collect data from diverse communication channels, including corporate websites, telephone, email, live chat, marketing materials, and social media (Naeem et al., 2022). Both public and private sector organizations see big data and its extraction as a major opportunity, with many making substantial investments to collect, integrate, and analyze data (Fallahi Modaresi & Zarei, 2022).

As communications become easier, the data volume related to citizens increases, making analysis more challenging. Here, big data analytics can be effective. With the identified applications of big data analytics, the question arises: do large government agencies—such as ministries and affiliated organizations—possess the capacity and conditions to deploy big data analytics in service of CRM, where the customer is the citizen?

Literature Review

Recent Developments in Adopting Big Data Analytics in Public Sector

Emergent technologies and big data analytics are proving transformative in their impact on organizational performance and public service delivery. Recent empirical evidence demonstrates accelerating adoption of big data analytics in governmental contexts worldwide. The United Kingdom National Health Service achieved more than 90% reduction in patients waiting over 18 months for treatment between September 2021 and May 2023 through the strategic use of big data and analytics (Shukla, 2024). Government departments globally increasingly recognize that becoming data-driven represents primarily a cultural transformation rather than merely a technical upgrade, requiring comprehensive attention to people, processes, and organizational readiness alongside technological infrastructure (Qodea, 2024).

However, government agencies frequently struggle with understaffed IT departments operating outdated legacy systems, making it difficult to adopt big data analytics while ensuring data quality and integrity across thousands of applications (Infosys Public Services, 2024). Political opposition and organizational cultures resistant to change often represent the biggest hindrances to legacy modernization and advanced analytics adoption (Infosys Public Services, 2024). Nevertheless, modern data platforms combined with advancements in AI and generative AI can enhance decision-making processes and improve public services when properly implemented (Shukla, 2024).

Research examining big data analytics in UAE government organizations found that big data analytics capability significantly impacts decision-making capability, with organizational culture and cognitive style of decision makers serving as important mediating factors (Faridoon et al., 2024). This underscores the multifaceted nature of big data adoption, where technical infrastructure alone proves insufficient without appropriate organizational culture and human factors.

Despite concrete evidence of meaningful outcomes, publicly accessible research into big data theory and applications in government sectors remains limited (Hossin et al., 2023). While data is gathered at unprecedented rates, public policy adoption of big data analytics lags due to lack of acceptance and several challenges that limit its utility. The capacity to analyze data has reached unprecedented heights due to IT advancements in both hardware and software, making previously impossible information access now feasible through digitization, AI, computational thinking, and automation (Hossin et al., 2023).

A Model of Technology Acceptance in Contemporary Big Data and AI Contexts

The Technology Acceptance Model (TAM) continues to serve as a robust theoretical framework for understanding technology adoption in the era of big data and AI. A comprehensive 2024 validation study confirmed the TAM's applicability to AI contexts, demonstrating that perceived usefulness remains the most significant predictor of attitude toward use, while perceived ease of use emerged as a significant predictor of both attitude and perceived usefulness (Ibrahim et al., 2024). These findings align with earlier TAM research while extending applicability to advanced analytics technologies.

Recent validation of an extended TAM version in AI contexts, integrating Big Five personality traits and AI mindset factors, confirmed that perceived usefulness is the strongest predictor of attitudes toward AI usage (Ibrahim et al., 2024). Notably, perceived ease of use exerted substantial influence on perceived usefulness, suggesting that easily usable technologies are more likely to be perceived as valuable. Recent applications of TAM have expanded to examine generative AI adoption, finding that simplifying technical complexity enhances the users' perceptions of utility and ease, thereby boosting adoption intentions (Singh, 2024). Key facilitating factors include effective organizational training, intuitive design, and strategic partnerships.

An extended TAM study on AI tool adoption showed that perceived usefulness positively affects attitudes toward using academic AI tools, and these attitudes subsequently predict behavioral intention, which ultimately determines the actual usage behavior (Oubdi & El-Mekkaoui, 2026). Similarly, research on AI tools in recruitment processes indicated that perceived usefulness significantly influences attitude toward using AI, while the relationship between perceived ease of use and behavioral intention was mediated through attitude (Costa et al., 2025). Research on medical students' acceptance of AI technology demonstrated that perceived usefulness, perceived ease of use, and attitude together explained 78% of variance in actual AI use (Asadpoor et al., 2024).

The application of TAM to big data adoption has revealed several critical determinants beyond core constructs. Rahman (2020) identified seven technology-related criteria through conducting a comprehensive analysis. Scalability, data storage and processing capability, performance expectancy, reliability, data analytics capability, flexibility, and output quality functioned as external variables influencing perceived usefulness and ease of use. Research has demonstrated that technological factors, combined with external variables and individual personality traits, positively influence perceived usefulness and perceived ease of use of AI-based technology, while environmental factors such as suggestions from others appeared disruptive to technology acceptance (Na et al., 2022).

Organizational Readiness and Data Governance

Organizational readiness has emerged as a critical factor of success for big data adoption, with data governance serving as a foundational element. Data governance adoption has risen dramatically, with 71% of organizations reporting formal data governance programs in 2024 compared to 60% in 2023 (Galvez, 2024). This surge is driven primarily by the imperative to support AI initiatives, as 62% of organizations identify data governance as the primary challenge inhibiting progress toward AI initiatives (Galvez, 2024).

Organizations with established data governance programs reported substantial benefits including improved data quality (58%), enhanced quality of data analytics and insights (58%), increased collaboration (57%), improved regulatory compliance (50%), and faster access to relevant data (36%) (Pangarkar, 2024). In 2024, more than 65% of data leaders declared data governance as their priority, surpassing AI (44%) and data quality (47%) (Pangarkar, 2024), reflecting strategic recognition that trusted, secure, and compliant data infrastructure is prerequisite to successful AI implementation.

Data governance has shifted from a "nice to have" function to a mainstream necessity, with enterprises increasingly adopting federated governance approaches where central leadership provides frameworks while business units maintain autonomy in implementation (Galvez, 2024). This decentralized-yet-coordinated model addresses the complexity of modern data ecosystems while maintaining organizational agility. Data mesh and data fabric architectures increased from 13% adoption in 2023 to 18% in 2024, further reinforcing the need for robust governance frameworks that support democratized, self-service data access (Pangarkar, 2024).

The year 2024 saw a surge in adoption of AI and machine learning for automating data governance tasks (Smith, 2024). AI's capabilities for pattern recognition and predictive analytics allowed businesses to improve data quality and associated governance processes. The demand for data governance is also driven by data privacy and security concerns, which ranked among the top three priorities for improving data integrity in 2024 (45%) (Galvez, 2024). Regulatory compliance emerged as a goal for 45% of organizations' governance programs, reflecting increased enforcement and severe consequences of non-compliance (Galvez, 2024).

CRM and Smart Cities

The application of big data analytics to CRM represents a convergence of technological capability and democratic governance imperatives. Recent research on digital dialogue in smart cities demonstrated that government response rate, timeliness, and quality significantly impact citizen satisfaction, with communication satisfaction, timeliness satisfaction, and resolution satisfaction all influenced by government responsiveness (Cao & Kang, 2025). This empirical finding underscores the importance of not merely collecting citizen data but responding effectively to citizen concerns.

CRM systems have been proven to be effective in initiating smart city services, enhancing public policy implementation, and improving government representativeness across multiple international contexts, including the 311 system in the United States, China's 12,345 hotline, and Taiwan's 1999 system (Cao & Kang, 2025). These systems leverage big data analytics to transform how governments interact with citizens and respond to public needs. However, implementation of CRM systems for public services can introduce complexity and political dimensions, as these initiatives are frequently used in election rhetoric or become topics of political debate, potentially limiting development and local-level applications (Cao & Kang, 2025).

Modern CRM solutions facilitate two-way communications through notifications, automated responses, and real-time updates, while serving as data management hubs that provide valuable insights into citizen engagement patterns and feedback trends (Rattletech 2021; Civita, 2025). This data-driven approach enables city officials to make informed decisions and adjust strategies based on evidence rather than intuition. Recent smart city governance research emphasized that active citizen engagement remains a key focus, with collaborative environments driven by, for, and with citizens seeking to build smart cities embedded in local realities (Baycan & Yigitcanlar, 2024).

Traditional barriers to citizen engagement persist, with town hall meetings and conventional surveys leaving citizen participation rates low and a majority of citizens uninformed about municipal activities (Beesmart City, 2025). Digital platforms that function 24/7, provide multiple access channels, and ensure data security are increasingly essential for meeting citizen expectations and fostering trust (Beesmart City, 2024). Transparency in data usage and demonstrable service improvements based on citizen input was proved to be critical for building and maintaining public confidence in government digital initiatives (Civita App, 2025).

Infrastructure and Technological Determinants

Prior studies underscored the critical importance of technological infrastructure in big data adoption. Fallahi Modaresi and Zarei (2022) demonstrated that understanding relative advantage and addressing technical readiness are key factors in adopting new technologies in tourism industry, while compatibility may have less significant impact than traditionally assumed. Noori et al. (2017) found that job position and organizational support structures significantly influence information technology adoption in human resource management contexts, suggesting that hierarchical and cultural factors mediate technology acceptance.

Alyusuf and Al-Rahmi (2022) applied TAM to explore the adoption of big data analytics in higher education, revealing that facilitating conditions and perceived risk are important determinants of attitudes toward use. Their findings emphasized that organizational infrastructure—including technical support, training programs, and risk mitigation strategies—directly shapes user perceptions and adoption intentions. Ghali et al. (2021) assessed big data adoption readiness using a Technology-Organization-Environment (TOE) framework, identifying the interdependence of technological capabilities, organizational culture, and environmental pressures in determining the success of adoption.

More recent research by Al-Dossari et al. (2023) examined factors influencing the adoption of big data analytics through systematic literature review, identifying executive support, training, and robust governance frameworks as key enabling factors. Their research emphasized that successful adoption requires coordinated attention to multiple organizational dimensions rather than focusing solely on technical infrastructure. Research has also investigated factors influencing smart city development using an integrated approach of big data technologies, Internet of Things (IoT), and cloud computing, demonstrating that technological integration must align with organizational readiness and strategic vision (Fahm Fāmm & Hamidi, 2018).

Research Gap

While the existing research has examined technology adoption across various contexts and explored the applications of big data in both private and public sectors, a significant gap remains in understanding how large governmental institutions—specifically provincial governorates—can assess and enhance their readiness to implement big data analytics for CRM. Previous studies have primarily focused either on technical aspects of adopting big data (e.g., Al-Dossari et al., 2023; Ghali et al., 2021) or on general technology acceptance in service organizations (e.g., Noori & Emamvirdi, 2015), but few have integrated these perspectives within the specific operational and political context of citizen-facing governmental agencies.

Moreover, while recent research has validated TAM in AI and advanced analytics contexts (e.g., Costa et al., 2025; Ibrahim et al., 2024), these studies have predominantly examined commercial organizations or educational institutions. The unique challenges facing large public sector organizations—including bureaucratic structures, political considerations, budget constraints, and complex stakeholder environments—require dedicated investigations. The integration of big data analytics into governmental CRM introduces additional complexities related to data privacy, transparency requirements, and democratic accountability that are less prominent in private sector contexts.

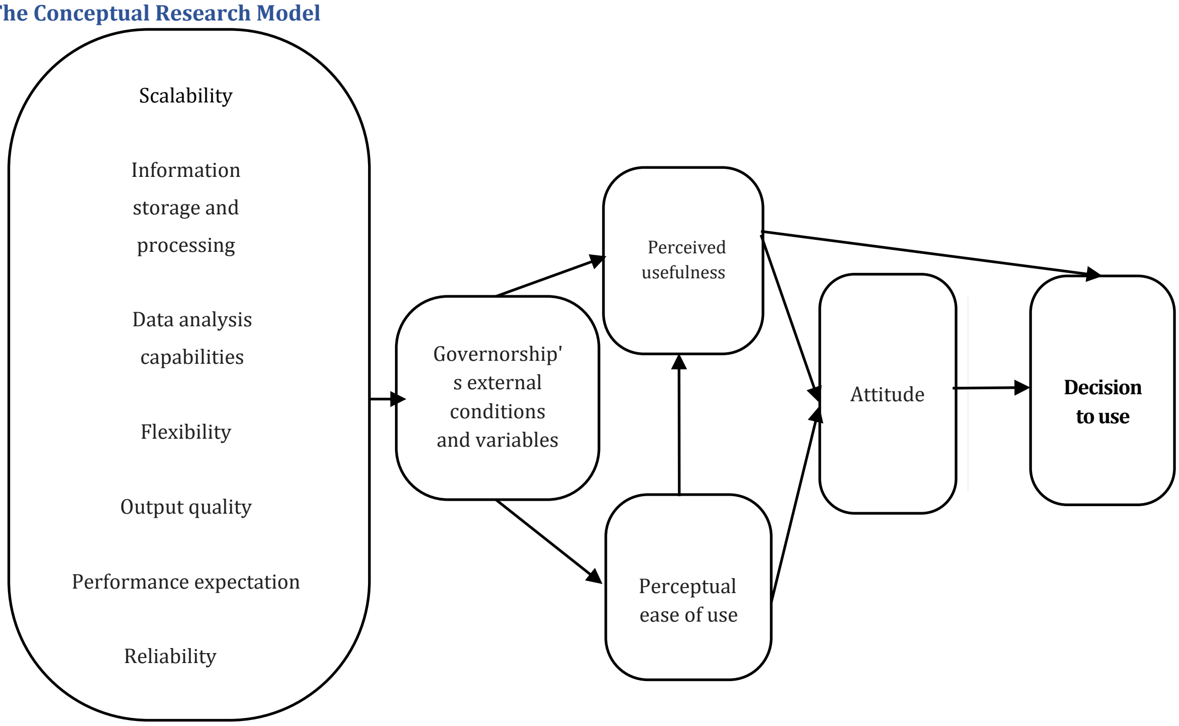
This study addressed these gaps by applying Davis's TAM to assess Tehran Province Governorate's readiness to adopt big data analytics for CRM. The research examined the interplay between external organizational factors (including scalability, data processing capabilities, flexibility, and reliability) and psychological acceptance factors (perceived usefulness, perceived ease of use, attitude, and behavioral intention). The study contributed to empirical evidence on how infrastructure capabilities and user perceptions interact in determining big data adoption readiness in a large-scale public sector context, providing insights relevant to similar governmental organizations facing digital transformation challenges worldwide.

Conceptual Model and Hypotheses

The Conceptual Framework

Based on Davis's TAM and the reviewed literature, this study proposed a conceptual model (Fig.1.) that integrates external organizational factors with core TAM constructs. The model regards assessing environmental conditions and initial needs as essential in the first stage of technology acceptance. Researchers have emphasized that for introducing new tools like big data analytics, it is necessary to examine infrastructure, drivers of use, and costs (Aldholay et al., 2022).

Figure 1.
The Conceptual Research Model



(Source: The Researcher's Findings)

The proposed model incorporates seven technology-related criteria identified by Rahman (2020):

- Scalability: The ability of software and hardware to handle increasing workloads and data;
- Data storage and processing capability: The ability to store and process hundreds of terabytes of data with modern models;
- Performance expectancy: The effectiveness of the technology in use and its importance for technology adoption;

- Reliability: Providing greater reliability while preserving data integrity across multiple nodes;
- Data analytics capability: The ability to uncover patterns and utilize data mining and machine learning;
- Flexibility: The possibility of extracting and processing data from diverse sources, both structured and unstructured;
- Output quality: The importance of preserving data quality and meaningful relationships for accurate decision-making.

Each of these external organizational factors represents a critical dimension of technological readiness and is theoretically linked to TAM's core constructs as follows: Scalability refers to the system's capacity to handle growth in data volume, user numbers, and analytical complexity without performance degradation. This factor directly influences the perceived ease of use. When systems scale seamlessly, users experience consistent performance regardless of workload, reducing friction and enhancing usability perceptions (Rahman, 2020). Data storage and processing capability encompasses the infrastructure's ability to store and process hundreds of terabytes of structured and unstructured data using modern distributed computing architectures. This capability is foundational to perceived usefulness because without adequate storage and processing power, big data analytics cannot deliver meaningful insights (Mikalef et al., 2020). Data analytics capability represents the system's ability to apply advanced techniques including data mining, machine learning, pattern recognition, and predictive modeling to extract actionable insights. This factor most directly impacts perceived usefulness (Maroufkhani et al., 2020). Flexibility indicates the system's capacity to integrate and process data from diverse sources in various formats. Flexible systems enhance both perceived usefulness and perceived ease of use (Rahman, 2020). Reliability ensures data integrity, system availability, and consistent performance across distributed nodes. High reliability builds user trust and confidence, directly influencing perceived usefulness (Ghali et al., 2021). These external factors collectively shape the technological environment within which users form perceptions about adopting big data analytics.

Big data analytics, together with IoT and cloud infrastructure, play a significant role in CRM, especially in smart cities. Key applications include smart cities and contactless technologies, various contactless programs leveraging big data analytics in public services, transportation, healthcare, and emergency management, using IoT sensors and environmental monitoring to collect and analyze data in real time, and assisting in effective management of emergency situations (Al Batayneh et al., 2021; Ashiku et al., 2021; Cabrera-Sánchez & Villarejo-Ramos, 2020).

Research Hypotheses

Davis's TAM provides a good fit for assessing the readiness of Tehran Province Governorate to use big data analytics for CRM.

Hypothesis 1: External variables (organizational conditions) at Tehran Province Governorate have a meaningful relationship with perceived usefulness of using big data.

The relationship between perceived usefulness of big data usage and internal organizational conditions is of substantial importance. Big data refers to large collections of data gathered from diverse sources such as sensors, social media, and transactional systems (Maroufkhani et al., 2020). Using big data analytics enables organizations to exploit vast data, extract patterns, relationships, and conceptual information (Mikalef et al., 2020). Organizational factors such as culture, staff capabilities, policies, and leadership significantly influence big data usage.

Hypothesis 2: Organizational conditions have a significant relationship with perceived ease of using big data.

Perceived ease of use indicates the extent to which users can interact with tools with ease (Mikalef et al., 2020). If users find big data tools simple and efficient, they are likely to use them for decision-making and analysis. Key organizational factors that can help improve perceived usefulness include relative advantage perception, organizational readiness, top management support, government regulation, and link to firm performance (Caffaro et al., 2020).

Hypothesis 3: Perceived ease of using big data has a significant relationship with perceived usefulness.

The Technology Acceptance Model suggests that when a technology is user-friendly, users find it more useful and hence use it more (Siagian et al., 2022). In the context of big data, user-friendly tools help people find data useful and make informed decisions. If system use is easy, it is perceived as more useful, especially given the volume, speed, and variety of data in big data contexts.

Hypothesis 4: Perceived usefulness of using big data has a significant relationship with attitude toward using big data analytics.

Attitude is recognized as a key variable in technology acceptance and exerts a strong influence on willingness to use technologic services. A positive attitude of citizens toward big data can lead to improved services (Kumar & Reinartz, 2018). If users regard the technology as useful, they develop a positive attitude that leads to greater acceptance and effective use of big data analytics (Arghashi & Yuksel, 2022).

Hypothesis 5: Perceived usefulness of using big data has a significant relationship with the decision to use big data analytics.

The perceived usefulness of big data plays an important role in decisions to employ data analytics (Kar & Dwivedi, 2020). The decision to use big data analytics is influenced by the perceived benefits that these analyses bring (Sarker, 2021). Training staff by senior management can improve employees' understanding of the technology and facilitate the decision to use it. To encourage use of big data analytics, its usefulness should be demonstrated concretely. For example by presenting successful case studies, training on potential applications, and ensuring user-friendliness of analytic tools (Xu et al., 2020).

Hypothesis 6: Perceived ease of using (PEOU) big data analytics tools is related to attitudes toward using them.

This relationship is essential for user acceptance and successful implementation of big data technologies. The attitude toward using big data analytics includes users' affective responses, encompassing perceived ease of use, perceived usefulness, and understanding of how to use the technology (Islami et al., 2021). When big data analytics tools are designed with the user in mind and assured of simplicity and ease of use, they are more likely to be adopted. To enhance attitude and better understanding of ease of use, employing a range of supports—such as providing help resources, training, providing a test-friendly environment and opportunities for hands-on experience, networking with peer organizations, and fostering a culture of innovation—is essential (Iriani & Andjarwati, 2020).

Hypothesis 7: Attitude toward using big data is significantly related to the intention to use big data.

A positive attitude toward big data is often a strong predictor of the intention to actually use big data analytics in practice (Kasilingam, 2020). This attitude reflects a general evaluation of data analytics, and if positive, it reinforces beliefs about the improved performance, insights, and outcomes. The intention to use big data results from attitude, where a positive attitude can lead to higher intention to use. Habits of using up-to-date tools can also influence attitude and adoption of new technologies (Aworh et al., 2021). To cultivate a positive attitude toward big data, it is crucial to demonstrate benefits, share success stories, ensure ease of use, and provide support and training to potential users.

Method

This study adopted a pragmatic research approach employing survey methodology for primary data collection. Given the nature of the conceptual model, the research approach is descriptive and of a correlational branch. To collect information, the study employed both library (documentary) and field methods. Initially, a literature review encompassed a range of books, articles, and specialized theses related to the research domain.

The study population comprised managers and staff from the Public Communications and Information Technology departments, along with subject matter experts in the research domain. A sample of 105 respondents was drawn based on staff numbers without prior acquaintance. Data were collected using a standardized questionnaire based on Davis's TAM. This questionnaire comprises five main dimensions, and its validity and reliability were confirmed by Randi et al. (2014). Cronbach's alpha for the questionnaire was approximately 0.78, indicating an acceptable level of reliability. Composite reliability and extracted average variance (AVE) were also above 0.75 and 0.5, respectively, demonstrating the reliability of the model.

While Rahman's (2020) original framework includes performance expectancy as a distinct construct, we operationalized this concept through the perceived usefulness dimension of TAM. The performance expectancy overlaps substantially with Davis's perceived usefulness construct. To avoid conceptual redundancy and maintain parsimony, we incorporated performance-related items within the perceived usefulness scale. Future research may benefit from explicitly distinguishing these constructs to examine their unique contributions.

In this study, Cronbach's alpha, composite reliability, and construct validity were calculated and reported. In the section on organizational characteristics, the extracted factors are presented and displayed in the conceptual model. Descriptive statistics include frequency, mean, and standard deviation. Normality of the variables was assessed via Skewness and Kurtosis. Pearson correlations and the validity and reliability of the questionnaire were examined using Confirmatory Factor Analysis. The theoretical model was tested with (SEM). SPSS and SmartPLS software were used for data analysis. The significance level (alpha) for hypothesis testing was set at 0.05.

Findings

Demographic Characteristics

Based on the collected data, the demographic characteristics are presented in Table 1.

Table 1.
Description of Demographic Variables with Frequency Counts and Percentages

Percent	Number	Classification	Variable
68.16	72	male	Gender
31. 4	33	female	
27.6	29	below the age of 30	Age
38.1	40	between 30 and 40 years old	
34.3	36	aged more than 40	
8.6	9	High school diploma	Education level
14.3	15	Associate degree	
49.5	52	Bachelor's degree	
27.6	29	Master's degree or higher	
43.8	46	Humanities	Field of study
21.0	22	Experimental Sciences	
19.0	20	Mathematics and Physics	
16.2	17	Other fields	
22.9	24	Less than 5 years	Activity history
30.5	32	5 to 10 years	
46.7	49	More than 10 years	
11.4	12	Very low	Computer familiarity
27.6	29	Low	
37.1	39	Adequate	
20.0	21	High	
3.9	4	Professional	
3.8	4	Very low	Internet familiarity
8.6	9	Low	
45.7	48	Adequate	
30.5	32	High	
11.4	12	Professional	

(Source: The Researcher's Findings)

The results indicated that 68.6% of respondents were male and 31.4% were female. The largest age group (38.1%) was between 30 and 40 years old. The bachelor's degree holders represented the largest educational category at 49.5%. The majority of respondents (43.8%) reported Humanities as their field of study. The largest share of respondents (46.7%) had more than 10 years of work experience. Regarding the computer familiarity, 37.1% had adequate familiarity, while 45.7% had adequate Internet familiarity.

Descriptive Statistics

Table 2.
Descriptive Statistics of Core Variables

Descriptive Statistics				Variables
Maximum Score	Minimum Score	Standard Deviation	Mean	
4.40	2.00	0.64	3.08	External Factors
5.00	1.83	0.84	3.33	Perceived Usefulness
4.75	1.50	0.72	2.89	Perceived Ease of Use
5.00	2.40	0.74	3.60	Attitude
5.00	2.67	0.65	3.65	Behavioral Intention to Use

(Source: The Researcher's Findings)

Table 2 revealed that the mean score for the "perceived ease of use" was below the theoretical average of 3, whereas all other variables exhibited mean scores above this threshold. The highest mean was observed for the "intention to use" scale, with a value of 3.65. The assumptions underlying SEM—including data distribution and absence of multicollinearity—were examined and confirmed, validating the suitability of the dataset for conducting SEM analysis.

Assessing Validity and Reliability

Table 3.
The Results of Confirmatory Factor Analysis

Cronbach’s Alpha	Composite Reliability	AVE	Variables
0.90	0.92	0.66	Perceived Usefulness
0.81	0.87	0.63	Perceived Ease of Use
0.86	0.97	0.64	Attitude
0.61	0.79	0.56	Behavioral Intention to Use
0.75	0.81	0.47	External Factors

(Source: The Researcher's Findings)

The results of validity and reliability tests indicated that all observed variables demonstrated acceptable construct validity. All factor loadings had t-values greater than 1.96, indicating statistical significance at a minimum confidence level of 95% ($p < 0.05$). Two items from the "external factors" construct—items 23 and 24—were excluded from the analysis due to factor loadings below 0.50 and weak validity and reliability.

The reliability analysis showed that composite reliability values ranged from 0.79 for "intention to use" to 0.92 for "perceived usefulness," confirming reliability via the composite reliability method. The Cronbach's alpha values ranged from 0.61 for "intention to use" to 0.90 for "perceived usefulness," indicating acceptable internal consistency. Given the novelty of the questionnaire and the limited number of items (only three) in the "intention to use" scale—and considering that Cronbach's alpha is sensitive to item count—values above 0.60 were deemed acceptable.

The convergent validity was assessed using the Average Variance Extracted (AVE) index. All AVE values were close to or exceeded the recommended threshold of 0.50. The lowest AVE value was 0.47 for the "external factors" scale, while the highest was 0.66 for "perceived usefulness," confirming the convergent validity. Discriminant validity was evaluated using both the Fornell-Larcker criterion and the HTMT ratio. Results from both methods supported the presence of discriminant validity. HTMT values for all constructs were below the 0.85 threshold, confirming the discriminant validity.

Correlation Analysis

Table 4.
The Pearson Correlation Matrix among Core Research Variables**

Behavioral Intention to Use	Attitude	Perceived Ease of Use	Perceived Usefulness	External Factors	Variables
				1	External Factors
			1	**0.41	Perceived Usefulness
		1	**0.49	**0.33	Perceived Ease of Use
	1	0.09	**0.37	**0.41	Attitude
1	0.62	*0.19	**0.39	**0.52	Behavioral Intention to Use

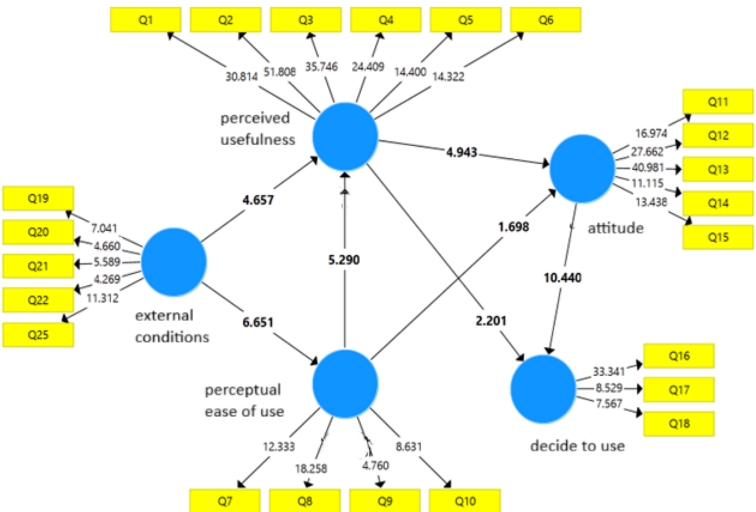
(Source: The Researcher's Findings)

The results indicated statistically significant relationships between the four predictor variables—external factors, perceived usefulness, perceived ease of use, and attitude—and the variable "intention to use" ($p< 0.05$). All four predictors were positively correlated with intention to use. The strongest association with intention to use was observed for attitude ($r= 0.62$), followed by external factors ($r= 0.52$), perceived usefulness ($r = 0.39$), and perceived ease of use ($r= 0.19$).

The Results of SEM

The conceptual model was tested using SEM based on Partial Least Squares (PLS). The analysis was conducted using SmartPLS software. Due to violation of the multivariate normality assumption, the PLS method was selected as an appropriate alternative.

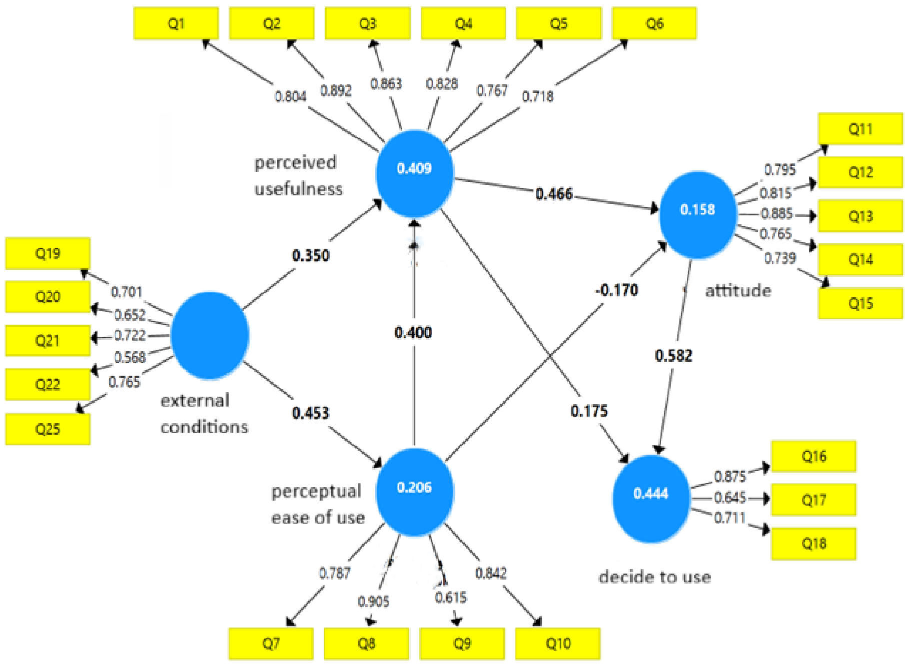
Figure 2.
The Research Model in T-value Mode



(Source: The Researcher's Findings)

Figure 2 presents the empirical model in terms of t-values. Statistically, if the absolute value of a t-statistic exceeds 1.96, the corresponding relationship is considered significant at a confidence level of at least 95% ($p < 0.05$). The findings indicated that out of seven paths or relationships in the model, six were statistically confirmed.

Figure 3.
The Research Model in standard Path Coefficients Mode



(Source: The Researcher's Findings)

Figure 3 presents the model in terms of standardized coefficients. The analysis of t-values indicated that out of seven paths in the model, six were statistically confirmed ($|t| > 1.96$, $p < 0.05$). The analysis of standardized coefficients revealed that the strongest effect within the model was the influence of attitude on intention to use, with a coefficient of 0.58. The second strongest effect was the impact of perceived usefulness on attitude, with a coefficient of 0.46.

The model's coefficient of determination (R^2) was 0.44, indicating that the predictor variables accounted for 44% of the variance in intention to use. This reflects reasonably strong explanatory power of the model.

Table 5.
The Research Model Fit Indices**

Standardized Root Mean Square Residual (SRMR)	Normed Fit Index (NFI)	Predictive Relevance Index (Q^2)	Coefficient of Determination (R^2)	Dependent Variable
0.166	0.32	0.23	0.44	Intention to Use

(Source: The Researcher's Findings)

According to Table 5, the Normed Fit Index (NFI) was calculated at 0.32, which falls below the acceptable threshold of 0.90. The Standardized Root Mean Square Residual (SRMR) was 0.166, exceeding the recommended threshold of 0.10. The predictive relevance (Q^2) for the construct of "intention to use" was 0.23, which lies between moderate and strong levels, suggesting that the model demonstrates acceptable predictive capability. The coefficient of determination (R^2) for "intention to use" was 0.44, exceeding the moderate benchmark of 0.33, reflecting satisfactory explanatory power.

The Explanation of the Model Fit Indices: The model fit indices revealed mixed results that warrant discussion. While the coefficient of determination ($R^2 = 0.44$) and predictive relevance ($Q^2= 0.23$) demonstrated acceptable to moderate levels, the Normed Fit Index (NFI= 0.32) and Standardized Root Mean Square Residual (SRMR = 0.166) fell below the conventional thresholds. Several factors may explain these weaker fit indices. First, the complexity of adopting big data in governmental contexts may involve additional unmeasured variables such as political factors, inter-departmental coordination, and bureaucratic processes not captured in the standard TAM framework. Second, the exclusion of two items from the construct of external factors due to low factor loadings may have affected the overall model fit. Third, the relatively small sample size (n=105) and the specific organizational context (a single governorate) may limit the model generalizability. Despite these limitations, the significant path coefficients and moderate explanatory power suggested that the model provides valuable insights into adoption dynamics. Future research should consider expanding the model to include context-specific variables relevant to public sector organizations and employ larger, multi-organizational samples to improve the model fit.

The Results of Hypothesis Testing

Table 6.
The Results of Hypothesis Testing

Status	p-value	t-value	Standard Error	Standardized Coefficient	type of relationship
confirmation	0.001<	4.66	0.07	0.35	← External Factors Perceived Usefulness
confirmation	0.001<	6.65	0.06	0.45	← External Factors Perceived Ease of Use
confirmation	0.001<	5.29	0.07	0.40	← Perceived Ease of Use Perceived Usefulness
confirmation	0.001<	4.94	0.09	0.46	← Perceived Usefulness Attitude
confirmation	0.028	2.20	0.07	0.17	← Perceived Usefulness Behavioral Intention to Use
Not confirmation	0.090	1.70	0.10	0.17-	← Perceived Ease of Use Attitude
confirmation	0.001<	10.44	0.05	0.58	← Attitude Behavioral Intention to Use

Sensitivity Analysis

To assess the robustness of our findings, we conducted several sensitivity analyses examining the model stability and potential biases. We re-estimated the model separately for key demographic subgroups to assess the stability of path coefficients. Results showed consistent patterns across education levels (bachelor's vs. master's and higher), age groups (under 40 vs. 40 and over), and work experience categories (under 10 years vs. 10+ years). The path coefficients varied by less than 0.10 across subgroups, and the pattern of significance remained consistent, indicating the model stability across respondent characteristics. Examination of standardized residuals identified three potential outliers (standardized residuals > ±3.0). Re-estimating the model after excluding these cases resulted in minimal changes to path coefficients (maximum change: 0.04) and no changes in hypothesis testing conclusions, confirming that results were not driven by extreme values. While we used PLS-SEM due to non-normality, we also estimated the model using covariance-based SEM (CB-SEM) with maximum likelihood estimation for comparison. Despite the normality violation, CB-SEM results showed similar path coefficients (correlations > 0.90 between PLS and CB estimates) and identical patterns of significance, providing convergent validity for our findings. We also conducted Harman's single-factor test to assess the potential common method bias. Exploratory Factor Analysis with all items showed that the first unrotated factor explained 32% of variance, well below the 50% threshold that would indicate substantial common method bias. Additionally, we examined the correlation matrix. The highest correlation between constructs was 0.62 (Attitude-Intention), below the 0.90 threshold suggesting method bias concerns. These results indicated that the common method bias is unlikely to substantially affect our findings. Collectively, these sensitivity analyses demonstrated that our findings are robust across analytical choices and not substantially influenced by outliers, demographic heterogeneity, or methodological artifacts.

Discussion

The findings indicated that external factors—such as technological advancements, system integration, and improved analytical output quality—have a significant impact on the perceived usefulness of big data utilization within Tehran Governorate. Advanced technologies enhance data collection and analysis capabilities, leading to more informed and innovative decision-making. These results align with studies examining the influence of technologies and organizational conditions on the adoption of emerging technologies (e.g., Al-Dossari et al., 2023; Ghali et al., 2021). Similarly, research has confirmed the role of infrastructure and big data analytics capabilities in project success (e.g., Faridoon et al., 2024; Shukla, 2024).

The results also showed that external factors—such as scalability, enhanced processing, big data capabilities, and system performance—significantly affect the perceived ease of using big data technologies in organizations. These factors contribute to reduced analysis time and improved user experience. These findings are consistent with studies confirming the influence of external factors on ease of technology use (Noori, A., Hatami, Z., & Ebrahimiān, H., 2017; Hamta, N., Mohammadzadeh, Y., Hemati, M., & Dehghanzadeh, R., 2020).

The findings revealed that perceived ease of use has a significant impact on perceived usefulness. When users can easily access and interact with big data systems, they are more likely to recognize the value and utility of the data. The results demonstrated that perceived usefulness of big data significantly influences users' attitudes toward its adoption. A positive perception of data utility can enhance the user trust and foster a more favorable overall attitude. This finding is consistent with studies confirming the impact of perceived usefulness on user attitudes (Barham, H., & Daim, T., 2020; Fallahi Modaresi, S., & Zarei, A., 2022).

Furthermore, the findings indicated that perceived usefulness significantly affects the users' decisions to adopt big data technologies. A positive perception of data utility increases trust and willingness to integrate big data into decision-making processes. This result is supported by studies confirming the role of perceived usefulness in adoption decisions (Noori, A., Hatami, Z., & Ebrahimiān, H., 2017; Hamta, N., Mohammadzadeh, Y., Hemati, M., & Dehghanzadeh, R., 2020).

The results showed that perceived ease of use does not significantly influence attitudes toward big data analytics. This suggests that ease of system interaction alone is insufficient to foster positive attitudes. Additional factors such as training and organizational culture are also required. A similar conclusion was reached in earlier research (e.g., Noori & Emamvirdi, 2015).

The non-significant relationship between perceived ease of use and attitude toward big data analytics (H6: $\beta = -0.170$, $p = 0.090$) warrants careful examination, given the central role of PEOU in the original TAM. From a theoretical perspective, this finding may reflect the complexity of adopting big data analytics in governmental contexts, where the perceived strategic value outweighs the operational convenience. Big data analytics represents sophisticated technology where users—especially senior managers and experts—may prioritize outcomes over ease of operation. Our findings support an alternative pathway: PEOU significantly influences perceived usefulness (H3: $\beta = 0.400$, $p < 0.001$), which in turn strongly affects attitude (H4: $\beta = 0.466$, $p < 0.001$). This suggests that ease of use indirectly shapes attitudes by first enhancing the users' beliefs about the system's utility. Contextually, the sample comprised primarily managers and technical experts with relatively high digital literacy. For technically sophisticated users, ease of use may be less salient in attitude formation because they already possess competencies to navigate complex systems. The finding aligns with previous research in public sector contexts where perceived usefulness emerged as a stronger predictor of technology acceptance than ease of use (Noori & Emamvirdi, 2015). From a practical standpoint, this suggests that organizations should prioritize demonstrating concrete values and strategic benefits rather than solely focusing on interface simplification. Training programs should emphasize use cases, success stories, and organizational benefits alongside technical skills development.

Additionally, the findings confirmed that user attitudes toward big data significantly influence their decision to adopt these technologies. A positive attitude facilitates faster and more effective acceptance within Tehran Governorate. This result aligns with studies validating the impact of attitude on decision-making.

The successful implementation of big data analytics in citizen relationship management requires appropriate infrastructure, skilled human resources, digital culture development, information security, and digital governance. These elements contribute to user trust and acceptance. Overall, this study demonstrated that big data analytics can enhance the efficiency and effectiveness of public services. By improving key factors, organizations can achieve more responsive and efficient citizen engagement.

Conclusions and Recommendations

This research examined the readiness of Tehran Province Governorate to adopt big data analytics for CRM using Davis's TAM. The findings provided valuable insights specific to this organizational context, with potential relevance to similar governmental organizations when appropriately adapted.

Findings Specific to Tehran Province Governorate: Based on our analysis of 105 managers and experts from Tehran Province Governorate, we found that external organizational factors (scalability, data storage and processing, flexibility, and reliability) significantly impact both perceived usefulness and perceived ease of using big data analytics. These findings underscored the critical importance of technological infrastructure at Tehran Governorate specifically. Current IT systems must be upgraded to support scalable architectures, enhanced storage capacity, flexible data integration, and robust reliability to facilitate the user acceptance. The study validated core TAM relationships in Tehran Governorate's context. Perceived usefulness emerged as a strong predictor of both attitudes and behavioral intentions among Governorate personnel, while perceived ease of use significantly influenced perceived usefulness. Notably, perceived ease of use did not directly impact attitude in this context, which may reflect the technical sophistication of our sample (managers and experts) and the strategic nature of big data analytics deployment in governmental settings. Attitude toward using big data analytics proved to be the strongest predictor of behavioral intention ($\beta = 0.582$) among Tehran Governorate respondents, highlighting the critical importance of fostering positive attitudes through demonstration of concrete benefits, sharing success stories, and creating supportive organizational culture within the Governorate.

Practical Implications for Tehran Province Governorate: Based on our findings, we propose the following recommendations specifically tailored to Tehran Province Governorate's current situation:

Infrastructure Development Priorities:

- Immediate: Assess and upgrade current data storage infrastructure to handle projected citizen data growth. Tehran Governorate currently manages citizen interactions through multiple channels (in-person offices, telephone hotlines, website contact forms, and social media). These channels generate fragmented data that requires unified storage and processing capability.
- Short-term (6-12 months): Implement scalable cloud-based or hybrid infrastructure capable of processing large volumes of citizen complaints, requests, and feedback data. Current systems likely cannot handle advanced analytics at scale.
- Medium-term (1-2 years): Deploy big data analytics platforms with flexible data integration capabilities to consolidate data from all citizen touchpoints, enabling comprehensive relationship management.

Specific Actions of Human Resource Development:

- Conduct needs assessment of current analytical skills among IT and public communication departments at Tehran Governorate.
- Design and implement targeted training programs focusing on big data analytics tools, emphasizing practical applications to CRM (e.g., complaint pattern analysis, service demand forecasting, citizen sentiment analysis).
- Recruit specialized data scientists and analysts with expertise in public sector analytics.
- Establish mentorship programs pairing technically sophisticated staff with that requiring skill development.

Demonstrating Concrete Values to Build Positive Attitudes: Given the strong role of attitude in predicting intention ($\beta = 0.582$), Tehran Governorate should prioritize initiatives that foster positive perceptions:

- Implement pilot projects analyzing citizen complaint patterns to identify service gaps and demonstrate tangible improvements.
- Showcase quick wins such as reduced response times to citizen inquiries through analytics-driven resource allocation.
- Develop dashboards visualizing citizen satisfaction trends and service performance metrics accessible to managers.
- Share success stories internally highlighting how data insights have improved decision-making Organizational Culture and Change Management:
- Secure visible commitment from senior leadership at Governorate level, with explicit endorsement of data-driven CRM.
- Establish cross-departmental working groups to break down data silos between IT, public relations, and service delivery departments.
- Create incentive structures rewarding data-driven decision-making and citizen-centric service innovations.
- Communicate the strategic importance of big data analytics through regular internal communications.

Data Governance and Citizen Trust:

- Establish clear data governance policies addressing citizen data privacy, security, and ethical use—critical for maintaining public trust- Implement robust cyber-security measures protecting sensitive citizen information.
- Develop transparent communications to citizens explaining how their data improves services while protecting privacy.
- Ensure compliance with relevant Iranian data protection regulations.

Phased Implementation Approach for Tehran Governorate:

Phase 1 (Months 1-6): Infrastructure assessment, pilot project selection, training needs analysis.

Phase 2 (Months 7-12): Infrastructure upgrades, initial training programs, first pilot project implementation.

Phase 3 (Year 2): Full-scale deployment, continuous improvement, expansion to additional use cases.

Expected Benefits Specific to Tehran Governorate Context:

- More responsive citizen services through rapid identification of emerging issues and concerns - Evidence-based resource allocation across Governorate districts based on citizen demand patterns.
- Improved transparency and accountability through data-driven performance monitoring - Enhanced ability to anticipate and address citizen needs proactively.
- Strengthened legitimacy and public trust through demonstrably improved services.

Limitations and Generalizability Considerations

This study has several important limitations that affect its generalizability. First, findings are based on a single organization (Tehran Province Governorate) at a single point in time. While insights may be relevant to other Iranian provincial governorates or similar governmental organizations in other countries, direct generalization requires caution. Organizational culture, technological maturity, budget constraints, political contexts, and citizen demographics vary substantially across jurisdictions. Second, our sample of 105 managers and experts, while appropriate for this organization, may not represent perspectives of front-line staff that interact directly with citizens daily. Their attitudes and perceptions may differ significantly. Third, the cross-sectional design captures intentions rather than actual adoption behavior. Longitudinal research tracking Tehran Governorate through implementation would provide more definitive evidence of actual adoption and sustained use. Fourth, the weaker model fit indices suggest that additional factors beyond our theoretical framework may influence adoption in governmental contexts. Political factors, inter-agency coordination requirements, budget approval processes, and public accountability mechanisms likely play important roles not captured by standard TAM.

Recommendations for Other Governmental Organizations

While our findings are most directly applicable to Tehran Province Governorate, similar governmental organizations considering big data analytics for CRM may find value in our results, with appropriate contextual adaptation. Organizations should:

- Conduct organization-specific readiness assessments before implementation.
- Recognize that infrastructure capabilities and user perceptions both critically influence adoption.
- Invest in change management and attitude-building alongside technical infrastructure- Consider local, political, cultural, and regulatory contexts when adapting our recommendations- Pilot projects in limited scope before full-scale deployment to build confidence and demonstrate value.

Future Research Directions

Future research should address current limitations by:

- Conducting longitudinal studies tracking Tehran Governorate (or similar organizations) through actual implementation to examine how perceptions evolve and predict the actual usage.
- Expanding to multi-organizational comparative studies across different

governorates to assess the model generalizability.

- Implementing qualitative methods (interviews, focus groups) to deeply understand organizational dynamics, political considerations, and cultural factors influencing the adoption.
- Extending the theoretical model to include context-specific variables such as political support, bureaucratic processes, inter-agency collaboration, and citizen participation levels.
- Examining the front-line staff perspectives alongside the managerial views.
- Investigating the moderating effects of organizational size, leadership style, technological maturity, and governance structures.
- Exploring the citizen perspectives on government use of big data analytics and privacy concerns.
- Conducting comparative studies across different national and cultural contexts.

In conclusion, this research demonstrated that Tehran Province Governorate's readiness to adopt big data analytics for CRM depends on both technological infrastructure and user acceptance factors. Successful implementation requires comprehensive attention to infrastructure development, human capacity building, organizational culture change, and governance frameworks. While findings are context-specific, the methodological approach and theoretical framework may guide similar assessments in other governmental organizations.

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