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From Digital Transformation to Responsible Generative AI: Mapping Human-Centered Readiness in Iranian Public Organizations

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A B S T R A C T

Objective: This study aimed to map human-centered readiness for responsible generative artificial intelligence in Iranian public organizations during the transition from digital transformation to AI-supported public administration.
Methods and Materials: This applied quantitative study employed a survey-based descriptive–analytical design and was conducted in 2025. The statistical population consisted of managers, experts, and administrative employees of selected public organizations in Tehran with active information technology, e-government, digital services, or digital transformation units. The sampling frame included public organizations from six functional domains: administrative–regulatory, economic–financial, social–welfare, health–service, educational, and digital-infrastructure sectors. Using multistage stratified cluster sampling, 384 valid responses were collected from managers and supervisors, IT and digital transformation experts, and administrative employees. Data were gathered through a researcher-made questionnaire measuring seven dimensions: technological preparedness, human resource readiness, ethical awareness, algorithmic trust, employee concerns, managerial and organizational support, and human-centered work practices. The validity of the instrument was examined through face and content validity procedures, including expert review, CVR, and CVI assessment. Reliability was evaluated using Cronbach's alpha. Data were analyzed using SPSS through descriptive statistics, one-sample t-test, Friedman test, independent-samples t-test, and one-way ANOVA.
Findings: The results showed that overall human-centered readiness was moderate to above average ($M = 3.25$, $SD = 0.54$) and significantly higher than the theoretical midpoint of the scale. Among the dimensions, employee concerns had the highest mean score ($M = 3.74$), indicating that perceived risks, confidentiality issues, responsibility ambiguity, and job-related concerns were highly salient. Technological preparedness ($M = 3.42$) and ethical awareness ($M = 3.36$) were also above average. In contrast, managerial and organizational support had the lowest mean score ($M = 2.96$) and was not significantly different from the theoretical midpoint, suggesting a weaker level of formal guidance, training, and policy support. Friedman ranking confirmed that employee concerns ranked first, whereas managerial and organizational support ranked last. Significant differences

were also observed in overall readiness according to job position and type of organization.
Conclusion: The findings indicate that readiness for responsible generative AI in Iranian public organizations is a multidimensional condition that extends beyond technological infrastructure. Although selected public organizations in Tehran have developed some foundations for digital transformation, responsible generative AI adoption requires stronger managerial support, clearer policies, employee training, ethical guidance, and human-centered governance mechanisms. The study provides a practical readiness map for policymakers and public-sector managers seeking to move from general digital transformation toward responsible, trustworthy, and employee-centered use of generative AI.
Keywords: *Digital Transformation; Responsible Generative AI; Human-Centered Readiness; Public Organizations; Survey Study; Iran.*

1 Introduction

Digital transformation has become a central strategic concern for contemporary public organizations as governments seek to improve administrative efficiency, service accessibility, institutional transparency, policy responsiveness, and citizen engagement. Growing public expectations, increasingly complex policy environments, fiscal constraints, and the rapid development of digital technologies have intensified pressure on public institutions to reconsider established administrative processes and organizational arrangements. Digital transformation, however, extends beyond the digitization of records, automation of individual tasks, or introduction of electronic service platforms. It involves a more fundamental reconfiguration of organizational structures, operational processes, decision-making practices, service-delivery models, employee competencies, and relationships with citizens and other stakeholders. Accordingly, digital transformation should be understood as an organization-wide process in which digital technologies generate significant changes in how public value is created, delivered, and sustained (Mergel et al., 2019; Vial, 2019).

From a multidisciplinary perspective, successful digital transformation requires the coordinated development of technological resources, strategic leadership, organizational culture, human capabilities, and adaptive governance. Organizations must not only acquire digital technologies but also develop the capacity to integrate them into existing routines, revise outdated processes, and support employees in adapting to new forms of work. Digital transformation can therefore produce meaningful organizational value only when technological change is accompanied by changes in strategy, structure, competence, and organizational behavior (Verhoef et al., 2021). This observation is particularly relevant to public organizations, where technological initiatives operate within formal legal frameworks, hierarchical structures, accountability requirements, bureaucratic routines, and public-service obligations. Consequently, readiness for digital innovation depends on the extent to which organizations possess appropriate resources, supportive leadership, learning capacity, shared commitment, and an institutional climate that enables technological experimentation and implementation (Lokuge et al., 2019).

Artificial intelligence represents a major new stage in this broader transformation. AI technologies can support public organizations through the automation of repetitive tasks, analysis of large datasets, identification of patterns, prediction of future conditions, detection of irregularities, and provision of decision support. Potential public-sector applications include document classification, fraud detection, resource allocation, policy analysis, citizen communication, case management, regulatory monitoring, and service personalization. Nevertheless, AI implementation in the public sector presents challenges that are not encountered to the same extent in ordinary information-system projects. These challenges include inadequate data quality, limited technical capacity, legal uncertainty, algorithmic opacity, organizational resistance, privacy risks, and questions regarding responsibility for AI-supported decisions (Wirtz et al., 2019). Thus, the movement toward AI-supported public administration cannot be understood solely as a technological upgrade; it is a socio-technical and institutional transition requiring coordinated attention to technology, employees, organizational processes, governance, and public accountability.

The emergence of generative artificial intelligence has further accelerated this transition. Generative AI refers to computational systems capable of producing new content, including text, images, software code, summaries, classifications, translations, and analytical responses, based on patterns learned from extensive training data. Unlike many earlier AI applications, which were often embedded in specialized systems and operated primarily by technical professionals, generative AI tools can be accessed directly

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by managers, experts, and administrative employees. Their conversational interfaces and general-purpose capabilities allow them to be integrated into a wide range of knowledge-intensive and communication-oriented activities (Feuerriegel et al., 2024). Within public organizations, employees may use generative AI to draft correspondence, summarize regulations, prepare reports, generate policy alternatives, retrieve and restructure information, design training materials, or support interactions with citizens.

Evidence indicates that generative AI can substantially improve performance in certain professional tasks. Experimental research has shown that access to generative AI can reduce the time required for writing-oriented assignments while improving the quality of outputs, particularly among workers who initially perform at lower levels (Noy & Zhang, 2023). Field evidence from workplace settings similarly suggests that generative AI assistance can increase productivity, improve service quality, and facilitate employee learning, although benefits differ according to employees' prior experience, task characteristics, and patterns of technology use (Brynjolfsson et al., 2025). At the macro-organizational level, generative AI may also affect innovation, entrepreneurship, productivity, occupational structures, and the distribution of expertise within organizations and economies (Calvino et al., 2025). These findings demonstrate the transformative potential of generative AI, but they also indicate that performance improvements are neither automatic nor uniform. Organizational conditions, employee capabilities, implementation practices, and governance arrangements significantly influence whether generative AI produces sustainable value or introduces new forms of risk.

The diffusion of generative AI within government is no longer merely hypothetical. Evidence from public-sector professionals indicates that generative AI tools are already being used across administrative roles, sometimes through informal or individually initiated practices rather than centrally governed organizational programs (Bright et al., 2025). Such decentralized adoption can allow employees to experiment with new technologies and identify useful applications, but it can also create inconsistent practices, undocumented data exposure, unequal access, and uncertainty about acceptable use. Public organizations may therefore face a situation in which employees begin using generative AI before formal training programs, procurement standards, accountability mechanisms, or data-protection procedures have been established. This gap between technological diffusion and institutional preparedness makes organizational readiness a critical issue.

Organizational AI readiness concerns whether an organization possesses the resources, capabilities, structures, and attitudes required to adopt, manage, and sustain AI technologies. Relevant factors include strategic alignment, leadership commitment, data availability, technological infrastructure, technical expertise, employee knowledge, interdepartmental coordination, organizational culture, and capacity for change. Organizations may be interested in AI while remaining unprepared to implement it because readiness requires the simultaneous alignment of technological, organizational, and environmental conditions (Jöhnk et al., 2021). Generative AI expands this readiness challenge because it enters areas of work involving language, interpretation, professional knowledge, communication, and judgment. Readiness must consequently be assessed not only in relation to infrastructure and data but also in relation to human competence, critical evaluation, ethical awareness, trust, perceived risks, managerial guidance, and human–AI collaboration.

Employee responses are particularly important because AI adoption can be interpreted either as a work resource or as a threat. When employees perceive AI as a resource that expands their capabilities, they may redesign tasks, seek new learning opportunities, and engage in constructive job crafting. When they perceive it as a threat to competence, autonomy, employment security, or professional identity, AI may increase uncertainty and inhibit adaptive behavior. Organizational AI adoption can therefore function as either a challenge or a hindrance depending on employees' evaluations of the technology and the organizational conditions surrounding its implementation (Cheng et al., 2023). Recent evidence concerning generative AI similarly indicates that adoption can influence job crafting and career commitment, while employees' attitudes toward AI affect the extent to which technological use produces positive or negative outcomes (Liu et al., 2025). These findings suggest that human resource readiness cannot be reduced to technical skill; it also encompasses confidence, motivation, willingness to learn, perceived control, and the ability to integrate AI into meaningful professional roles.

At the same time, employee concerns represent legitimate indicators of organizational preparedness rather than simple resistance to technological innovation. Generative AI may produce inaccurate, fabricated, biased, incomplete, or contextually inappropriate outputs. Employees may also be uncertain about whether confidential organizational information can be entered into external AI systems, who is responsible for errors in AI-assisted documents, and whether reliance on AI could weaken professional expertise or affect job security. These concerns are especially consequential in public organizations because administrative outputs may influence citizens' rights, eligibility for services, access to public resources, regulatory decisions, and public trust. Employees therefore need clear guidance regarding appropriate use, prohibited data, documentation requirements, verification procedures, and the boundaries of AI-supported decision-making.

Responsible AI provides a normative and operational framework for addressing these challenges. Responsible AI generally requires that AI systems be developed and used in ways that respect human autonomy, prevent harm, promote fairness, support explicability, and establish accountability. An influential ethical framework emphasizes beneficence, non-maleficence, autonomy, justice, and explicability as interconnected principles for achieving socially beneficial AI (Floridi et al., 2018). Comparative analyses of international AI ethics guidelines have similarly identified recurring principles such as transparency, fairness, privacy, responsibility, security, and human oversight, although the practical implementation of these principles remains uneven (Jobin et al., 2019). Responsible AI must therefore extend beyond declarations of ethical values and become embedded in organizational policies, work procedures, technical controls, employee responsibilities, and monitoring mechanisms.

The organizational governance of AI is nevertheless complex. A systematic assessment of AI governance research shows that responsible implementation involves multiple actors, governance levels, mechanisms, and organizational functions, including risk management, accountability allocation, regulatory compliance, data governance, performance evaluation, and stakeholder participation (Batool et al., 2025). Generative AI further complicates governance because its behavior is influenced by model architecture, training data, user prompts, organizational context, evolving applications, and interactions among users and systems. It can consequently be conceptualized as part of a complex adaptive system in which outcomes emerge from dynamic relationships among technical tools, institutional rules, human actors, and changing environments (Janssen, 2025). Static policies alone may therefore be insufficient; organizations require adaptive governance arrangements capable of learning from incidents, revising procedures, and responding to emerging use cases and risks.

Risk-management frameworks offer a practical basis for operationalizing responsible AI. The Artificial Intelligence Risk Management Framework emphasizes governance, contextual mapping, risk measurement, and risk management as interconnected functions for improving the trustworthiness of AI systems (National Institute of & Technology, 2023). Within public-sector settings, these functions require organizations to define intended uses, identify affected stakeholders, evaluate potential harms, document responsibilities, monitor system performance, and maintain mechanisms for human intervention. Public-sector guidance also emphasizes that AI adoption must be consistent with democratic values, institutional accountability, safety, security, transparency, and the protection of fundamental rights (Oecd & Unesco, 2024). Such frameworks demonstrate that responsible AI readiness involves organizational capacity to recognize, evaluate, communicate, and manage risk throughout the AI lifecycle.

Large language models, which underlie many generative AI applications, create additional evaluation requirements. Their outputs cannot be adequately assessed only through technical performance indicators because risks may arise at the levels of the model, the application through which it is deployed, and the broader governance context. A layered auditing approach can therefore examine the technical properties of the model, the specific application and its users, and the institutional processes through which risks are governed (Mökander et al., 2024). For public organizations, this implies that algorithmic trust should not mean unconditional confidence in generated content. Trust should instead be calibrated, evidence-based, and accompanied by verification, documentation, professional judgment, and meaningful human oversight.

This requirement connects responsible generative AI directly to the principles of human-centered AI. Human-centered AI seeks to develop systems that increase human performance while preserving human control, responsibility, safety, and dignity. Rather than treating automation and human control as mutually exclusive, human-centered design aims to achieve high levels of automation alongside high levels of meaningful human control (Shneiderman, 2020). From a human–computer interaction perspective, AI systems should be designed around users' needs, values, abilities, limitations, and work contexts, with particular attention to interpretability, controllability, usability, and collaboration (Xu, 2019). In public administration, this means that generative AI should strengthen employees' capacity to serve citizens and exercise professional judgment rather than displacing accountability or transforming employees into passive recipients of algorithmic outputs.

Human-centered readiness therefore represents a multidimensional condition. Technological preparedness is required to provide secure systems, reliable connectivity, appropriate data, controlled access, and technical support. Human resource readiness is needed to ensure that employees possess the knowledge, skills, confidence, and learning opportunities necessary to use generative AI critically. Ethical awareness enables users to recognize issues involving privacy, bias, transparency, confidentiality, accountability, and appropriate use. Algorithmic trust concerns whether employees can rely on AI-supported outputs while maintaining appropriate skepticism and verification. Employee concerns reveal perceived risks involving job security, errors, overreliance, data exposure, and responsibility ambiguity. Managerial and organizational support includes leadership commitment, training, policy clarity, resource provision, and institutional guidance. Finally, human-centered work practices determine whether AI augments professional judgment, preserves employee agency, and maintains meaningful oversight.

These dimensions are especially relevant in Iranian public organizations. Although public institutions have invested in e-government, digital service delivery, electronic records, and administrative information systems, digital maturity and organizational capability may vary substantially across sectors and occupational groups. Managers and digital transformation experts may have greater exposure to strategic technology initiatives, whereas administrative employees may encounter generative AI through informal experimentation or individual use. Differences in infrastructure, leadership commitment, training opportunities, organizational mission, and regulatory sensitivity may also produce uneven readiness across administrative–regulatory, economic–financial, social–welfare, health-service, educational, and digital-infrastructure organizations. Assessing readiness at an aggregate level without considering these distinct dimensions could therefore conceal important organizational strengths and vulnerabilities.

The regulatory environment further increases the importance of this assessment. Governments worldwide are moving from broad ethical discussion toward more concrete regulation, risk classification, accountability, and institutional oversight of generative AI. Public administrations must navigate emerging regulatory expectations while continuing to innovate and improve services (Weerts, 2025). In countries where organizational adoption develops more rapidly than formal regulation, public-sector institutions may need to establish internal safeguards before comprehensive national rules are available. Empirical readiness mapping can assist this process by identifying whether employees and managers have the technological support, ethical understanding, trust, skills, organizational guidance, and human-centered work conditions required for responsible use.

Despite the rapid expansion of scholarship on digital transformation, AI readiness, generative AI productivity, AI ethics, and public-sector governance, these areas have frequently been studied separately. Digital transformation research explains broad organizational change, while AI readiness research focuses on implementation capabilities, responsible AI research emphasizes principles and governance, and workplace studies examine productivity or employee outcomes. Less empirical attention has been given to the integrated human-centered readiness conditions through which public organizations move from conventional digital transformation toward responsible generative AI. This gap is particularly evident in non-Western public-sector environments, where institutional structures, administrative cultures, regulatory arrangements, and technological capacities may differ from those in settings that dominate existing research.

Accordingly, the aim of this study was to map the technological preparedness, human resource readiness, ethical awareness, algorithmic trust, employee concerns, managerial and organizational support, and human-centered work practices that constitute readiness for responsible generative AI among managers, experts, and administrative employees in selected Iranian public organizations.

2 Methods and Materials

From the perspective of research objectives, the present study was applied in nature, as its findings were intended to provide practical evidence for public-sector managers, policymakers, and digital transformation officers regarding the human-centered readiness of public organizations for responsible generative AI. In terms of methodological orientation, the study employed a quantitative, survey-based, descriptive–analytical design.

The study was conducted in 2025. The statistical population consisted of managers, experts, and administrative employees working in selected public organizations in Tehran that had active information technology, e-government, digital services, or digital transformation units. For operational clarity, the sampling frame was restricted to central offices and affiliated agencies of selected public-sector organizations in Tehran, including organizations affiliated with the Ministry of Information and Communications Technology, Ministry of Economic Affairs and Finance, Ministry of Interior, Ministry of Cooperatives, Labour and Social Welfare, Ministry of Health and Medical Education, Ministry of Education, the Administrative and Recruitment Affairs Organization, and selected public service organizations with formal digital service structures. These organizations were selected because they were directly involved in administrative digitalization, electronic service delivery, citizen-oriented digital processes, or internal digital transformation initiatives.Given the large and relatively heterogeneous population, a multistage stratified cluster sampling method was used. In the first stage, public organizations were grouped according to their functional domain, including administrative–regulatory, economic–financial, social–welfare, health–service, educational, and digital-infrastructure sectors. In the second stage, several organizations were selected from each sector as clusters. In the third stage, participants were selected proportionally from three occupational groups: managers and supervisors, IT or digital transformation experts, and administrative employees who regularly used digital systems in their work. This sampling strategy was adopted to ensure that the sample represented different organizational functions and occupational experiences related to digital transformation and potential generative AI use.

The sample size was determined using Cochran's formula for large populations. Considering a confidence level of 95%, a margin of error of 0.05, and the maximum variability assumption of p = q = 0.50, the required sample size was estimated at 384 participants (Cochran, 1977). To compensate for possible non-response and incomplete questionnaires, 420 questionnaires were distributed. After excluding incomplete or inconsistent responses, 384 valid questionnaires were retained for final analysis.

Data were collected using a researcher-made questionnaire developed on the basis of prior literature on digital transformation, organizational AI readiness, responsible AI, and human-centered AI. The initial item pool was developed after reviewing theoretical and empirical sources related to digital transformation in public organizations, AI readiness, AI risk management, responsible AI principles, and human-centered work practices (Jöhnk et al., 2021; Mergel et al., 2019; NIST, 2023). The questionnaire consisted of two main sections. The first section included demographic and organizational information, such as gender, age, educational level, organizational position, work experience, type of organization, and level of experience with digital systems or AI-based tools. The second section included items measuring human-centered readiness for responsible generative AI.

The final version of the questionnaire included 42 items organized into seven dimensions: technological preparedness, human resource readiness, ethical awareness, algorithmic trust, employee concerns, managerial and organizational support, and human-centered work practices. Technological preparedness referred to the perceived adequacy of digital infrastructure, access to digital systems, data availability, and organizational capacity for supporting AI-based tools. Human resource readiness measured employees' perceived knowledge, skills, learning needs, and confidence in working with generative AI. Ethical awareness assessed respondents' understanding of privacy, transparency, accountability, bias, confidentiality, and responsible use of AI-generated outputs. Algorithmic trust referred to the degree to which employees trusted AI-supported outputs while maintaining critical judgment. Employee concerns covered perceived risks such as job insecurity, errors, overreliance, confidentiality threats, and ambiguity of responsibility. Managerial and organizational support measured the extent of leadership support, training opportunities, policy clarity, and institutional guidance. Human-centered work practices assessed the extent to which AI use was perceived as supporting human judgment, employee agency, professional responsibility, and meaningful human oversight.

All questionnaire items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Higher scores indicated a higher level of perceived readiness, except for the employee concerns dimension, in which higher scores indicated stronger perceived concerns and risks. Before the main data collection, the questionnaire was reviewed for clarity, content coverage, and contextual appropriateness.

The validity of the instrument was examined in several stages. First, face validity was assessed by asking a small group of managers and employees to comment on the clarity, readability, and practical relevance of the items. Second, content validity was evaluated by a panel of 10 experts in business administration, public administration, digital transformation, information systems, and organizational behavior. The experts assessed each item in terms of necessity, relevance, clarity, and representativeness. The content validity ratio (CVR) was calculated according to Lawshe's method, and items with insufficient necessity scores were revised or removed (Lawshe, 1975). The content validity index (CVI) was also calculated at the item level and scale level to evaluate the relevance and clarity of the items, following the recommendations of Polit and Beck (Polit & Beck, 2006; Polit et al., 2007). Items that did not meet the acceptable content validity criteria were revised based on expert feedback.A pilot study was then conducted with 30 participants who were similar to the main sample but were not included in the final analysis. The purpose of the pilot study was to examine the clarity of the questionnaire, estimate the time required for completion, identify ambiguous items, and conduct preliminary reliability analysis. Based on the pilot results, minor wording revisions were made to several items to improve clarity and contextual fit.

The reliability of the questionnaire was assessed using Cronbach's alpha coefficient. Internal consistency was calculated for the overall questionnaire and for each dimension separately. Cronbach's alpha was selected because it is widely used for estimating the internal consistency of multi-item scales (Cronbach, 1951). Coefficients of 0.70 or higher were considered acceptable for the purposes of this study.

Data analysis was performed using SPSS software. Before conducting the main analyses, data were screened for missing values, outliers, response patterns, and distributional characteristics. Descriptive statistics, including frequency, percentage, mean, and standard deviation, were used to describe the demographic characteristics of participants and the status of each readiness dimension. The Kolmogorov–Smirnov test, skewness, and kurtosis values were used to examine the distribution of the main variables. The Kaiser–Meyer–Olkin (KMO) index and Bartlett's test of sphericity were used to assess the suitability of the data for exploratory factor analysis when examining the internal structure of the questionnaire.

To answer the main research purpose, mean scores were calculated for each dimension of human-centered readiness. One-sample t-tests were used to compare the mean scores of readiness dimensions with the theoretical midpoint of the scale. The Friedman test was used to rank the dimensions of human-centered readiness and determine which areas were perceived as stronger or weaker by respondents. Independent-samples t-tests and one-way analysis of variance (ANOVA) were used to compare readiness perceptions across demographic and occupational groups, including gender, education level, work experience, organizational position, and type of organization. Where significant differences were found in ANOVA, post hoc comparisons were conducted to identify the specific group differences.the analytical strategy focused on describing the current status of human-centered readiness, identifying priority areas, and comparing perceptions across organizational and occupational groups.

Ethical considerations were observed throughout the research process. Participation in the study was voluntary, and respondents were informed about the purpose of the study before completing the questionnaire. No personally identifying information was collected. The confidentiality of responses was ensured, and data were used only for academic research purposes.

3 Findings and Results

The sample includes participants from different age, education, and work-experience groups, which makes the data suitable for explaining demographic description in a survey study.

Table 1

Demographic Characteristics of Participants

Variable	Category	n	%
Gender	Male	220	57.3
	Female	164	42.7
Age group	30 years or younger	58	15.1
	31-40 years	142	37.0
	41-50 years	130	33.9
	Over 50 years	54	14.1
Educational level	Bachelor's degree	102	26.6
	Master's degree	212	55.2

	Doctoral degree	70	18.2
Work experience	5 years or less	66	17.2
	6-10 years	104	27.1
	11-15 years	94	24.5
	More than 15 years	120	31.3

The largest educational group is participants with a master's degree, suggesting that the sample is appropriate for examining perceptions of digital transformation and responsible generative AI in public organizations.

Table 2

Means and Standard Deviations of Human-Centered Readiness Dimensions

Dimension	M	SD	Descriptive status
Technological preparedness	3.42	0.69	Above average
Human resource readiness	3.18	0.72	Moderate
Ethical awareness	3.36	0.65	Above average
Algorithmic trust	3.08	0.71	Moderate
Employee concerns	3.74	0.68	High concern
Managerial and organizational support	2.96	0.75	Average
Human-centered work practices	3.21	0.66	Moderate to above average
Overall human-centered readiness	3.25	0.54	Moderate to above average

Employee concerns had the highest mean, indicating that perceived risks such as confidentiality, errors, responsibility ambiguity, and job-related concerns are salient among respondents. Managerial and organizational support had the lowest mean, suggesting that formal guidance, training, and leadership support may require greater attention.

Table 3

One-Sample t-Test Results for the Status of Readiness Dimensions

Dimension	Test value	M	SD	Mean difference	t	df	p
Technological preparedness	3.00	3.42	0.69	0.42	11.93	383	< .001
Human resource readiness	3.00	3.18	0.72	0.18	4.90	383	< .001
Ethical awareness	3.00	3.36	0.65	0.36	10.85	383	< .001
Algorithmic trust	3.00	3.08	0.71	0.08	2.21	383	.028
Employee concerns	3.00	3.74	0.68	0.74	21.32	383	< .001
Managerial and organizational support	3.00	2.96	0.75	-0.04	-1.05	383	.296
Human-centered work practices	3.00	3.21	0.66	0.21	6.24	383	< .001
Overall human-centered readiness	3.00	3.25	0.54	0.25	9.07	383	< .001

Technological preparedness, human resource readiness, ethical awareness, algorithmic trust, employee concerns, human-centered work practices, and overall readiness were significantly above the theoretical midpoint.

Managerial and organizational support was not significantly different from the midpoint, showing that this dimension is comparatively weaker and should be interpreted as an area for improvement.

Table 4

Friedman Test Results for Ranking Human-Centered Readiness Dimensions

Dimension	Mean rank	Rank order
Employee concerns	5.72	1
Technological preparedness	4.55	2
Ethical awareness	4.38	3
Human-centered work practices	4.04	4
Human resource readiness	3.63	5
Algorithmic trust	3.15	6
Managerial and organizational support	2.53	7

Employee concerns ranked first, indicating that perceived risk management is the most salient issue in readiness for responsible generative AI. Managerial and organizational support ranked last, showing that support systems, policy clarity, and structured training should be prioritized in future interventions.

Table 5

Comparison of Overall Human-Centered Readiness by Job Position and Type of Organization

Variable	Group	n	M	SD	F	df	p
Job position	Managers and supervisors	76	3.42	0.51	12.84	2, 381	< .001
	IT/digital transformation experts	118	3.36	0.48			
	Administrative employees	190	3.13	0.55			
Type of organization	Administrative-regulatory	62	3.18	0.52	3.92	5, 378	.002
	Economic-financial	72	3.28	0.49			
	Social-welfare	58	3.20	0.53			
	Health-service	64	3.31	0.50			
	Educational	66	3.15	0.56			
	Digital-infrastructure	62	3.43	0.46			

Overall readiness differed significantly by job position; managers and IT/digital transformation experts reported higher readiness than administrative employees. Overall readiness also differed significantly by type of organization; digital-infrastructure organizations showed the highest mean readiness, while educational organizations showed the lowest mean readiness.

4 Discussion

The present study examined human-centered readiness for responsible generative artificial intelligence in selected Iranian public organizations during their transition from general digital transformation toward AI-supported public administration. The findings showed that overall human-centered readiness was moderate to above average and significantly higher than the theoretical midpoint. This result indicates that the surveyed organizations possessed several preliminary conditions for adopting generative AI, including established digital infrastructure, some employee familiarity with digital systems, awareness of ethical issues, and emerging forms of human–AI interaction. Nevertheless, readiness was not uniformly developed across the seven dimensions. Employee concerns received the highest score, whereas managerial and organizational support received the lowest score and did not differ significantly from the midpoint. These findings suggest that public organizations may be technologically closer to generative AI adoption than they are managerially, institutionally, and psychologically prepared to govern its use.

The moderate-to-above-average level of overall readiness is consistent with the proposition that digital transformation creates an important organizational foundation for AI adoption. Public organizations that have already developed electronic services, information systems, digital records, and digitally mediated administrative processes are more likely to possess the infrastructure and organizational experience necessary for experimenting with generative AI. However, digital transformation is not equivalent to AI readiness. Digital transformation involves changes in technologies, structures, strategies, processes, and value-creation mechanisms, while AI adoption requires additional capacities involving data governance, specialized knowledge, risk management, and human oversight (Verhoef et al., 2021; Vial, 2019). The present findings therefore imply that prior digitalization efforts in Iranian public organizations have created a partial platform for generative AI, but this platform has not yet been fully translated into integrated responsible-AI capability.

This interpretation is also consistent with organizational readiness research. Readiness for digital innovation depends on the alignment of technological resources, managerial support, organizational culture, employee commitment, and capacity for organizational learning (Lokuge et al., 2019). Similarly, AI readiness is shaped by strategic alignment, available data, technological infrastructure, skills, leadership, and organizational acceptance (Jöhnk et al., 2021). The moderate overall score obtained in the present study may therefore reflect the coexistence of enabling and constraining conditions. Public organizations may have access to digital systems and employees who are increasingly aware of AI, while still lacking formal policies, specialized training, clearly assigned responsibilities, and systematic risk-management mechanisms. Readiness should consequently be understood as an evolving organizational condition rather than a fixed state achieved merely through the acquisition of AI tools.

Employee concerns constituted the most prominent finding. Respondents reported high concern regarding confidentiality, incorrect outputs, ambiguity of responsibility, excessive reliance on AI, and possible job-related consequences. The Friedman test also ranked employee concerns first among all dimensions. This result indicates that perceived risk is central to how public employees understand generative AI. Such concern should not automatically be interpreted as resistance, technological pessimism, or unwillingness to innovate. Instead, it may represent a rational response to a technology whose outputs can appear coherent and authoritative despite containing factual errors, fabricated information, embedded biases, or contextually unsuitable recommendations. Generative AI systems generate probabilistic outputs and may therefore create risks when employees assume that linguistic fluency is equivalent to accuracy (Feuerriegel et al., 2024).

Employee concerns are particularly understandable in public administration, where the consequences of inaccurate or inappropriate AI-generated content may extend beyond internal work quality. Administrative reports, public communications, regulatory interpretations, eligibility assessments, and policy recommendations may influence citizens' rights and access to public services. Earlier public-sector research has already identified privacy, accountability, security, transparency, bias, and legal responsibility as major challenges of AI implementation (Wirtz et al., 2019). The present findings support this literature by showing that such issues are not only abstract governance concerns but are salient to employees who may be expected to use AI-supported tools in routine work. High concern may therefore indicate that employees recognize the possible consequences of unregulated generative AI use even when formal organizational procedures remain limited.

The prominence of employee concerns is also compatible with ethical and responsible-AI scholarship. Ethical frameworks consistently emphasize non-maleficence, justice, autonomy, explicability, transparency, privacy, accountability, and human oversight (Floridi et al., 2018; Jobin et al., 2019). When these principles have not been converted into clear workplace procedures, employees may remain uncertain about whether they are permitted to use generative AI, what information may be entered into a system, how outputs should be verified, and who is accountable when an AI-assisted decision produces harm. The Artificial Intelligence Risk Management Framework similarly emphasizes that organizations should identify the context of AI use, measure potential risks, define governance responsibilities, and continually manage identified harms (National Institute of & Technology, 2023). The high concern observed in this study may thus be interpreted as evidence of a gap between awareness of risk and the institutional capacity to manage that risk.

Technological preparedness was the second-highest-ranked dimension and was significantly above the theoretical midpoint. This finding suggests that many participating organizations had already established basic digital conditions such as information systems, access to technology, data resources, connectivity, and experience with digitally supported administrative processes. This result is plausible given that the sample was drawn from organizations with active information technology, e-government, digital-service, or digital-transformation units. The finding is aligned with the broader trajectory of digital transformation in public institutions, through which governments have progressively moved from isolated digital tools toward more integrated digital service and administrative systems (Mergel et al., 2019). Such infrastructure is essential because generative AI cannot be sustainably adopted in the absence of secure networks, accessible data, technical support, and established digital workflows.

Nevertheless, technological preparedness alone cannot guarantee responsible implementation. Generative AI enters cognitive and communicative aspects of work and can be used directly by employees without being formally embedded in an organizational information system. Consequently, technologically mature organizations may still experience uncontrolled use, inconsistent verification, confidentiality breaches, or inappropriate dependence on external platforms. Evidence that generative AI is already widely used by public-sector professionals illustrates how adoption may occur through employee initiative before organizations establish comprehensive policies (Bright et al., 2025). The relatively strong technological score, when considered alongside weak managerial support, may therefore indicate a potentially risky imbalance: employees have sufficient technological access to use generative AI, but institutional controls and guidance have not developed at the same pace.

Ethical awareness was also significantly above average and ranked third. Respondents appeared aware of issues such as privacy, accountability, transparency, confidentiality, and bias. This is an encouraging finding because ethical awareness is an important prerequisite for responsible use. Employees who recognize ethical risks are more likely to question AI-generated outputs, protect sensitive information, and seek clarification when responsibility is uncertain. However, awareness does not necessarily produce ethical practice. Responsible AI governance requires the translation of ethical principles into concrete organizational responsibilities, procedures, monitoring systems, and implementation tools (Batool et al., 2025). Therefore, the relatively high ethical-awareness score should be viewed as a valuable organizational resource that must be supported by operational policies and training.

The need to move from ethical awareness to operational governance is also supported by auditing scholarship. Large language models should be evaluated at multiple levels, including the underlying model, the specific application, and the organizational context in which the system is used (Mökander et al., 2024). Public employees may be generally aware that generative AI can create bias or confidentiality risks, but they still require practical guidance concerning approved platforms, prohibited data categories, verification standards, record keeping, human review, and escalation of incidents. Public-sector guidance similarly emphasizes the importance of transforming broad principles into actionable governance practices that can be applied within agencies (Oecd & Unesco, 2024). The present results therefore suggest that ethical awareness exists among employees, but its organizational value depends on whether managers convert it into usable procedures.

Human resource readiness was moderate but significantly above the midpoint. This finding indicates that employees had some perceived knowledge, confidence, and capacity to learn about generative AI, yet did not consider themselves fully prepared. Generative AI can support administrative writing, information synthesis, communication, and knowledge work, and empirical studies have shown that it can improve productivity and output quality in appropriate tasks (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Nevertheless, these benefits depend on employees' ability to formulate appropriate prompts, evaluate generated content, identify errors, protect confidential information, and integrate AI assistance with professional expertise. The moderate score may indicate that employees recognize the potential usefulness of generative AI but remain uncertain about how to use it competently and responsibly.

Employee adaptation to AI is influenced by how the technology is framed and experienced. AI adoption may encourage proactive job crafting when employees perceive the technology as a challenge that expands their capabilities, but it may inhibit constructive adaptation when it is perceived as a hindrance or threat (Cheng et al., 2023). Generative AI adoption may similarly affect job crafting and career commitment, with employee attitudes toward AI shaping the consequences of use (Liu et al., 2025). The moderate human-resource readiness found in this study may therefore reflect mixed perceptions. Some employees may view generative AI as a learning and productivity resource, whereas others may associate it with deskilling, increased monitoring, or job displacement. Effective readiness programs must address both technical competence and the psychological meaning employees assign to AI-supported work.

Algorithmic trust was only slightly above the midpoint and ranked sixth. This finding reflects cautious rather than strong confidence in AI-generated outputs. Such caution may be appropriate because responsible use requires neither unconditional trust nor complete rejection. Human-centered AI emphasizes the combination of technological capability with meaningful human control, safety, reliability, and accountability (Shneiderman, 2020). From this perspective, employees should be able to benefit from generative AI while retaining authority to question, revise, reject, or override its outputs. Human-centered system design similarly stresses interpretability, user control, and alignment with human needs and capabilities (Xu, 2019). The relatively moderate level of trust may therefore provide a useful foundation for calibrated trust, provided that employees receive sufficient training in verification and critical evaluation.

Managerial and organizational support was the weakest dimension. Its mean was slightly below the midpoint, its one-sample test was not significant, and it ranked last in the Friedman analysis. This finding suggests that employees perceived limited formal guidance, policy clarity, training opportunities, resource allocation, and leadership support concerning responsible generative AI. This result is crucial because managerial support connects technological capacity with organizational practice. Without clear leadership, employees may use generative AI informally, avoid it entirely, or adopt inconsistent standards. Organizational readiness studies identify leadership commitment, strategic vision, coordination, and resource provision as essential conditions for AI implementation (Jöhnk et al., 2021). Therefore, the weak managerial-support score may be the principal barrier preventing existing technological and ethical capacities from becoming coherent organizational readiness.

The governance of generative AI also requires adaptive leadership because the technology, its applications, and its risks evolve rapidly. Generative AI can be understood as part of a complex adaptive system involving interactions among technologies, users, institutional rules, and organizational environments (Janssen, 2025). Public managers cannot rely only on a one-time policy document; they must establish mechanisms for continuous review, incident reporting, employee feedback, updating of acceptable-use rules, and evaluation of emerging applications. Regulatory developments in the United States and European Union further show that public institutions are operating within an environment of increasing legal and governance attention to generative AI (Weerts, 2025). The weakness of managerial support found in the present study therefore represents not only an internal organizational issue but also a potential challenge to future regulatory compliance.

Human-centered work practices were moderate to above average and significantly exceeded the midpoint. This result indicates that respondents generally believed AI should support rather than replace human judgment and that human responsibility should remain central to administrative work. This orientation is compatible with the core principles of human-centered AI, according to which technological systems should enhance human performance while preserving agency, oversight, and responsibility (Shneiderman, 2020). The finding is important because public-sector work frequently involves contextual interpretation, legal reasoning, ethical judgment, and sensitivity to citizens' circumstances. Generative AI may assist with information processing, but final responsibility cannot be transferred to an algorithmic system.

The analyses also identified significant differences in overall readiness according to job position. Managers and supervisors reported the highest readiness, followed by IT and digital-transformation experts, whereas administrative employees reported the lowest readiness. Managers may have greater exposure to strategic discussions, organizational modernization programs, and policy planning. Technical experts may possess more knowledge of digital infrastructure and emerging technologies. Administrative employees, in contrast, may encounter AI primarily through changes in everyday tasks and may receive less specialized training or information. This occupational gap reinforces the need to distribute readiness-building opportunities across all organizational levels. A public organization cannot be considered ready when strategic and technical personnel are prepared but frontline employees remain uncertain.

Readiness also differed significantly across organizational types. Digital-infrastructure organizations had the highest mean, whereas educational organizations had the lowest. This difference is consistent with the assumption that organizational readiness is influenced by digital maturity, technical resources, workforce composition, and exposure to innovation. Organizations responsible for digital infrastructure are likely to have more specialized personnel, stronger information systems, and greater experience with emerging technologies. Educational public organizations may face more limited technical support, dispersed work structures, resource constraints, or fewer formal AI initiatives. These differences confirm that a uniform national strategy may be insufficient. Sector-specific readiness programs are required because organizational missions, data sensitivity, professional practices, and technical capacities vary considerably.

5 Conclusion

Overall, the study demonstrates that readiness for responsible generative AI in Iranian public organizations is multidimensional and uneven. Technological foundations and ethical awareness appear relatively developed, but employee concerns, moderate skills, cautious trust, and weak managerial support reveal important vulnerabilities. Generative AI can improve productivity, innovation, and organizational performance, but its benefits depend on complementary investments in skills, governance, work redesign, and institutional capacity (Calvino et al., 2025). Responsible adoption therefore requires public organizations to move beyond tool acquisition toward an integrated model in which technological preparedness, human competence, ethical safeguards, managerial leadership, and meaningful human oversight reinforce one another.

This study has several limitations. First, it was conducted among selected public organizations in Tehran, and the results may not represent public organizations in other Iranian provinces or smaller administrative units with different technological resources and organizational cultures. Second, the findings were based on self-reported perceptions rather than direct observation of actual generative AI use, technical capability, or compliance with responsible-AI practices. Third, the cross-sectional design captured readiness at one point in time and could not determine how perceptions change as employees acquire experience or as formal AI policies are introduced. Fourth, the researcher-made questionnaire, despite undergoing validity and reliability procedures, requires further psychometric evaluation in different organizational samples. Finally, the descriptive–analytical design did not establish causal relationships among technological preparedness, employee concerns, managerial support, trust, and overall readiness.

Future research should examine human-centered generative AI readiness through longitudinal, comparative, and mixed-methods designs. Longitudinal studies could evaluate changes in readiness before and after the introduction of AI policies, training programs, or pilot projects. Comparative research could include public organizations in different provinces, municipalities, universities, state-owned enterprises, and private organizations. Qualitative interviews and organizational case studies could clarify why employees trust or distrust generative AI, how informal use occurs, and which organizational conditions reduce concern. Future studies should also conduct confirmatory factor analysis and structural equation modeling to test the relationships among readiness dimensions and examine whether managerial support, ethical awareness, or human resource readiness predicts responsible use. Additional outcomes could include service quality, innovation, employee performance, public trust, and the frequency of AI-related incidents.

Public organizations should establish coordinated readiness programs rather than permitting generative AI adoption to develop through fragmented individual use. Managers should formulate clear acceptable-use policies, identify approved AI platforms, specify which organizational data must not be entered into external systems, and define responsibility for reviewing AI-assisted outputs. Training should be tailored to occupational roles and should include prompt design, output verification, confidentiality, bias recognition, documentation, and human oversight. Administrative employees should receive the same attention as managers and technical experts because they are likely to use generative AI in routine service and communication tasks. Organizations should also create internal committees or designated officers for AI governance, establish reporting procedures for errors or data exposure, and periodically assess employee concerns, skills, trust, and emerging use cases. Generative AI should be introduced as a tool for augmenting professional judgment and public-service quality rather than as an uncontrolled substitute for human responsibility.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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