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Validation of the Digital Transformation Model in Human Resource Management of the Civil Registration Organization

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Abstract

This study aimed to validate the digital transformation model in human resource management of the Civil Registration Organization of Iran. The research method was mixed (qualitative–quantitative) and employed a descriptive–analytical approach. In the qualitative phase, by applying grounded theory and conducting interviews with experts, the main and subcategories of digital transformation were extracted, followed by open, axial, and selective coding. Then, based on the qualitative findings, a questionnaire was designed and implemented in the quantitative phase with a sample of 380 managers and specialists. The data were analyzed using structural equation modeling (PLS-SEM) and validity and reliability tests. The reliability of the questionnaire was confirmed with Cronbach's alpha above 0.7 and composite reliability above 0.8. Convergent validity was verified with AVE greater than 0.5, and discriminant validity was confirmed with HTMT less than 0.9. The findings indicated that digital transformation in human resource management is a multidimensional process influenced by causal conditions ($\beta = 0.34$), intervening conditions ($\beta = 0.49$), and contextual conditions ($\beta = 0.56$). Strategies such as organizational culture development, human resource empowerment, smart network development, and continuous monitoring were identified as key drivers. The outcomes of this transformation emerged at three levels — individual, organizational, and social — including enhanced employee performance, increased organizational agility, and improved social capital. The modeling results showed that all hypotheses were statistically significant ($t > 1.96$). Additionally, the coefficient of determination ($R^2 = 0.20$) and the global goodness-of-fit index (GOF = 0.411) indicated an acceptable model fit. Ultimately, the proposed model can serve as a comprehensive framework for digital human resource management in the Civil Registration Organization and similar organizations.

Keywords: Digital transformation; Human resource management; Civil Registration Organization

1. Introduction

The accelerating wave of digital transformation (DT) has fundamentally reshaped the way organizations manage and develop their human capital. Once confined to transactional automation, digital technologies are now embedded in strategic human resource management (HRM), affecting workforce planning, talent acquisition, performance management, and employee development. This transformation is driven by disruptive technologies such as artificial intelligence (AI), big data analytics, cloud-based platforms, and digital communication ecosystems, which together create opportunities to reconfigure HR practices and organizational capabilities for greater agility and competitiveness (Dwivedi et al., 2021; Richard et al., 2022; Susanti et al., 2021). For public and service-oriented organizations, such as the Civil Registration Organization of Iran, digital transformation is not merely a technological upgrade but a systemic change that demands cultural adaptation, strategic alignment, and employee empowerment (Rana et al., 2021; Tuukkanen et al., 2022).

HRM has evolved from an administrative function to a strategic enabler of organizational performance, and digitalization has amplified this shift (Karuppannan et al., 2024; Tortorella et al., 2021). Digital HR platforms integrate recruitment, training, compensation, and employee engagement with analytics and decision support, allowing HR leaders to make evidence-based, agile, and future-focused decisions (Susanti et al., 2021; Zhang & Chen, 2023). In parallel, organizations now recognize the strategic importance of aligning digital initiatives with HR development goals, as seen in the banking sector where digital strategies directly impact human resource competencies and adaptability (Al-Hmesat et al., 2025; Ghimire, 2025). These transformations also demand new forms of leadership and culture capable of supporting experimentation, distributed decision-making, and employee-driven innovation (Rosfeldt & Lorentzen, 2022; Tuukkanen et al., 2022).

Moreover, the digitization of HRM is closely tied to enterprise-wide digital strategy. Research shows that HR departments act as catalysts by translating technology adoption into improved skills, motivation, and organizational learning (Gao, 2024; Yadnya et al., 2023). However, digital HRM initiatives cannot succeed without understanding contextual and cultural factors. In highly regulated or public service environments, such as national civil registration systems, transformation must balance technological efficiency with inclusivity and service quality (Seifi et al., 2024; Shariati et al., 2024).

Artificial intelligence and advanced analytics have revolutionized HR processes by enhancing predictive capabilities in talent management, improving performance appraisals, and fostering employee well-being (Dwivedi et al., 2021; Hajian & Hajian, 2024). AI-based platforms personalize career development pathways, automate routine tasks, and provide managers with real-time workforce intelligence (Hameed et al., 2024; Hidayat & Basuil, 2024). At the same time, digital HRM introduces new competencies such as data-driven decision-making, algorithmic management, and ethical use of employee information (Ghonim et al., 2024; Richard et al., 2022). This paradigm shift moves HR from a compliance-focused discipline to a proactive strategic partner capable of influencing business transformation outcomes (Karuppannan et al., 2024; Kavand, 2024).

However, the adoption of these technologies is not without challenges. Concerns about privacy, fairness, and transparency in algorithm-driven HR processes have become pressing research and policy questions (Dwivedi et al., 2021; Rosfeldt & Lorentzen, 2022). Employees' digital readiness, organizational trust, and the availability of digital skills are critical for successful implementation (Tortorella et al., 2021; Zhang & Chen, 2024). In developing economies, the tension between rapid technological adoption and the maturity of HR systems further complicates transformation efforts (Ghimire, 2025; Hameed et al., 2024).

Culture and leadership play a decisive role in shaping digital HRM outcomes. Organizations with learning-oriented, adaptive, and innovative cultures are better positioned to exploit digital tools for workforce empowerment and strategic agility (Rana et al., 2021; Rosfeldt & Lorentzen, 2022). Studies highlight that distributed leadership approaches foster collaboration and employee engagement during transformation (Tuukkanen et al., 2022). Moreover, in public sector institutions, cultural resistance and hierarchical decision-making structures can hinder the diffusion of digital HR systems, requiring careful change management and leadership interventions (Seifi et al., 2024; Tiwow, 2023).

Another dimension of cultural readiness involves aligning digital HRM with organizational values and social responsibility. As HR processes become more data-driven, ethical concerns about inclusivity and fairness in recruitment, performance evaluation, and training intensify (Hajian & Hajian, 2024; Richard et al., 2022). Thus, HR leaders must integrate ethical frameworks and human-centered design principles into digital platforms to maintain employee trust and organizational legitimacy (Karuppannan et al., 2024; Rosfeldt & Lorentzen, 2022).

Digital HRM is also a driver of process innovation and capability development. Technologies such as electronic human resource management (e-HRM) enable real-time collaboration, self-service functions, and decentralized decision-making

(Hidayat & Basuil, 2024; Karuppannan et al., 2024). By adopting process- and metadata-based approaches, organizations can design more adaptive HR systems that respond to dynamic market conditions (Kavand, 2024). Moreover, integrating HR analytics with organizational learning allows firms to anticipate skills shortages, design targeted development interventions, and strengthen knowledge sharing (Yadnya et al., 2023; Zhang & Chen, 2023).

Within large and bureaucratic institutions, such as national civil registration agencies, these innovations improve operational efficiency and employee experience by simplifying workflows, reducing redundancy, and enhancing service responsiveness (Seifi et al., 2024; Shariati et al., 2024). In such environments, digital transformation also supports talent retention and job satisfaction by providing modern working conditions, continuous feedback mechanisms, and personalized development opportunities (Al-Hmesat et al., 2025; Ghimire, 2025).

Digital transformation directly influences human resource development (HRD) by expanding access to learning and career growth resources (Al-Hmesat et al., 2025; Ghimire, 2025). Digital platforms facilitate microlearning, immersive training, and AI-driven content personalization, allowing organizations to develop agile, innovation-ready employees (Hajian & Hajian, 2024; Hameed et al., 2024). Studies emphasize that HRD strategies integrated with digital tools increase engagement, support reskilling, and improve both financial and non-financial rewards (Ghimire, 2025; Ghonim et al., 2024). This is particularly relevant to institutions like the Civil Registration Organization, which require highly skilled personnel to implement and sustain national digital infrastructure.

Furthermore, digital HR initiatives positively impact organizational performance by increasing productivity, service quality, and employee agility (Gao, 2024; Tiwow, 2023). The synergy between human resource digitalization and business transformation creates competitive advantages even in public service contexts (Rana et al., 2021; Yadnya et al., 2023). Evidence also shows that organizations integrating AI and digital tools in HR functions report stronger adaptability to crises, enhanced innovation, and improved employee satisfaction (Dwivedi et al., 2021; Tortorella et al., 2021).

Despite the growing body of knowledge, gaps remain in contextualizing digital HRM for public service organizations with large-scale, citizen-facing operations. Existing research has predominantly focused on private-sector enterprises or technology-driven companies (Richard et al., 2022; Zhang & Chen, 2024). Studies in emerging economies highlight the need for frameworks tailored to regulatory constraints, cultural diversity, and public accountability (Seifi et al., 2024; Shariati et al., 2024). Moreover, while the adoption of e-HRM and AI-based solutions is accelerating, limited empirical evidence exists on the readiness, success factors, and outcomes in government agencies (Tiwow, 2023; Yadnya et al., 2023).

Addressing these gaps is crucial for organizations like the Civil Registration Organization of Iran, which plays a vital role in digital identity infrastructure and public data governance. Understanding how digital transformation impacts HR strategies, employee competencies, and organizational culture can inform policy and managerial decisions to ensure sustainable and human-centered modernization (Al-Hmesat et al., 2025; Ghonim et al., 2024).

Given these theoretical and practical considerations, this study aims to validate a comprehensive digital transformation model in human resource management tailored to the Civil Registration Organization of Iran.

2. Methods and Materials

The present study was conducted using a mixed-methods (qualitative–quantitative) design with a descriptive–analytical approach to simultaneously capture both the depth of concepts and statistical breadth. In the first stage, qualitative data were collected and analyzed; subsequently, the findings of this phase served as the foundation for designing the quantitative instrument. The objective of this design was to develop a localized theory regarding digital transformation in human resource management within the Civil Registration Organization of Iran.

In the qualitative section, the systematic grounded theory method (Strauss & Corbin's approach) was employed. The research process began with in-depth, unstructured interviews with experts and specialists. The stages of open, axial, and selective coding were systematically implemented, and the main and subcategories were derived based on the collected data. The use of grounded theory in this study was chosen due to its inductive nature in theory development and its flexibility in accurately identifying key components within the real organizational context. Unlike hypothesis-driven approaches, this method allows the final theory to emerge directly from the data and enables a deeper analysis of participants' experiences and perspectives.

The qualitative statistical population consisted of managers, human resource and information technology specialists in the Civil Registration Organization, as well as university professors and experts in the fields of management and digital transformation. Given the qualitative nature of the study, purposive and snowball sampling methods were used, and interviews continued until theoretical saturation was achieved. In total, 200 individuals participated in the qualitative phase. Inclusion criteria included job relevance to the research topic, willingness to collaborate, and specialized experience in the related domains.

In the quantitative phase, a questionnaire was designed based on the findings of the qualitative section. Initially, it was pilot-tested with a sample of 30 participants, and after calculating Cronbach's alpha and refining the questions, the final version was distributed to the main sample. The quantitative statistical population comprised managers, deputies, and specialists of the Civil Registration Organization of Iran. Due to research objectives and practical constraints, non-probability sampling methods were applied. To ensure the validity of the instruments in the qualitative phase, triangulation of data sources, peer review, and participant validation of findings were conducted. In the quantitative phase, content validity of the instrument was assessed using the Content Validity Ratio (CVR) and Content Validity Index (CVI) through expert evaluation, and construct validity was examined using confirmatory factor analysis with statistical software. The reliability of the instruments was confirmed by calculating Cronbach's alpha and composite reliability using SPSS and LISREL software.

For data analysis, the qualitative section was analyzed through the three stages of grounded theory coding. Data analysis began concurrently with data collection, and the categories were systematically developed. In the quantitative section, the questionnaire data were analyzed using descriptive and inferential statistical methods to evaluate the validity of the final model.

3. Findings and Results

After open coding, the purpose of the axial coding stage is to establish relationships among the categories generated during open coding. This coding is termed "axial" because it revolves around a central research category, namely "proposing a digital transformation model in human resource management of the Civil Registration Organization of Iran." This category was selected as the core category and positioned at the center of the model since its influence and presence were clearly observable across most data and interviewees' quotations. Therefore, this category can be placed at the center of the model, linking other categories to it. For axial coding in this study, Strauss and Corbin's paradigm model was used. This paradigm helps theorists develop a holistic understanding of the theoretical process. The components of the paradigm model for axial coding include the core category, causal conditions, contextual conditions, intervening conditions, strategies, and consequences. The relationships among other categories and the core category follow this paradigm.

Table 1. Example of Axial Coding

Core Category (Secondary Code)	Open Code
Individual Characteristics	Collaborative spirit (collectivism)
	Flexibility and adaptability to the environment
	Understanding telework based on online procedures
	Systems thinking
	Critical thinking
	Learning ability and rapid knowledge transfer
	Intuition and perceptiveness
	Conflict management
	Personal integrity and consistency (alignment of speech and action)
	Courage and boldness
	Prudence and foresight
Perceived Ease and Speed	Improved information access
	Increased collaboration speed
	Process optimization systems for repetitive organizational tasks
	Ease of interaction
	Advancement of user interfaces
	Improved quality
	Perceived reduction of human error
	Better workplace experience

Mental Characteristics	Faster access to top management Easier access to related organizations Emotional intelligence Employees' mental adaptation to rapid business and organizational changes Cultural intelligence Political intelligence Mathematical and numerical intelligence Individual creativity Analytical thinking Logical thinking

From the identified factors, axial coding was carried out using the paradigm, and based on this, the linear relationships among the research categories — including causal conditions, core categories, contextual conditions, intervening conditions, strategies, and consequences — were determined.

After deriving the model, it is necessary to confirm the adequacy of the measurement models for the research variables. Therefore, the measurement models for these variables are presented below, which were evaluated using structural equation modeling. It should be noted that structural equation modeling defines the relationships between latent and observed variables. In graphical representations, latent variables are usually shown with circles and observed variables (dimensions of each concept) with rectangles.

To describe the main research variables, indices such as mean, standard deviation, and other descriptive measures were used. These indicators are presented in Table 2.

Table 2. Descriptive Statistics of Research Variables

Variables	N	Mean	Skewness	Kurtosis	Variance	Minimum	Maximum
Causal Factors	380	3.790	0.766	0.002	0.490	2	5
Contextual Factors	380	3.546	1.461	-0.584	0.446	1.67	5
Intervening Factors	380	4.084	-0.058	-0.263	0.231	2.67	5
Strategies	380	3.825	-0.216	0.566	0.225	3	5
Consequences	380	3.673	-0.496	0.314	0.339	2.75	5

Based on the obtained means, it is clear that the response option "high" was more frequent among participants. The highest mean was associated with causal factors compared to other variables. Additionally, according to the skewness and kurtosis values, the data are within the acceptable range (-2 to +2), indicating symmetry and a normal distribution.

In this study, the Kolmogorov–Smirnov test was used to assess the normality of the data. If the data distribution is normal, inferential statistical tests can be applied. For testing normality, the null hypothesis assumes that the data follow a normal distribution. The test is performed at a 5% error level. If the significance level is greater than or equal to 0.05, there is no reason to reject the null hypothesis, and the data are considered normally distributed. The statistical hypotheses for normality testing were formulated accordingly. The results of the normality test are shown in Table 3.

Table 3. Kolmogorov–Smirnov Normality Test Results

Main Factor	K–S Statistic	Significance Level
Causal Factors	0.381	0.088
Contextual Factors	0.386	0.076
Intervening Factors	0.398	0.061
Strategies	0.377	0.065
Consequences	0.386	0.066
Core Category	0.391	0.075

Based on the results of the Kolmogorov–Smirnov test, the significance levels for all variables were greater than the error threshold (0.05). Therefore, there is no reason to reject the null hypothesis, and the data distribution is normal.

Before evaluating the structural relationships, multicollinearity must be examined to ensure that the regression results are unbiased. In statistics, the Variance Inflation Factor (VIF) assesses the severity of multicollinearity in ordinary least squares regression analysis. The intensity of multicollinearity can be analyzed by reviewing the magnitude of the VIF value. This index indicates how much the variance of the estimated coefficients is increased due to collinearity. If the VIF value is greater than 5, the inflation level is considered critical; the ideal VIF value is 3 or lower.

Table 4. Multicollinearity Test (VIF)

Variable	VIF
Causal Factors	1
Contextual Factors	1.488
Intervening Factors	1.428
Strategies	1
Consequences	1
Core Phenomenon	0.494

According to the results in Table 4, the VIF values of all research components are less than 3; therefore, the constructs of the study do not have multicollinearity issues.

In the present study, the partial least squares structural equation modeling (PLS-SEM) approach was used to test the measurement model and research hypotheses. The PLS method is advantageous due to its lower dependency on sample size, its independence from normality assumptions, and its focus on maximizing explained variance. Unlike LISREL and AMOS, PLS is more suitable for practical applications. Each research hypothesis was analyzed separately using the PLS technique, and finally, the overall research model was also tested using this method. In the PLS technique, several key considerations are critical:

1. **Factor Loadings:** The strength of the relationship between a latent construct and its observed variable is indicated by the factor loading. Factor loadings range from 0 to 1. In the standardized measurement model, if the loading of an item on its associated dimension is less than 0.4, the item should be removed. According to Hair et al. (2013), items with factor loadings between 0.3 and 0.7 should also be examined for potential removal, while the recommended threshold is 0.7 or higher.
2. **Significance Testing:** Once the correlations between variables are identified, their significance must be tested. To test the significance of observed correlations, bootstrapping or jackknife resampling methods can be used. In this study, the bootstrapping method was applied, which provides the *t*-value. At a 5% error level, if the *t*-value from bootstrapping is greater than 1.96, the observed correlations are significant.

In general, relationships among variables in the PLS technique are categorized into two models:

- **Outer Model:** Equivalent to the measurement model (confirmatory factor analysis) in SEM, showing the relationships between latent and observed variables.
- **Inner Model:** Equivalent to the structural model (path analysis) in SEM, examining the relationships among latent variables.

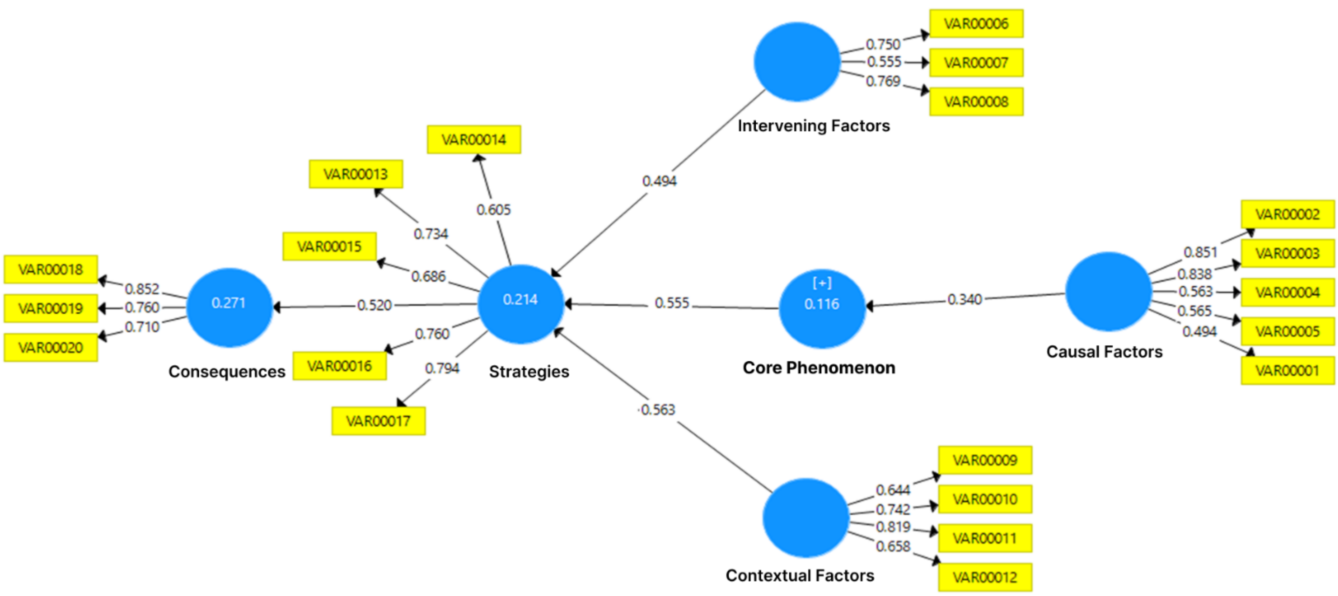

Figure 1. Factor Loadings of the Research Model (Outer Model)

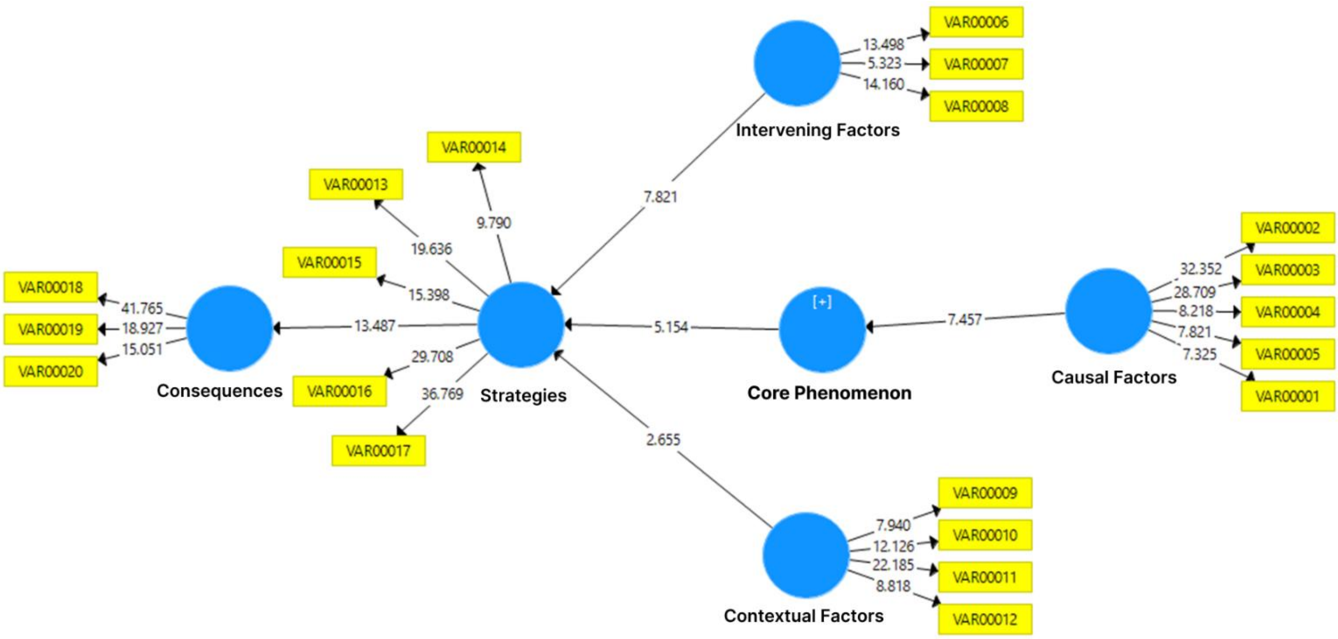

Figure 2. Bootstrapping t-Values of the Research Model (Outer Model)

To assess and evaluate the validity and reliability of the constructs in the measurement models under PLS-SEM, Cronbach's alpha, composite reliability (CR), convergent validity (AVE), and discriminant validity (Fornell–Larcker criterion) were calculated and reported.

- **Construct Validity:** As mentioned, the outer model is equivalent to confirmatory factor analysis. To verify the model, the relationships between the latent variables and their measurement items were assessed. The outer model ensures that the questionnaire items adequately measure the intended latent constructs; without this confirmation, testing the structural paths would be invalid.
- **Cronbach's Alpha (CA):** Cronbach's alpha was calculated to examine internal consistency reliability. Its values range from 0 to 1. Values greater than 0.7 are acceptable, while values below 0.6 are undesirable.
- **Composite Reliability (CR):** CR is considered a better and more accurate measure of internal consistency compared to Cronbach's alpha because, unlike Cronbach's alpha (which assumes equal item weighting), CR assigns greater importance to items with higher factor loadings. CR values above 0.7 are accepted, and values below 0.6 are inadequate.
- **Convergent Validity (AVE):** Convergent validity was also assessed. When one or more attributes are measured through two or more methods, the correlation between these measures indicates convergent validity. A questionnaire demonstrates convergent validity if the correlations between scores measuring the same attribute are high. The average variance extracted (AVE) is used for this purpose. AVE values above 0.5 are considered acceptable.
- **Rho Coefficient (ρA):** Composite reliability can also be calculated using Jöreskog's formula, and the Rho coefficient is an additional indicator of internal consistency reliability. Chin (1998) suggested that the Rho coefficient provides more reliable results than Cronbach's alpha. Its value should exceed 0.7.

Table 5. Convergent Validity and Reliability of Research Variables

Variable	Cronbach's Alpha	AVE	CR	Rho
Causal Factors	0.761	0.60	0.833	0.781
Contextual Factors	0.736	0.687	0.825	0.744
Intervening Factors	0.769	0.651	0.828	0.769
Strategies	0.793	0.678	0.734	0.731
Consequences	0.774	0.659	0.833	0.778

Core Phenomenon	0.736	0.682	0.845	0.745

According to the results in Table 5, Cronbach's alpha values for all variables were greater than 0.7; therefore, the reliability of all constructs was confirmed. The average variance extracted (AVE) for all constructs was greater than 0.5, confirming convergent validity. Composite reliability (CR) values were higher than both AVE and 0.7, indicating adequate construct reliability and validity. Additionally, the Rho coefficient values were all above 0.7.

Discriminant validity is another criterion for evaluating the fit of measurement models and addresses two issues:

(a) comparing the correlation of each construct with its indicators against the correlations of these indicators with other constructs, and

(b) comparing the correlation of a construct with its own indicators against its correlation with other constructs.

Fornell–Larcker Criterion: This method compares the square root of AVE for each construct with the correlations between that construct and others. Acceptable discriminant validity is achieved when a construct has stronger interactions with its own indicators than with other constructs. Specifically, the square root of AVE for each construct should be greater than the shared variance (squared correlations) with other constructs. This evaluation is performed using a correlation matrix where the diagonal cells contain the square roots of AVE. A model has acceptable discriminant validity if the diagonal values are higher than the corresponding values below them.

The main characteristic of this matrix is that the principal diagonal equals one. Then, the values on the principal diagonal are replaced with the square roots of the AVE (Average Variance Extracted) values, and, finally, Table 6 is presented.

Table 6. Fornell–Larcker Criterion

	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Consequences	Core Phenomenon
Causal Factors	0.774					
Contextual Factors	0.551	0.828				
Intervening Factors	0.478	0.598	0.806			
Strategies	0.418	0.474	0.536	0.823		
Consequences	0.513	0.509	0.587	0.470	0.811	
Core Phenomenon	0.613	0.591	0.480	0.401	0.503	0.825

As shown in Table 6, the values on the principal diagonal are greater than all other values in their respective columns, indicating that the model has acceptable discriminant validity. Recent studies by Henseler et al. (2015) show that the Fornell–Larcker criterion may not perform well when construct loadings differ only slightly. Therefore, Henseler et al. proposed the HTMT criterion as an alternative. If all column entries in this method are less than 0.9, the model possesses acceptable discriminant validity.

Table 7. HTMT Results for Assessing Discriminant Validity

	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Consequences	Core Phenomenon
Causal Factors						
Contextual Factors	0.737					
Intervening Factors	0.620	0.797				
Strategies	0.430	0.573	0.711			
Consequences	0.748	0.684	0.485	0.739		
Core Phenomenon	0.414	0.710	0.638	0.592	0.630	

Given Table 7, since the obtained values are less than 0.9, HTMT discriminant validity is acceptable.

After confirming the measurement models through reliability, convergent validity, and discriminant validity, the results of the structural model can be reported. Unlike measurement models, the structural section does not consider the questionnaire items and observed variables; it examines only the latent variables and the relationships among them. To assess model fit, the structural model fit indices R2, effect size F2, and Q2 are used.

R2 connects the measurement and structural parts of structural equation modeling and indicates the proportion of variance in each endogenous variable explained by the exogenous variables. A key point here is that R2 is calculated only for endogenous (dependent) constructs and equals zero for exogenous constructs. The higher the R2 for the endogenous constructs of a model, the better the model fit. Chin (1998) identified the values 0.19, 0.33, and 0.67 as weak, moderate, and strong, respectively.

$R^2 = (0.116 + 0.214 + 0.271) / 3 = 0.200$

Based on the R2 results, the endogenous constructs of the research model are satisfactory. The coefficient of determination for the performance of dependent components shows that 26 percent of the variance in the model's variables is explained by the combined effects of the independent and dependent variables, which is strongly acceptable.

The GOF pertains to the overall part of structural equation models. This index enables the researcher, after evaluating the fit of both the measurement and structural sections, to also check the overall model fit. GOF was introduced by Tenenhaus et al. (2005) and is computed as follows: Communalities indicate the mean shared variance of each construct, and R^2 is the mean explained variance of the model's endogenous constructs. Wetzels et al. (2009) introduced 0.01, 0.25, and 0.36 as weak, moderate, and strong GOF benchmarks.

$GOF = \sqrt{0.847 \times 0.200} = 0.411$

Therefore, based on GOF, the model is also supported.

Q^2 Criterion (Predictive Relevance or Redundancy)

Q^2 is another criterion for evaluating the structural model. Model predictive capability can be assessed with the nonparametric Stone–Geisser test (1974), while Q^2 evaluates the success of this prediction. Hair et al. (2019) describe the predictive strength for endogenous constructs as 0 (none), 0.25 (medium), and 0.50 (strong). In PLS software, Q^2 is calculated using the blindfolding technique.

Table 8. Effect Size (Cohen's f^2) and Predictive Relevance (Q^2)

Variable	Q^2	F^2 – Causal Factors	F^2 – Contextual Factors	F^2 – Intervening Factors	F^2 – Strategies	F^2 – Consequences
Causal Factors	0.455	—	0.312	0.284	0.485	0.226
Contextual Factors	0.849	0.297	—	0.335	0.430	0.244
Intervening Factors	0.500	0.276	0.308	—	0.512	0.263
Strategies	0.711	0.362	0.348	0.387	—	0.640
Consequences	0.516	0.291	0.305	0.272	0.361	—
Core Phenomenon	0.518	0.309	0.296	0.288	0.354	0.277

As shown in Table 8, the obtained Q^2 values, which indicate the model's predictive power for endogenous constructs, suggest that the predictive power of the research constructs is strong.

In the overall research model, as depicted in the figures, the measurement model (relationships between each observed variable and its latent construct) and the path model (relationships among latent constructs) are estimated. Figure 1 presents the factor loadings of the research variables. In this model, which is the output of SmartPLS, the standardized factor loadings summarizing the relationships of the research variables are reported. To assess the significance of the relationships, t-statistics were calculated using the bootstrapping technique, as shown in Figure 2. The research hypotheses are tested separately below based on the relationships among the variables.

In this section, based on the partial least squares results using factor loadings and bootstrapping, the research hypotheses were examined:

Table 9. Hypothesis Testing and Path Analysis

No.	Hypothesis	Path Coefficient	t-Statistic	p-Value	Status
	Causal conditions have a significant effect on the core category.	0.340	7.457	0.000	Supported
	The core category has a significant effect on strategies.	0.555	5.154	0.000	Supported
	Strategies have a significant effect on consequences.	0.520	13.487	0.000	Supported
	Intervening conditions have a significant effect on strategies.	0.494	7.821	0.000	Supported
	Contextual conditions have a significant effect on strategies.	0.563	2.655	0.000	Supported

Based on the structural equation modeling results, the path coefficients for all hypotheses exceed 0.3. The significance levels for all hypotheses are less than 0.05. Although it cannot be asserted with absolute certainty that all hypotheses are confirmed, the confidence in the soundness of the analysis and the validity of the hypotheses is very high, which itself supports the reliability and validity of the study's hypotheses.

4. Discussion and Conclusion

The purpose of this study was to validate a digital transformation model for human resource management (HRM) in the Civil Registration Organization of Iran and to empirically examine the interplay among causal conditions, contextual and intervening factors, strategies, and organizational outcomes. The results strongly support the conceptual model developed through grounded theory and structural equation modeling. All proposed hypotheses were confirmed, with significant path coefficients linking the core phenomenon of digital HRM transformation to strategies ($\beta = 0.555$, $t = 5.154$, $p < 0.001$) and showing that strategies significantly impact key organizational outcomes ($\beta = 0.520$, $t = 13.487$, $p < 0.001$). Additionally, both contextual ($\beta = 0.563$, $t = 2.655$, $p < 0.001$) and intervening conditions ($\beta = 0.494$, $t = 7.821$, $p < 0.001$) were found to influence the effectiveness of transformation strategies, confirming the multifactorial and systemic nature of digital change in HRM. The model demonstrated robust reliability and validity, with Cronbach's alpha and composite reliability values exceeding the accepted thresholds, average variance extracted (AVE) greater than 0.5, and discriminant validity confirmed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT). Global goodness-of-fit (GOF = 0.411) indicated strong overall model adequacy.

These findings align with the growing body of scholarship emphasizing the strategic and multidimensional character of HR digitalization. Several studies have argued that successful digital transformation is not limited to technology deployment but requires integrating cultural, structural, and individual dimensions (Rana et al., 2021; Rosfeldt & Lorentzen, 2022; Tuukkanen et al., 2022). Our results corroborate this, showing that causal factors such as technological readiness, leadership support, and employee digital literacy form the foundation for transformation. In public service contexts, where hierarchical structures and regulatory complexity often impede agility, the finding that contextual conditions significantly shape digital HRM echoes prior evidence from public organizations that culture and institutional readiness are decisive enablers (Seifi et al., 2024; Tiwow, 2023).

Furthermore, the identification of key strategies — including organizational culture-building, human resource empowerment, development of smart networks, and continuous monitoring — is consistent with frameworks advanced in earlier research. For instance, the conceptual work on e-HRM underscores the importance of enabling technologies alongside capability development and organizational learning (Karuppannan et al., 2024; Kavand, 2024). Similarly, studies in banking and service sectors confirm that when digital HR strategies are coupled with training and employee empowerment, they lead to improved adaptability and service quality (Al-Hmesat et al., 2025; Ghimire, 2025). This study extends those findings to a government institution that has both high data intensity and public accountability, demonstrating that the same principles hold in complex bureaucratic systems.

The robust relationship between strategies and organizational outcomes found here further supports the growing evidence base linking digital HRM to performance enhancement. Outcomes identified — such as improved employee performance, increased organizational agility, and enhanced social capital — mirror those reported by (Gao, 2024) in Chinese enterprises undergoing HRM digital reform and by (Yadnya et al., 2023) in Indonesian organizations seeking agility through strategic HR development. In addition, our results resonate with research showing that digital HR interventions improve service responsiveness and reduce operational redundancy, especially in organizations with national-level data governance responsibilities (Seifi et al., 2024; Shariati et al., 2024). By demonstrating statistically significant pathways from strategies to outcomes, this study strengthens the argument that digital transformation in HR goes beyond efficiency gains to create broader organizational value.

An important insight emerging from our findings is the dual role of technology and culture. While technical readiness and infrastructure are necessary, cultural adaptability and distributed leadership behaviors have a powerful effect on transformation success (Rosfeldt & Lorentzen, 2022; Tuukkanen et al., 2022). This echoes (Rana et al., 2021), who found that digital change in the public sector hinges on cultivating innovation-oriented norms and trust. Our model suggests that leaders in public organizations must not only invest in systems but also proactively build a digital mindset among employees, foster open communication, and reduce resistance to change. These implications are especially relevant where hierarchical decision-making remains strong and can slow digital initiatives.

Our results also validate the relevance of artificial intelligence (AI) and advanced analytics as enabling technologies for HR performance improvement. The significance of causal conditions such as technological infrastructure and data-driven decision-making is aligned with research emphasizing AI's role in enhancing HR functions, from recruitment to talent development (Dwivedi et al., 2021; Hajian & Hajian, 2024). By confirming the relationship between core digital HRM and organizational outcomes, this study adds empirical weight to calls for integrating AI ethically and effectively into public HR processes (Ghonim et al., 2024; Hameed et al., 2024). Ethical and human-centered design considerations remain essential, as highlighted by (Richard et al., 2022) and (Karuppannan et al., 2024), to avoid employee distrust or unintended bias.

Moreover, the interplay of contextual and intervening conditions in our model underscores the complexity of digital HR transformation. Intervening factors such as change management capacity and stakeholder engagement had a substantial influence on strategy success, echoing (Tiwow, 2023) who found that organizational agility mediates digital transformation outcomes in universities. Contextual conditions — including policy frameworks, external technological environment, and institutional support — also proved critical, reinforcing (Seifi et al., 2024) and (Shariati et al., 2024) who argue that the external ecosystem profoundly shapes the speed and sustainability of HR digitalization in education and government services.

By applying structural equation modeling to a public organization with high national importance, this study also contributes to the broader debate about digital transformation maturity models. Prior research has proposed frameworks for private industry (Zhang & Chen, 2023, 2024), but there has been less empirical validation in public administrative systems. Our findings indicate that constructs such as cultural readiness, technology capability, and HR empowerment are transferrable and predictive even in non-market-driven settings. At the same time, our results reinforce that digital maturity in government HR requires deliberate adaptation to regulatory, social, and citizen-service imperatives (Rana et al., 2021; Yadnya et al., 2023).

Finally, the confirmation of model fit indices, including R^2 and GOF, demonstrates that the proposed framework provides a reliable analytical tool for diagnosing and guiding HR digital transformation in complex organizations. The model's explanatory power ($R^2 = 0.20$) and strong GOF (0.411) are comparable to those reported in recent empirical digital HR studies (Al-Hmesat et al., 2025; Gao, 2024; Ghimire, 2025). This validation suggests that public sector managers can use such frameworks to systematically assess readiness, identify critical leverage points, and design tailored transformation roadmaps.

Despite its contributions, this study has several limitations. First, while the sample size was adequate for structural equation modeling, the study focused exclusively on one national organization — the Civil Registration Organization of Iran. This limits the generalizability of findings to other sectors or countries with different institutional, regulatory, and cultural contexts. Second, data were collected primarily from managers and HR experts; including perspectives from a broader employee base might have provided deeper insights into cultural barriers and user experiences with digital HR systems. Third, while the mixed-method approach enhanced the robustness of the model, qualitative insights were derived from self-reported interviews, which may introduce social desirability bias or selective recall. Additionally, the cross-sectional design does not capture the longitudinal dynamics of digital transformation; digital maturity evolves over time, and causal relationships may shift as technologies and cultures adapt.

Future studies could expand this work by testing the validated model in other public service organizations, private enterprises, and across different national contexts to explore cross-cultural and cross-industry applicability. Longitudinal research would provide valuable insight into how HR digital transformation capabilities mature and how the interplay of causal, contextual, and intervening factors evolves over time. Additionally, researchers could integrate new constructs such as algorithmic fairness, data ethics, and employee well-being, reflecting the growing importance of human-centered AI in HR. Comparative studies between highly regulated public institutions and agile private firms could also illuminate how governance and compliance shape transformation trajectories. Finally, employing multi-source data, including employee surveys, system usage analytics, and HR performance metrics, could strengthen causal inferences and reduce common method bias.

For practitioners, this study highlights the need to approach digital HR transformation as a holistic organizational change rather than a purely technical project. Leaders should invest in building a digital culture by fostering openness, continuous learning, and psychological safety, while also strengthening digital competencies across all HR levels. Change management strategies must actively involve employees, reduce resistance, and create shared ownership of transformation outcomes. Integrating AI and analytics into HR functions should be done transparently, ensuring fairness, explainability, and ethical use of employee data. Finally, managers should continually monitor transformation progress using the validated model, adapting strategies to contextual changes and aligning HR digital initiatives with broader organizational and national digital agendas.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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