Digital Governance as a Mediator and Transformational Leadership as a Moderator of Digital Innovation Performance in UAE Public Sector Organizations: An Empirical Investigation Using PLS-SEM

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Abstract

Background: Public sector organizations in the United Arab Emirates (UAE) are undergoing rapid digital transformation, yet empirical evidence on the factors driving digital innovation performance in this context remains scarce. A conceptual framework integrating data ethics, digital transformation, technology adaptation, digital governance (mediator), and transformational leadership (moderator) has been proposed (Alhammadi, manuscript under review) but requires empirical validation.

Methods: A cross-sectional survey was administered to 404 employees across 26 public sector organizations in the UAE, spanning utilities, municipalities, health, and education sectors. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS, assessing a reflective measurement model and a structural model encompassing nine hypotheses involving direct effects, mediation, and moderation.

Results: The measurement model demonstrated satisfactory reliability (Cronbach's $\alpha > 0.84$; composite reliability > 0.89) and validity (AVE > 0.50) for all constructs. The structural model explained 71.2% of the variance in digital innovation performance ($R^2 = 0.712$) and 57.1% in digital governance ($R^2 = 0.571$). Digital transformation exhibited the strongest direct effect on digital innovation performance ($\beta = 3.705$, $p < 0.001$). Digital governance significantly mediated the relationships between both digital ethics ($p = 0.029$) and digital transformation ($p = 0.002$) and innovation performance. Transformational leadership significantly moderated the digital ethics–innovation relationship ($p = 0.047$) and the technology adaptation–innovation relationship ($p = 0.003$).

Conclusions: The findings confirm that digital governance and transformational leadership are critical intervening mechanisms in driving digital innovation performance in UAE public sectors. Practical implications for policymakers and organizational leaders are discussed.

Keywords: PLS-SEM; digital innovation performance; digital governance; data ethics; digital transformation; technology adaptation; transformational leadership; UAE public sector

1. Introduction

The government sector is one of the key areas of digital innovation, especially in an emerging economy with an agenda of transformation led by the government which is the primary driver of national competitiveness. The United Arab Emirates has become one of the leaders in the digitalization of the public sector, the strategic plans of which include the UAE Vision 2021, UAE Centennial Plan 2071, and UAE Strategy for Artificial Intelligence [1,2]. These have enhanced the need to have evidence-based knowledge of the issues that facilitate or discourage digital innovation performance in government agencies.

Although there is much conceptual development, limited studies have been conducted empirically on the interrelationships between data ethics, digital transformation, technology adaptability, digital governance, transformational leadership, and digital innovation performance, especially in the case of the Gulf Cooperation Council (GCC) public sector [3,4]. Alhammadi (manuscript under review) has developed a conceptual framework that considers such relationships based on the Diffusion of Innovation (DOI) theory [5], Transformational Leadership theory [6], Institutional theory [7] and Teleological Ethical theory. The framework hypothesizes data ethics, digital transformation, and technology adaptation to be independent predictors of digital innovation performance where digital governance mediates and transformational leadership moderates.

The current research is the initial systematic empirical experiment of this integrative model. Through survey data on 404 employees in 26 organizations in the UAE public sector, the research incorporates Partial Least Squares Structural Equation Modeling (PLS-SEM) and tests nine hypotheses that include direct effects, mediation effects and moderation effects. These are four-fold research objectives: (a) the psychometric characteristics of the measurement tools are to be examined; (b) the direct impact of data ethics, digital transformation, and technology adaptation on the performance of digital innovations are to be tested; (c) the mediating impact of digital governance is to be tested; (d) the moderating impact of transformational leadership is to be tested.

In this research, the literature is enriched in three aspects. First, it makes use of the empirical evidence representing an underrepresented regional setting the UAE public sector, which contributes to the generalizability of theories formulated in Western contexts mostly of the private sector. Second, it also examines both mediating and moderating outputs in one unified model, which provides a more detailed explanation of the phenomenon of digital innovation performance compared to research that focuses on each single pathway. Third, the results provide practical implications to the UAE policymakers and leaders of the public sector to streamline their digital transformation initiatives.

2. Literature Review and Hypotheses Development

The theoretical underpinnings and hypotheses of this study were developed in a companion conceptual paper (Alhammadi, manuscript under review). This section provides a summary of the key theoretical arguments and the nine hypotheses tested in this empirical investigation.

2.1 Direct Effects on Digital Innovation Performance

Yoo et al. (2010) described digital innovation, as applying new combinations of digital and physical elements to create new products [8]. In the context of major organizations in the public sector, the digital innovation performance is predetermined by several antecedents working in accordance with various theoretical frameworks. Information privacy, intellectual property, accuracy, and transparency, which are ethical aspects of data, establish the conditions of trust and governance within the organization that favor innovation [9,10]. Innovation is supported by technological infrastructure which is created through digital transformation and digital transformation is described as an organizational process of utilising and integrating digital technologies in new forms and ways to radically change an organisation [11]. Technology adaptation, which denotes the processes and activities that involve the movement of technology out of the controlled settings to its operations environment [12], dictates the capability of an organization to be able to use the new technologies to produce innovation results.

H1: Data ethics has a significant impact on digital innovation performance.

H3: Technology adaptation has a significant impact on digital innovation performance.

H5: Digital transformation has a significant impact on digital innovation performance.

2.2 Mediating Role of Digital Governance

Based on the DOI theory and the institutional theory, the digital governance was theorized as an intermediary process where data ethics, technology adaptation, and digital transformation affect the outcome of innovation [5,13]. Digital governance represents structural practices (data ownership, value assessment), procedural (retention policies, monitoring, classification) and relational practices (user education, communication about policy) [14]. The moderating effect of governance is evidenced by the fact that the performance of organizations in central network location with stronger governance systems suffers more and more innovative performance [15,16].

H2: Digital governance mediates the relationship between data ethics and digital innovation performance.

H4: Digital governance mediates the relationship between technology adaptation and digital innovation performance.

H6: Digital governance mediates the relationship between digital transformation and digital innovation performance.

2.3 Moderating Role of Transformational Leadership

Transformational leadership theory posits that leaders who exhibit idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration create organizational conditions that amplify innovation processes [6,17]. The moderating role of transformational leadership was hypothesized on the basis that leadership behaviors condition the strength of the relationships between technology-related antecedents and innovation outcomes [18,19].

H7: Transformational leadership positively moderates the relationship between data ethics and digital innovation performance.

H8: Transformational leadership positively moderates the relationship between technology adaptation and digital innovation performance.

H9: Transformational leadership positively moderates the relationship between digital transformation and digital innovation performance.

3. Research Methodology

3.1 Research Design

This study employed a cross-sectional survey design using closed-ended questionnaires. Both nominal and ordinal scales were used to collect data from the targeted population. The nominal scale was used to capture demographic profiles, while the ordinal scale was used to rank non-numerical data hierarchically [20]. The research adopted a quantitative, deductive approach to test the theoretically derived hypotheses within the proposed structural model.

3.2 Pilot Study

Before the actual data collection, a pilot study was carried out on a sample of 30 employees picked among the various public sectors in the UAE, that include the Ministry of Education (MOE), Ministry of Health

(MOH), Sharjah Electricity, Gas and Water Authority (SEWGA), Dubai Electricity and Water Authority (DEWA), as well as Sharjah Municipality. The main criterion involved in the selection of the section heads was to test the validity and reliability of the questionnaire. Also, pre-test was done on 19 firms to confirm that the face and content validity of items were met and the respondents were able to comprehend the survey questions as intended [21].

3.3 Sampling and Participants

The research was conducted on the public sector organizations in the UAE with the help of non-probability convenience sampling technique. The sampling was dependent on the availability and willingness of convenient organizations to take part in the specified period and the government entities were sampled based on their activities [22]. The criteria used to select employees had to have a minimum of one year in the organization, and those with greater experience in the organization as heads of sections and higher positions were to be preferred since they had encountered managerial roles.

Twenty-six organizations in the public sector were contacted. Four hundred and four valid responses were obtained, which gave a response rate of 90%. The included organizations were divided into different groups based on their size: 5 small (10 -100 employees, 100 respondents), 15 medium (100-500 employees, 130 respondents), and 6 large (500 employees, 174 respondents). The sample was divided by the type of sector as 4 utilities organizations (75 respondents), 2 municipalities (35 respondents), 2 health organizations (120 respondents), and 5 education organizations (174 respondents).

Table 1
Demographic Profile of Respondents (N = 404)

Characteristic	Category	n	%
Gender	Male	204	50.25%
	Female	200	49.75%
Age group	18–24 years	47	11.63%
	25–34 years	89	22.03%
	35–44 years	174	43.07%
	45–54 years	106	26.24%
	55+ years	21	5.20%
Work experience	0–5 years	38	9.40%
	5–10 years	99	25.50%
	10–20 years	181	44.80%
	20+ years	86	21.28%
Education level	Diploma	51	12.62%
	Bachelor’s degree	245	60.64%
	Postgraduate degree	108	26.73%

The demographic profile reveals a near-equal gender distribution (50.25% male, 49.75% female). The majority of respondents (43.07%) were aged 35–44 years, and 44.80% had 10–20 years of work experience. Regarding education, 60.64% held a bachelor's degree and 26.73% held a postgraduate degree, indicating a well-educated sample with substantial professional experience relevant to assessing organizational digital innovation processes.

3.4 Instruments and Measurement

Multi-item scales were used to measure all constructs generated on the basis of the existing literature. The 14 item scale that was used to measure data ethics (DE) is based on information privacy, intellectual property, copying software, accuracy, further dissemination of information, and inaccuracy of information. The technology adaptation (TA) was determined through 12 measures that evaluated the perceived usefulness and perceived ease of use of technology at workplace. Digital transformation (DT) has been assessed on 12 items (with 4 items dropped as their loading was lower than 0.70) of drivers and enablers such as customer expectation, business ecosystem, speed of operational processes, big data, cloud computing, IoT, social media and benefits of digital transformation. The measurement of digital governance (DG) was done based on 9 items that included structural, procedural, and relational governance practices. Transformational leadership (TL) was assessed based on 4 items, which included commitment, motivation, new opportunities, and leading force. The performance of digital innovation was (I) determined by 8 items that provide the level of market introduction of technologically innovative products, product extensions, replacement rates, proportion of innovative products and performance of the entire product innovation. Some of the control variables were the size of the organization, the sector in which it operated, and the level of employees.

3.5 Analytical Approach

The analysis of data was performed with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS software [23]. The PLS-SEM was chosen due to its support of complex models with multiple mediating and moderating relationships, non-normal data distributions, predictive research requirements, and appropriate sample size of this study [24,25]. The analysis was done in two steps. The reflective measurement model was tested in the first phase on the basis of the internal consistency reliability (Cronbachs alpha, composite reliability), convergent validity (Average Variance Extracted, outer loadings), and discriminant validity (Fornell-Larcker, Heterotrait-Monotrait ratio). The second stage involved the assessment of collinearity (VIF) of the structural model, path coefficients, coefficient of determination (R^2) and effect size (f^2), predictive relevance (Q^2) and mediating and moderating effects significance through the process of bootstrapping [24].

In the case of mediation analysis, the variance accounted (VAF) method was used, in which a value of VAF of 80 percent and above signifies complete mediation, 20 to 80 percent signifies partial mediation, and 20 to 0 percent signifies no mediation [24]. The moderating analysis adopted the two-stage procedure of Chin et al., (2003), whereby the Stage 1 assumes the estimation of the main effects model in order to derive the latent variable scores, whereas Stage 2 involves the product of the exogenous and moderator variables score to form the interaction term [26].

4. Results

4.1 Measurement Model Assessment

4.1.1 Internal Consistency Reliability

Internal consistency reliability was assessed using Cronbach's alpha (α) and composite reliability (CR). As shown in Table 2, all constructs exceeded the recommended threshold of 0.70 for both metrics [27]. Cronbach's alpha values ranged from 0.840 (transformational leadership) to 0.978 (technology adaptation), and composite reliability values ranged from 0.893 (transformational leadership) to 0.980 (technology adaptation). These results indicate excellent internal consistency reliability for all measurement scales.

Table 2
Reliability and Convergent Validity of Constructs

Construct	Items	α	CR	AVE
Data Ethics (DE)	14	0.949	0.954	0.599
Digital Governance (DG)	9	0.948	0.956	0.706
Digital Transformation (DT)	12	0.916	0.929	0.545
Technology Adaptation (TA)	12	0.978	0.980	0.805
Transformational Leadership (TL)	4	0.840	0.893	0.676
Digital Innovation Perf. (I)	8	0.909	0.926	0.611

Note. CR = Composite Reliability; AVE = Average Variance Extracted. All values exceed recommended thresholds.

4.1.2 Convergent Validity

Convergent validity was assessed using Average Variance Extracted (AVE) and outer loadings of indicators. Every AVE value was above the 0.50 level suggested by Fornell and Larcker (1981) [28], with the range of values between 0.545 (digital transformation) and 0.805 (technology adaptation) (Table 2). All retained indicators had outer loadings that were greater than 0.70, with technology adaptation items having the highest loadings (0.875 to 0.917), followed by the digital governance items (0.810 to 0.882), data ethics items (0.737 to 0.815), digital innovation performance items (0.724 to 0.807), transformational leadership items (0.783 to 0.870), and digital transformation items (0.692 to 0.778). Four items of digital transformation (DT7, DT10, DT11, DT12) were dropped due to their loading factors below 0.70; item DT5 (0.692) was kept due to the fact that its deletion did not benefit composite reliability or AVE [29]. These findings demonstrate that the constructs have satisfactory convergent validity.

4.1.3 Discriminant Validity

Discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. Under the Fornell-Larcker criterion, the square root of AVE for each construct was compared against the inter-construct correlations. As presented in Table 3, the square root of AVE for each construct (on the diagonal) exceeded all corresponding inter-construct correlations, confirming discriminant validity [28]. The HTMT analysis further confirmed discriminant validity, with all values below the conservative threshold of 0.85 [30], except the TL–I correlation (0.924), which approached but did not exceed the liberal threshold of 0.90 [31].

Table 3
Discriminant Validity: Fornell-Larcker Criterion

	DE	DG	DT	I	TA	TL
DE	**0.774**					
DG	−0.185	**0.840**				
DT	−0.057	0.742	**0.733**			
I	−0.093	0.728	0.731	**0.782**		
TA	0.601	0.019	0.159	0.087	**0.897**	
TL	−0.133	0.750	0.737	0.808	0.080	**0.822**

Note. Diagonal values (bold) represent the square root of AVE. Off-diagonal values are inter-construct correlations.

4.2 Structural Model Assessment

4.2.1 Collinearity Assessment

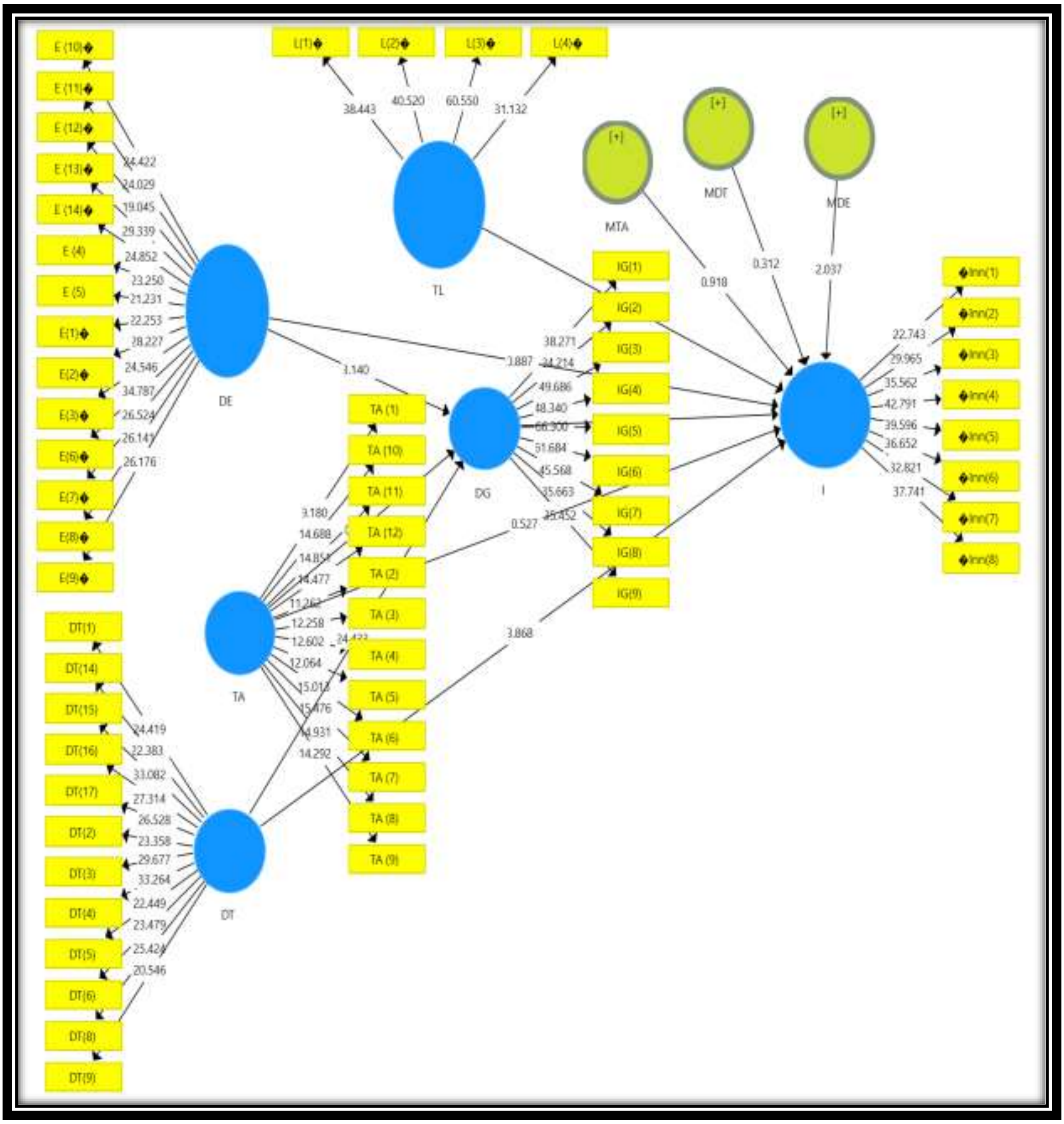
All inner VIF values for the predictor constructs of digital governance ranged from 1.066 to 1.663, and for the predictors of digital innovation performance ranged from 1.816 to 3.224. None exceeded the critical threshold of 5.0 [24], confirming that multicollinearity does not bias the structural model estimates.

4.2.2 Coefficient of Determination (R^2)

The R^2 value for digital innovation performance was 0.712 (adjusted $R^2 = 0.707$), indicating that the model explains approximately 71% of the variance a substantial level of predictive accuracy. The R^2 value for digital governance was 0.571 (adjusted $R^2 = 0.568$), indicating a moderate-to-substantial level of explanation [24].

4.2.3 Effect Size (f^2) and Predictive Relevance (Q^2)

The overall effect size was $f^2 = 0.087$, representing a medium effect [32]. Stone-Geisser's Q^2 values for both endogenous constructs exceeded zero, confirming adequate predictive relevance [33,34,35].



[FIGURE 2 Insert Inner Model / Structural Model from thesis (Figure 14). The model depicts all path coefficients among DE, TA, DT, DG, TL, MDE, MDT, MTA, and I with significance levels indicated.]

4.3 Hypotheses Testing: Direct Effects

Table 4

Direct Effects: Path Coefficients and Significance

Hyp.	Path	β	t	p	Result
H1	DE → I	0.033	0.894	0.372	Not supported
H3	TA → I	−0.026	0.549	0.583	Not supported

H5	DT → I	0.379	3.705	< 0.001	Supported

Hypothesis 1 (data ethics → innovation performance) was not supported (β = 0.033, p = 0.372). Hypothesis 3 (technology adaptation → innovation performance) was not supported (β = −0.026, p = 0.583). Hypothesis 5 (digital transformation → innovation performance) was supported (β = 0.379, p < 0.001), confirming digital transformation as the only significant direct predictor of digital innovation performance among the three independent variables.

4.4 Hypotheses Testing: Mediation Effects

Table 5

Mediation Analysis: Indirect Effects Through Digital Governance

H	Path	Indirect	t	p	VAF	Result
H2	DE → DG → I	−0.024	2.189	0.029	16%	Supported*
H4	TA → DG → I	−0.004	0.542	0.588	67.5%	Not supported
H6	DT → DG → I	0.134	3.127	0.002	22%	Supported

Note. *H2: statistically significant but VAF (16%) below 20% threshold.

The path from DT to DG was the strongest (β = 0.738, t = 23.492, p < 0.001). DG significantly predicted innovation performance (β = 0.182, t = 3.110, p = 0.002). Digital governance partially mediates the DT–DIP relationship (H6 supported, VAF = 22%), representing a significant channeling mechanism. The DE–DG–DIP indirect path was significant (p = 0.029) but the VAF of 16% falls below the 20% threshold for substantive mediation. The TA–DG–DIP path was not significant (H4 not supported).

4.5 Hypotheses Testing: Moderation Effects

Table 6

Moderation Analysis: Interaction Effects of Transformational Leadership

Hyp.	Interaction	p-value	Result
H7	DE × TFL → I	0.047	Supported
H8	TA × TFL → I	0.003	Supported
H9	DT × TFL → I	0.572	Not supported

Transformational leadership significantly moderates the DE–DIP relationship (H7, p = 0.047) and the TA–DIP relationship (H8, p = 0.003), but not the DT–DIP relationship (H9, p = 0.572). The moderation findings are particularly noteworthy for H7 and H8, where the direct effects were not significant, yet leadership activation strengthened these pathways to significance.

4.6 Model Fit and Comprehensive Summary

The Goodness of Fit (GoF) index was 0.645 ($\sqrt{(0.64 \times 0.65)}$), substantially exceeding the 0.35 threshold [36], confirming satisfactory overall model fit.

Table 7

Comprehensive Summary of All Hypotheses

Hyp.	Relationship	Result
H1	DE → DIP (direct)	Not Supported
H2	DE → DG → DIP (mediation)	Supported

H3	TA → DIP (direct)	Not Supported
H4	TA → DG → DIP (mediation)	Not Supported
H5	DT → DIP (direct)	Supported
H6	DT → DG → DIP (mediation)	Supported
H7	DE × TFL → DIP (moderation)	Supported
H8	TA × TFL → DIP (moderation)	Supported
H9	DT × TFL → DIP (moderation)	Not Supported

5. Discussion

5.1 Digital Transformation as the Primary Driver

The observation that the only independent variable, which has a significant direct influence on the performance of digital innovations (H5), is the digital transformation in the organization provides the key message about the importance of the digital transformation of the organization in facilitating innovation outcomes. This finding is correlated with Nambisan et al. (2019) and Tronvoll et al. (2020) [37,38]. The non-significant direct impact of data ethics (H1) and technology adaptation (H3) imply that these variables work not on a direct basis but on an indirect one - through the moderating influence of governance and leadership. This is in line with Floridi (2018) about indirect ethics-innovation pathway [9] as well as Beltagui et al. (2020) about mediated technology adaptation pathways [39].

5.2 The Channeling Role of Digital Governance

That digital transformation investments are steered by governance structures into innovation outcomes through the mediation of digital governance (H6, VAF = 22%) is confirmed by the high mediation of the digital governance in the DT–DIP relationship. The most significant line of DT to DG ($\beta = 0.738$) shows that it is the digital transformation which drives the development of governance, and subsequently promoting innovation ($\beta = 0.182$, $p = 0.002$). These results are in line with the theoretical hypothesis based on the DOI and institutional theories that governance mediates the correlation between technology adoption and innovation performance [5,13]. The comparatively low VAF of the DE-DG-DIP route (16%) could occur due to the infantile nature of official data ethics frameworks in the UAE state organs.

5.3 Transformational Leadership as a Catalyst

The large moderating implications on the DE–DIP (H7) and TA–DIP (H8) associations, although the direct effects are not significant, are a significant contribution. This evidence goes to show that transformational leadership taps into hitherto latent connections between organizational inputs (ethics and technology adaptation) and innovation outputs. The leaders who have idealized influence, intellectual stimulation, and inspirational motivation will convert ethical frameworks and technology adaptation initiatives into cultures that support innovation [6,18,19]. The non-significant moderating effect of the DT–DIP relationship (H9) could be due to a ceiling effect: the strong direct effect of digital transformation ($\beta = 0.379$) needs less support by leadership.

6. Conclusion

The present research offers the initial detailed empirical support of an integrative model of data ethics, digital transformation, technology adaptation, digital governance, transformational leadership, and digital performance of innovation in organizations of the UAE in the sphere of the public sector. The study relies on 404 respondents in 26 organizations using PLS-SEM and indicates that the model is able to explain the 71.2% variation in innovation performance. The main driving force is digital transformation; a major mediating factor is digital governance, and pathways between ethics, technology adaptation, and innovation are otherwise dormant and activated by transformational leadership. Such results not only present a theoretical addition to the literature on digital innovation but also provide practical advice to the leaders of the UAE public sector dealing with digital transformation.

7. Limitations

To start with, the cross-sectional type does not allow any causation; longitudinal research is required. Second, the use of self-reported data on single key informants is prone to common method bias and future research must apply multi-informant designs. Third, sampling is inconvenient and the study is restricted to UAE public sectors, which restricts generalizability. Fourth, the COVID-19 pandemic influenced the data collection process to some extent and necessitated online completion. Fifth, the study was originally focused on Dubai but was extended to all emirates fearing of access problems and this added geographic variation not explicitly modeled.

8. Future Directions

Longitudinal designs should be used in future studies that establish causes before effect. External validity would be improved through comparative studies between GCC countries. Surveys and qualitative interviews would be better mixed-methods approaches to give more mechanistic insights. Bigger stratified samples would facilitate multiple group-based analyses of the organization size, sector, and emirate. Other moderators like the digital leadership, change acceptance and digital HR practices are to be investigated. Self-reported measures would be supplemented with objective innovation performance indicators (patent filing, new service launches, digital adoption rates). Lastly, there could be a qualitative factor with interviews with senior leaders that will shed light on the operational processes behind the quantitative data.

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