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Revisiting UTAUT: Coordination Capability and Emotional Intelligence in Public Sector Innovation Performance

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Abstract
Purpose: This study extends the Unified Theory of Acceptance and Use of Technology by examining how digital adoption influences public sector innovation performance, with coordination capability and emotional intelligence as key enabling mechanisms.
Research Methodology: A quantitative explanatory design was employed using survey data collected from civil servants in a regional government institution that implemented electronic performance management. The model combines technology acceptance constructs with emotional intelligence, coordination skills, education, and work experience. Data were analysed using structural equation modelling to test the proposed relationships
Results: Digital system acceptance improves employee performance, and this effect is strengthened by the coordination capability and emotional intelligence. Education and experience indirectly enhance outcomes by fostering adaptive behaviors. These findings extend the UTAUT by showing that the impact of technology performance depends on complementary human capabilities.
Conclusions: Digital adoption enhances public sector performance only when it is supported by coordination capability and emotional intelligence. Therefore, digital transformation should be accompanied by human capability development and not merely technology implementation.
Limitations: This study focused on a single local government context, limiting generalizability. Future research should compare multiple administrative levels and institutional settings to validate models across governance systems.
Contributions: Public organizations should pair digital governance with interpersonal and coordination skill development to maximize electronic performance management benefits.

Keywords: *Coordination Skills, Digital Governance, Emotional Intelligence, Public Employee Performance*

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1. Introduction

Public organizations are required to achieve high performance because superior performance directly impacts the productivity and quality of services received by the public (Aida, 2021; Elo, Pätäri, Sjögrén, & Mättö, 2024; Kroukamp & Cloete, 2018). In the context of government, the quality of public services is the most tangible indicator of organizational effectiveness, as citizens assess government performance through fast, easy, and accountable service experiences (Agostino, Arnaboldi, & Lema, 2021; Lapuente & Van de Walle, 2020). However, various studies have shown that improving the quality of public services still faces structural and managerial challenges, including complex procedures, slow delivery, and low bureaucratic responsiveness (Demir, Maroof, Sabbah Khan, & Ali, 2021). Public management literature confirms that human resources (HR) are a key determinant of the effectiveness of public sector organizations (Al-Swidi, Gelaidan, & Saleh, 2021; Becker, Belkin, Tuskey, & Conroy, 2022). Systematic and sustainable development of the competency, professionalism, and commitment of civil servants is a prerequisite for improving operational performance (Davletbayeva, Utepkaliyeva, Dussipov, & Torebekova, 2024; Lo & Nguyen, 2023). In the digital era, these demands are intensifying with the adoption of electronic government technology. The UTAUT model explains that perceived usefulness, ease of use, and organizational support influence technology acceptance and ultimately impact performance (Ursavaş, 2022). In the Indonesian context, the implementation of the Electronic-Based Government System (SPBE), including the E-Kinerja application, is designed to improve accountability, transparency, and the objective measurement of official performance (Zulvie, 2023). However, the effectiveness of this system is determined not only by technological factors but also by individual characteristics, such as emotional intelligence, coordination skills, education level, and work experience.

2. Literature Review and Hypothesis Development

In this study, we use four concepts related to the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Ursavaş (2022): (1) Performance Expectations, (2) Effort Expectations, (3) Social Influence, and (4) Supporting Conditions. This study is also based on the Theory of Emotional Coordination Synergy in Service Performance.

2.1. Performance Expectations

The perception that technology will improve employee efficiency, effectiveness, and productivity (Moturi, Wekesa, & Juma, 2022). According to Cai, Parker, Chen, and Lam (2019); Hackman and Porter (1968);(Silva, Nuzum, & Schaltegger, 2019), performance expectancy is a person's level of belief that using a particular technology or system will improve their performance or productivity in achieving a specific goal. Individuals are more likely to adopt technology if they believe it will provide tangible benefits in their work or daily activities. This factor is often influenced by perceptions of the efficiency, effectiveness, or improved work quality of the technology. Performance expectancy is typically higher if the technology offers innovative, relevant, and easy-to-understand features.

> *H_1:* If employees feel that technology can help them achieve their work goals better, they tend to be more motivated to use it, resulting in improved performance.

2.2. Effort Expectation

The theory of work motivation processes has received considerable theoretical and empirical attention. The perception that technology is easy to use and does not require much effort to learn. Effort Expectancy is the extent to which a person believes that a technology is easy to understand and use. Technologies with intuitive interfaces and user-friendly designs are more likely to be adopted because individuals are less likely to have to exert effort to learn new things. Perceptions of ease of use are often influenced by prior experience, the user's level of technological literacy, and support provided during the adoption process. If the expected effort exceeds the perceived benefits, users are more likely to refuse to use technology.

> *H_2:* Easy-to-use technology will reduce employees' cognitive load, allowing them to focus on Their primary tasks ultimately increase productivity.

2.3. Social Influence

The influence of the social environment or authority on employees' intentions to use technology has been introduced by (Kuciapski, 2019; Park & Park, 2021), where Social Influence is the extent to which individuals feel that others who are important to them (e.g., friends, colleagues, or superiors) believe that they should use a particular technology. According to Al-Emran (2023) and Goldsmith and Goldsmith (2011), social influence often originates from the workplace, community, or social groups that support the adoption of a particular technology. This factor can be driven by social norms, collective beliefs, or authority pressure. The greater the social pressure, the more likely a person will use the technology, even if the benefits are perceived as less significant (Al Hadwer, Tavana, Gillis, & Rezania, 2021).

> *H_3:* Support from superiors, coworkers, or social norms will influence the level of technology adoption by employees. When technology is widely adopted, it creates a more integrated and an efficient work environment.

2.4. Supporting Conditions

According to Peñarroja, Sánchez, Gamero, Orengo, and Zornoza (2019), the availability of adequate resources, infrastructure, and organizational support is essential for using technology. Supporting Conditions refer to the extent to which a person believes that there is adequate infrastructure and resources to support the use of a technology (Gupta & Hayath, 2022). Technology adoption is easier if users perceive that they have access to training, compatible hardware or software, and technical support. The absence of enabling conditions, such as poor Internet access or a lack of training, can hinder technology adoption, even if the technology is perceived as beneficial. This factor emphasizes the importance of creating an environment that supports technology adoption. These theories complement each other in explaining the factors that influence a person's intentions and behaviors when using technology.

> *H_4:* The availability of adequate training, infrastructure, and technical support enables employees to optimally utilize technology, contributing to improved performance.

2.5. Coordination Skills

This study is also based on the Emotional-Coordination Synergy Theory in Service Performance. Wiltshire, Philipsen, Trasmundi, Jensen, and Steffensen (2020), where the success and performance of an organization can be seen from the work results achieved by its employees. Therefore, organizations demand that their employees display optimal performance because good or bad performance achieved by employees will affect the improvement of the organization's performance and overall success. De Waal (2018) found that eleven theoretical success factors and eight practical success factors. These factors matched by 63.6 percent, indicating a moderate overlap between what theory predicts and what can be observed in practice. Furthermore, the practical cases revealed two success factors that were particularly important for the HPO transformation. The HPO transformation approach allows for a structured review of interventions, providing insight into how the case study companies conducted successful HPO transformations. Thus, this study makes both theoretical and practical contributions (De Waal & Kraaijveld, 2022).

> *H_5:* Coordination skills have a positive effect on employee performance

2.6. Emotional Intelligence

From this theoretical perspective, emotional Intelligence (EI) specifically refers to the collaborative combination of intelligence and emotions (Antariksa, 2025). Here, no unusual claims regarding the potential of EI are found; instead, the researchers seek to expose popular claims as baseless, given the evidence available to date. Many studies view EI as a member of a class of intelligences that includes social, practical, and personal intelligences, which we refer to as hot intelligences. This theory starts from the premise that optimal service performance depends on the harmonious interaction between an individual's emotional intelligence and coordination abilities in the work environment (Arsintescu, Chachad, Gregory, Mulligan, & Flynn-Evans, 2020). In the service context, Emotional Intelligence (EI) is important for building positive relationships with customers and handling conflict constructively. The main dimensions of EI include: 1) self-awareness, 2) emotional regulation, 3) empathy, and 4) social skills (b) Coordination Ability, namely the ability to align tasks, communication, and responsibilities between individuals or teams to achieve common goals. In the service sector, effective coordination enables consistent, fast, and responsive service delivery. (c) Service Performance, which is measured by the ability of an individual or organization to meet or exceed customer expectations (Mangesti & Asmara, 2025).

H_6: Emotional Intelligence has a positive influence on employee performance

2.7. Service Performance

Service performance in provincial government is a tool used to assess the extent to which the provincial government provides effective and efficient services that meet the needs of the community. Some frequently used service performance indicators are (a) Service Effectiveness Indicator, (b) Efficiency Indicator, (c) Service Quality Indicator, (d) Accessibility and Inclusiveness Indicator, (e) Transparency and Accountability Indicator, (f) Public Satisfaction Indicator, and (g) Innovation Indicator. This theory is built on three main pillars: (a) Emotional Intelligence, defined as the ability to recognize, understand, and manage one's own and others' emotions (Fianko, Jnr, & Dzogbewu, 2020). (b) Kemampuan Koordinasi dan Kinerja Layanan, koordinasi yang baik dalam tim layanan meningkatkan efisiensi, mencegah kesalahan, dan memastikan konsistensi dalam interaksi pelanggan. (c) Interaksi dan Koordinasi Kecerdasan Emosional, menurut Khosravi, Rezvani, and Ashkanasy (2020) Emotional Intelligence helps create strong interpersonal relationships among team members, thus improving coordination. These three pillars are interrelated, with individuals with high Emotional Intelligence better able to respond appropriately to customer needs, manage emotional stress, and create positive service experiences. Conversely, good coordination allows individuals with high Emotional Intelligence to focus more on customer needs because the workload is more structured. This theory emphasizes that Emotional Intelligence and coordination skills are key elements in providing superior service. The synergy between the two creates a foundation for achieving consistent service performance that exceeds customer expectations (Mitsea, Drigas, & Skianis, 2023).

H_7: Service performance will increase if employees have high emotional intelligence and good coordination skills.

2.8. Technology Adaptation and Technology Use

New technologies are crucial for achieving the three pillars of sustainable development: the environment, economy, and society. These technologies can have either positive or negative effects on sustainable development. Information Systems theories such as TAM, UTAUT, and UTAUT2 have provided valuable information on the factors influencing technology use and adoption, but they ignore the post-use impacts of technology (Al-Emran, 2023). Amini and Jahanbakhsh Javid (2023) state that from a sustainability perspective, this requires a holistic theoretical framework that goes beyond existing information system theories/models by examining the direct impact of technology use on environmental, economic, and social sustainability. Technological innovation, in its various forms and applications, has demonstrated significant potential for strengthening the three pillars of sustainable development (Shahadat, Nekmahmud, Ebrahimi, & Fekete-Farkas, 2023). In the environmental realm, advanced technologies have provided us with renewable energy systems, smart grid infrastructure, and precision farming techniques that help decarbonize our economy, increase resource efficiency, and protect biodiversity.

H_8: Employees will be more likely to use technology if they experience direct benefits from its use, and organizational support influences the success rate of technology adoption in improving performance.

2.9. Employee Performance

Employee performance is not only measured by perfect skills, but also by the ability to master and manage oneself, as well as the ability to build working relationships with others (Latham, 2023). This ability is called Emotional Intelligence by Daniel Goleman. Goleman and Cherniss (2000) through his research said that emotional intelligence can contribute 80% of the determining factors for a person's success in an organization, while the remaining 20% is determined by Intelligence Quotient (Fianko et al., 2020). Pulido-Martos, Gartzia, Augusto-Landa, and Lopez-Zafra (2024) stated that emotional intelligence, which is included in the competency system for each position created, can actually be developed for many HR functions, from recruitment and training to career development to performance appraisal. If this is done, the human resource management system can motivate employees to develop their emotional intelligence, thereby not only developing technical competence but also increasing productivity and performance (Singh & Chouhan, 2023). Measurements are made on the efficiency, effectiveness, and quality of employee work results after adopting technology.

H_9: Technology adaptation and use have a positive and significant impact on employee performance.

Based on the theoretical foundation and previous research, various relationships between variables are identified, as described in the following research framework model:

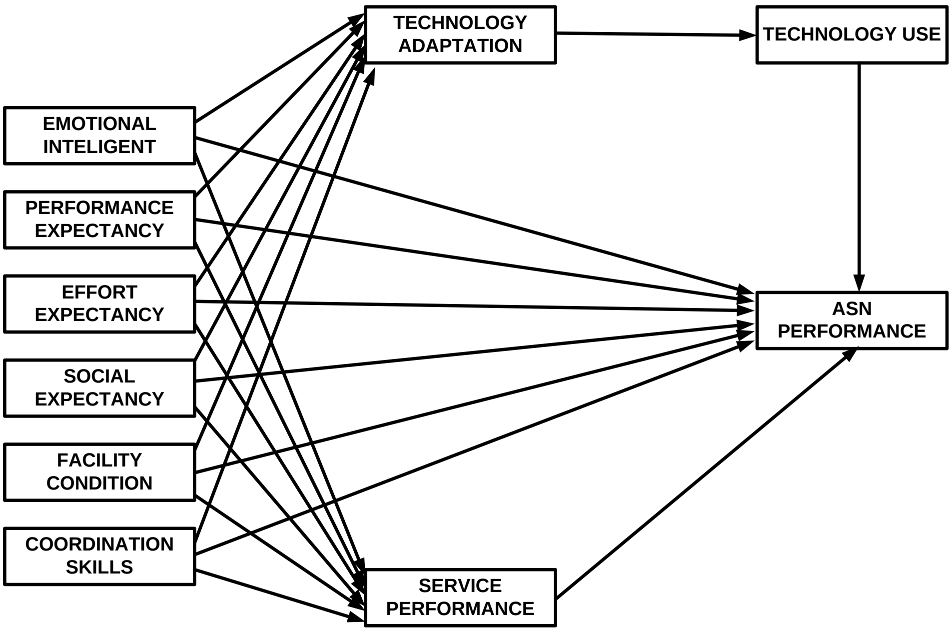

Figure 1. Research framework

3. Methodology

3.1. Sample dan Data Collection

The data were collected using a purposive sampling approach, with criteria such as civil servants in provincial governments who have adopted and used technology in public-service activities. The sample was obtained by distributing questionnaires to government employees involved in public services in several cities and regencies in the South Sumatra Province. Most of the sample came from Palembang City, followed by surrounding cities and regencies in the province. Data collection was conducted online between January and September 2024, and a pilot survey was analyzed in December 2023 to test validity and reliability with 30 respondents.

Responses to the pilot survey questions were used to refine the final survey questionnaire, specifically by changing unclear information in the measurement statements to more direct, unambiguous, and precise language. Subsequently, 400 participants completed the questionnaire, and the distribution of the sample data is shown in Figure 2. Joseph F Hair, Risher, Sarstedt, and Ringle (2019) states that if the population is unknown, the minimum sample can be calculated by adding the indicators and latent variables then multiplying by 5*22 indicators plus 7 latent variables; the minimum sample size is 145 respondents. In addition, based on the G*Power software approach with a 95% confidence level estimated at 0.80, 160 respondents were needed. A total of 400 respondents exceeded the minimum required sample size.

Figure 2. Data sample distribution

3.2. Measure

Using the PLS-SEM approach, the drivers of technology adoption were investigated by extending the UTAUT (Performance Expectancy, Effort Expectancy, Social Expectancy, Facilitating Conditions) model and Coordination and Intelligence skills such as technology adaptation, technology use, service performance, and employee performance as exogenous variables. This analysis included a two-stage assessment: first, the construct validity and reliability of each indicator were used to test the measurement model; finally, the model's suitability to test the causal correlation between the latent variables. While developing the survey for data collection, the measurement items of the construct were adapted from past research. Section A of the survey focused on the personal information of respondents (e.g., gender, age, education, work period, and employee ranked grade), whereas the other section was about the measurement items. Moreover, UTAUT (performance expectancy, effort expenctancy, social influence and facilitating conditions) was measured using 14 items adapted from (Bandoh, Akweittey, Lotey, Gordon, & Appiagyei, 2024). Additionally, the emotional intelligence features in this study were based on four items adapted from earlier research (Singh & Chouhan, 2023). Coordinationoskillslwerewmeasureduusingufourh 4 items (Wiltshire et al., 2020). Technology adaptation and use were also measured based on seven items. Finally, services performance Njeje, Chepkilot, and Ochieng (2018) measured according to 6 items, while personal competency Yustini, Alie, and Amrullah (2023) is measured through 5 items. A Likert scale ranging from strongly disagree (1) to strongly agree (5) was used across all measurement items.

3.3. Data Analysis Technique

Studi ini menggunakan penelitian kuantitatif dengan teknik *Structural Equation Modeling* (SEM). As the study model (Figure.1) incorporates later variables that are not readily observable, the structural equation model (SEM) was considered the most acceptable approach (Babin, Hair, & Boles, 2008; Joseph F Hair et al., 2019). The two-step procedure of data analysis Anderson and Gerbing (1988) was followed in this analysis. First, Confirmatory Factor Analysis (CFA) with AMOS 23 was conducted to check internal reliability via Cronbach's alpha (α) and Composite Reliability, whereas convergent validity and discriminant validity were checked via average variance extracted (AVE) to optimize the measurement model. After attaining satisfactory values. Finally, a structural model using maximum likelihood estimation with path analysis was used to examine the causal links among the latent variables.

4. Results and Discussions

4.1. Characteristics of the Respondents

Table 1. Respondents' characteristics

Characteristic	Criteria	FRequency (*n* = 400)	Percentage (%)
Gender	1. Male	212	53
	2. Female	188	47
Age Level	1. 21 – 30 Years	26	6.5

	2. 31 – 40 Years 3. 41 – 50 Years 4. More Than 50 Years	129 130 115	32.3 32.5 28.7
Education	1. Diploma (D3) 2. Bachelor’s Degree (S1/D4) 3. Master’s Degree (S2) 4. Doctorate (S3)	20 283 69 28	5.0 70.8 17.2 7.0
Work Period	1. 1 – 5 Years 2. 6 – 10 Years 3. 11 – 15 Years 4. More Than 15 Years	18 135 142 105	4.5 33.8 35.5 26.2
Employee Rank Grade	1. Grade II.c – II.d 2. Grade IIL.a – III.d 3. Grade IV.a – IV.e	15 148 327	3.8 37.0 59.2

Based on the frequency data above, the description of respondent identification based on characteristics is as follows: in this study, the majority of respondents were male (n=212; 53%), with a comparison of female respondents (n=188; 47%). Respondents were aged between 21 and 30 years (n=26; 6.5%), respondents were aged between 31 and 40 years (n=129; 32.3%), and 41 and 50 years (n=188; 47%). When viewed from the level of education, almost half of the respondents had a bachelor’s degree (S1/D4) (n=283; 70.8%). Education Level other than Diploma (D3), (n=20; 5%), Masters (S2) (n=69; 17.2%), and Doctorate (S3): (n=28; 7%). In addition, when this time is divided based on the length of service, the pattern of participants can be divided into: 1–5 years of service: (n=184; 5%), 6-10 years: (n=135; 33.8%), another group is 11-15 years (n=142; 35.5%), and more than 15 years of service: 105 respondents (26.2%). The majority of respondents had a long working period (6–15 years), longer than half of the total respondents (n=105; 26.2%). The final discussion on respondent characteristics relates to the characteristics of respondents at the employee position level, (n=327; 59.2%) are in Grade IV.a-IV. e category. Grade II.c–II.d: (n=15; 3.8%), Grade III.a~III.d: (n=148; 37%).

4.2. Research Model

This study uses the Variance-Based Partial Least Square Structural Equation Modeling (PLS-SEM) method, where the path diagram in this study is shown in Figure 2 below.

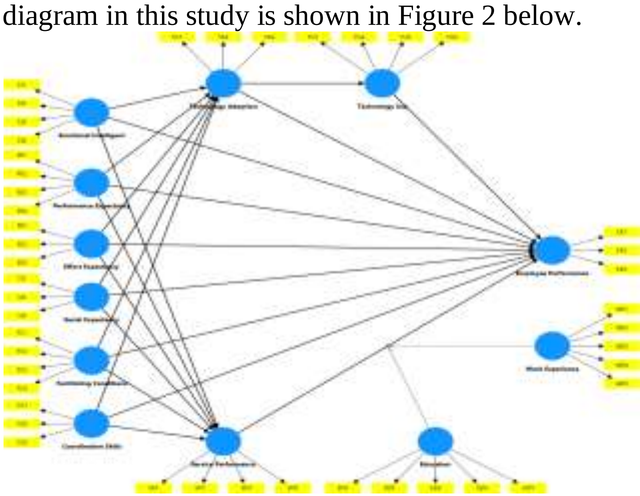

Figure 3. Research struktural Model-Partial Least Square SEM

4.2.1. Evaluation of the Outer Measurement Model

In this study, two methods were used to obtain the evaluation results of the outer measurement model: Validity Testing and Composite Reliability Testing.

4.2.1.1. Convergent Validity Testing

In this study, the factor loads on the indicators measuring the research constructs were used to obtain the estimated convergent validity test results in PLS with the reflective indicators used in this research model. If the factor load value is greater than 0.7, the indicator was considered valid. The estimated data from the factor load test using SmartPLS software are presented in Table 2. The results of the convergent validity test indicate that all data related to the construct items were valid. This conclusion is based on the loading factor, where the research constructs show a loading factor value of more than 0.7. Consequently, it can be concluded that all the construct items in this study are valid and suitable for inclusion in the subsequent data estimation process for convergent validity testing. If the Composite Reliability value exceeds 0.7, the criteria for that variable are considered to meet the Composite Reliability requirements.

Table 2. Tabulation of loading factor data estimates

Variable	**Construct**	**Outer Loading**	**Cronbach's Alpha's**	**Composite Reliability**		**Average Variance Extracted (AVE)**
				Rho_a	**Rho_c**	
Employee Performance	EP1	0.9645	0.9447	0.9541	0.9645	0.9005
	EP2	0.9355				
	EP3	0.9467				
Coordination Skills	CS1	0.9551	0.9506	0.9522	0.9681	0.9100
	CS2	0.9556				
	CS3	0.9511				
Education	ED1	0.8964	0.9347	0.9393	0.9503	0.7929
	ED2	0.9125				
	ED3	0.8605				
	ED4	0.9000				
	ED5	0.8820				
Effort Expectancy	EE1	0.9363	0.9031	0.9146	0.9389	0.8368
	EE2	0.8788				
	EE3	0.9281				
Emotional Intelligent	EI1	0.9516	0.9520	0.9551	0.9653	0.8742
	EI2	0.9401				
	EI3	0.9193				
	EI4	0.9287				
Facilitating Conditions	FC1	0.8859	0.8958	0.9039	0.9273	0.7613
	FC2	0.8681				
	FC3	0.8574				
	FC4	0.8783				
Performance Expectancy	PE1	0.8695	0.8970	0.9029	0.9279	0.7630
	PE2	0.8846				
	PE3	0.8857				
	PE4	0.8538				
Service Performance	SP1	0.9591	0.9686	0.9689	0.9770	0.9140
	SP2	0.9501				
	SP3	0.9567				
	SP4	0.9581				
Social Expectancy	SE1	0.9530	0.8940	0.9086	0.9346	0.8270
	SE2	0.8310				
	SE3	0.9393				
Technology Adoption	TA1	0.9431	0.9030	0.9100	0.9393	0.8378
	TA2	0.8765				
	TA3	0.9250				
Technology Use	TU1	0.9267	0.9435	0.9549	0.9592	0.8545
	TU2	0.9172				
	TU3	0.9226				
	TU4	0.9311				
	WE1	0.8853	0.9383	0.9541	0.9527	0.8010

Work Experience	WE2	0.9038				
	WE3	0.9082				
	WE4	0.8757				
	WE5	0.9016				

In addition to the Composite Reliability value, this study also used Cronbach's alpha to determine reliability criteria. According to the table above, the data estimation results indicate that the constructs or indicators being evaluated relatively meet the requirements and conditions of previous theory. Both the Cronbach's Alpha and Composite Reliability values exceeded 0.7.

4.2.2. Model Fit Test.

a. Effect Size (F^2Test)

Effect Size (F^2 Test) is used to test the magnitude of the influence between variables or the effect size. F2 is the change in R2 when an exogenous variable is removed from the model. The Effect Size Criteria the F2 value for an endogenous latent variable is: $F^2 \geq 0.35$ (large), $0.15 \leq F^2 < 0.350$ (moderate), $0.02 \leq F2 < 0.150$ (small), and < 0.02 (Insignificant/Very Small). The estimation results are presented in the following table.

Table 3. Effect Size (F^2 Test)

Interaction Between Variables	F Square Test	Information
Coordination Skills to Employee Performance	0.0071	Not significant
Coordination Skills to Service Performance	0.1765	Medium
Coordination Skills to Technology Adoption	0.3866	Large
Education to Employee Performance	0.0335	Small
Effort Expectancy to Employee Performance	0.1096	Small
Effort Expectancy to Service Performance	0.0210	Small
Effort Expectancy to Technology Adoption	0.0718	Small
Emotional Intelligent to Employee Performance	0.0001	Not Significant
Emotional Intelligent to Service Performance	0.4825	Large
Emotional Intelligent to Technology Adoption	0.0868	Small
Facilitating Conditions to Employee Performance	0.0034	Not Significant
Facilitating Conditions to Service Performance	0.2128	Medium
Facilitating Conditions to Technology Adoption	0.0880	Small
Performance Expectancy to Employee Performance	0.3647	Large
Performance Expectancy to Service Performance	0.0306	Small
Performance Expectancy to Technology Adoption	0.0679	Small
Service Performance to Employee Performance	0.8953	Large
Social Expectancy to Employee Performance	0.1700	Medium
Social Expectancy to Service Performance	0.1005	Small
Social Expectancy to Technology Adoption	0.1971	Medium
Technology Adoption to Employee Performance	0.1278	Small
Technology Adoption to Technology Use	0.0106	Small
Technology Use to Employee Performance	0.0002	Not significant
Work Experience to Employee Performance	0.0837	Small

The conclusion of the effect size test estimation using the F^2 Test method is presented in Table 4.3. The results of the estimation of most of the variable interactions are relatively dominated by low and small Effect Size interactions (there are interactions of 20 variables and no interactions of 4 variables). Based on the above data, it is necessary to apply research to a larger number of research samples to understand the interactions between variables in more detail and complexity. Using a large number of research samples, the interactions between research variables will be more clearly visible because there will be more heterogeneous characteristics of respondents, so the scope of research results will be more general.

4.2.3. Q^2 Test

Q-squared (Q^2) or predictive relevance in Structural Equation Modeling is a parameter used to measure the predictive relevance of a model. Q^2 can be used to determine whether the model has a good predictive ability. If the Q^2 value is > 0 (positive), then it can be said to have a good observation value, whereas if the Q^2 value is < 0 (negative), then it can be stated that the observation value is not good. The predictive relevance of Q2 for structural models measures how well the conservation value generated by the model and its parameter estimates. A Q^2 value > 0 indicates that the model has predictive relevance; on the other hand, if the Q^2 value ≤ 0, it indicates that the model has poor predictive relevance.

Table 4. Q^2 Test estimation results

Variabel	Q^2predict	RMSE	MAE
Employee Performance	0.1428	0.9292	0.8059
Service Performance	0.2005	0.8976	0.7777
Technology Adoption	0.4463	0.7461	0.5430
Technology Use	0.0160	0.9954	0.9133

From the data estimation results, the estimation results show that all Q^2 prediction values have a Q2 value > 0 (Positive) which indicates that the model has good prediction relevance.

4.2.4 R^2 Test

R-squared Statistics (R^2) explain the variance in endogenous variables explained by exogenous variables. According to Joe F Hair, Matthews, Matthews, and Sarstedt (2017) stated that the R2 value for endogenous latent variables is assessed as: 0.75 (substantial/high), 0.50 (moderate), 0.25 (weak).

Table 5. R^2 test

Variabel Endogen	R-square	R-square adjusted
Employee Performance	0.7604	0.7523
Service Performance	0.5451	0.5382
Technology Adoption	0.5022	0.4946
Technology Use	0.0105	0.0080

Explanation of tabulated estimation results.

1) R^2 = 0.7604 for the endogenous variable (Employee Performance), indicating that the exogenous variable significantly explains the endogenous variable.
2) The endogenous variable, Service Performance, has an R^2 of 0.5451. This statement indicates that the exogenous variable explains the endogenous variable moderately.
3) R^2 = 0.5022 for the endogenous variable (Technology Adoption). This indicates that the exogenous variable significantly explains the endogenous variables.
4) The endogenous variable (Technology Use) had an R^2 of 0.0105. This indicates that the exogenous variable only weakly explains the endogenous variables.

4.2.5 CV-PAT Test

The CVPAT measure is a Cross-Validated Predictive Ability Test (CVPAT), which is a form of validation of the predictive power of the PLS model, and whether the proposed PLS model has acceptable predictive power. This measure was developed as a complement to the proposed PLS prediction. The SEM of PLS requires validation as the SEM of the prediction path where the proposed model is acceptable. The CVPAT is calculated by comparing the predictive power of the PLS model algorithm with the Mean Indicator algorithm and the Linear Model (LM) algorithm. The model has a high prediction accuracy if the prediction error indicated by the difference in the average loss is negative and statistically significant (Sharma & Rajput, 2021). CVPAT estimation is performed by comparing the value of the Average Loss Indicator IA and the Linear Model (LM) with the PLS value. If the values of the Average Loss Indicator (IA) and the Linear Model (LM) are greater than the PLS Loss value, it will cause the Average Loss Difference Value <0 (Negative), where the Average Loss Difference value is the value of the Average Loss Indicator (IA) and the Linear Model (LM) minus the PLS Loss value, meaning that the model is able to predict better than its competitors' predictions, namely the Average Loss Indicator (IA) and the Linear Model (LM).

Table 6. Estimation results CVPAT

Variabel	PLS loss	IA loss	Average loss difference	t value	p value
Employee Performance	2.0371	2.5063	-0.4693	5.6644	0.0000
Service Performance	2.4288	2.8101	-0.3813	4.2047	0.0000
Technology Adoption	1.8982	2.5069	-0.6087	6.5089	0.0000
Technology Use	2.5502	2.6166	-0.0665	3.8376	0.0001
Overall	2.3155	2.6444	-0.3289	7.7928	0.0000

The estimation results in the form of tabulation above show that the value of the average IA Loss Indicator and the Linear model (LM) is greater than the PLS Loss value, which will cause the Average Loss Difference Value <0 (Negative), meaning that the model is able to predict better than its competitors' predictions, namely the average IA Loss Indicator and the Linear model (LM), or in other words, the predictor model is declared good. This is supported by a p-value below 0.05 (p-value <0.05), which confirms that the model has a good predictive ability.

4.2.6. SRMR Test

The Standardized Root Mean Squared Residual (SRMR) in Structural Equation Modeling (SEM) tests the fit of the data to a structural equation model. SRMR is a fit indicator that indicates the average difference between the observed correlation and the implied correlation matrix of the model.

Table 7. Goodness of fit model test

Criteria	Saturated model	Estimated model
SRMR	0.0362	0.0397
Chi-square	2545.0422	2526.4320
NFI	0.8619	0.8629

The estimated value of the model in the Standardized Root Mean Square Residual (SRMR) model fit test was 0.0362, thus providing a fit index with the recommended value of less than 0.08. The measurement of model fit in research using the SRMR category is intended to assess the average difference between the observed and expected correlations. The SRMR value of 0.0362 < 0.08 is a measure of model fit for PLS-SEM, which can be used to avoid model specification errors.

4.2.7 Normalized Goodness-of-Fit Index (NFI) Test

The Normalized Fit Index (NFI) is a measure of model fit calculated by comparing the chi-square value of the proposed model with that of the null model. NFI values range from 0 to 1, with values closer to 1 indicating a better fit. Referring to the data estimation results displayed by the tabulation of data estimation results in Table 5 above, the NFI value is close to 1 or 0.8619; thus, the model fit is considered relatively good.

4.2.8 Multikolinearitas Test

The variable inflation factor (VIF) is used in multicollinearity tests. This value is used as a criterion to identify multicollinearity in linear regression involving more than two independent variables. The VIF test criteria indicate the presence of a multicollinearity problem if the VIF value is more than 5, and vice versa; if the VIF value is less than 5, it indicates that there is no multicollinearity problem.

Table 8. Multikolinearitas test

Variables	VIF
Coordination Skills -> Employee Performance	1.6292
Coordination Skills -> Service Performance	1.0189
Coordination Skills -> Technology Adoption	1.0189
Education -> Employee Performance	1.1494
Effort Expectancy -> Employee Performance	1.1479

Effort Expectancy -> Service Performance	1.0217
Effort Expectancy -> Technology Adoption	1.0217
Emotional Intelligent -> Employee Performance	1.6379
Emotional Intelligent -> Service Performance	1.0326
Emotional Intelligent -> Technology Adoption	1.0326
Facilitating Conditions -> Employee Performance	1.4042
Facilitating Conditions -> Service Performance	1.0709
Facilitating Conditions -> Technology Adoption	1.0709
Performance Expectancy -> Employee Performance	1.3133
Performance Expectancy -> Service Performance	1.0832
Performance Expectancy -> Technology Adoption	1.0832
Service Performance -> Employee Performance	2.2134
Social Expectancy -> Employee Performance	1.3516
Social Expectancy -> Service Performance	1.0137
Social Expectancy -> Technology Adoption	1.0137
Technology Adoption -> Employee Performance	2.0425
Technology Adoption -> Technology Use	1.0000
Technology Use -> Employee Performance	1.0445
Work Experience -> Employee Performance	1.0721

The overall VIF value was below 5.00, according to the table above. Thus, it can be concluded that there is no multicollinearity or a low correlation between the exogenous variables.

4.3. Hypothesis Testing

Geisser two bootstrap resampling was adopted to test the hypothesis of differences between endogenous constructs versus exogenous constructs and endogenous constructs versus exogenous constructs. Using the resampling method and t-test statistical calculations, we used freely distributed data without the assumption of a normal distribution and magnitude. The structural model assessment procedure Ruscio and Ruscio (2002) is used to determine whether the structural model relationships, such as the construct relationships suggested in the hypothesized theoretical model, are significant and relevant. In this study, the critical value was 1.96 at the 5% level (one-tailed test). A relationship was considered significant if the t value was > 1.96 and the P value was < 0.05. The results of the direct influence research data estimation are presented in Table 4.8. This research hypothesis includes eight direct effect hypotheses, indirect effect hypotheses, and moderation effect hypotheses, which are summarized in the table above. The findings from the data estimation revealed several insights. Emotional Intelligence did not have a significant direct impact on Employee Performance (H_{1a}; P-value = 0.8441). However, Emotional Intelligence significantly influenced Employee Performance when mediated by the Service Performance variable.

It should be noted that the results indicate that Emotional Intelligence does not have a substantial influence on Employee Performance unless reflected through Service Performance, especially considering that Civil Servants are predominantly engaged in public service activities, prioritizing Service Performance in their roles (H_{1c}; P-value = 0.0029). Employees with higher levels of Emotional Intelligence typically demonstrate greater adaptability to technological advances owing to their emotional management skills, ability to deal with uncertainty, and ability to learn from new challenges (H_{1b}; P-value = 0.0000). Another interesting finding is that when a technology is too common or mandatory, the effect of Emotional Intelligence on Technology Adoption or Use appears to be negligible (H_{1d}; P-value = 0.1569). These results align with research by Eshuis, De Boer, and Klijn (2023); Pong and Leung (2023) which showed that the effect of EI on performance tends to be weak when unmediated by specific work behaviors. In other words, EI is a personal potential that requires behavioral manifestation to affect performance. Conversely, this study found that EI significantly influenced Employee Performance through Service Performance (p = 0.0029). This means that emotional intelligence improves performance only when it is manifested in service quality. Employees who can demonstrate empathy, emotional control, and interpersonal communication produce better service, which is then assessed as performance. This finding is consistent with Ashkanasy and Kay (2023), who asserted that EI acts as an enabling capability in service work through improved service behaviors. Thus, in the public sector, the relationship between EI and performance is indirect (mediated effect) through Service Performance (Liao, Hu, & Huang, 2022).

Performance Expectancy significantly influences Employee Performance both directly and indirectly (H_{2a}; P-value = 0.0000; H_{2b}; P-value = 0.0000; H_{2c}; P-value = 0.0007). Conversely, data analysis indicates that if Performance Expectancy (belief that technology will improve performance) does not have supporting factors such as training, incentives, or management support, its impact on technology adoption and use may be minimal (H_{2d}; P-value = 0.1603). Effort Expectancy also significantly influenced Employee Performance both directly and indirectly (H_{3a}; P-value = 0.0000; H_{3b}; P-value = 0.0001; H_{3c}; P-value = 0.0029). However, this relevance often decreases in the later stages of technology use (H_{3d}; P-value = 0.1578).

This finding aligns with the model Ursavaş (2022), who asserted that the belief that technology improves performance is a key predictor of system usage and performance outcomes. However, when supported by training, incentives, and management support (p = 0.1603), the influence of PE on technology utilization weakened. This is consistent with Compeau, Correia, and Thatcher (2022) who emphasize the importance of organizational support for technology optimization. Effort Expectancy (EE) also significantly impacted Employee Performance ($p < 0.01$), supporting the finding that ease of use increases work effectiveness. However, its influence decreased with continued use (p = 0.1578), indicating that perceived ease of use was more important in the initial adoption phase than in the ongoing use phase. Overall, PE was the strongest predictor of performance, while EE was dominant in the early implementation phase and required organizational support to optimally impact employee performance (Joa & Magsamen-Conrad, 2022).

Social Expectations significantly influence Employee Performance directly and indirectly (H_{4a}; P-value = 0.0000; H_{4b}; P-value = 0.0000; H_{4c}; P-value = 0.0492). However, when technology becomes commonplace or mandatory in the workplace, social influence becomes less significant, as technology adoption is not based on Social Expectations (H_{4d}; P-value = 0.1435). Supportive Conditions do not significantly influence Employee Performance (H_{5a}; P-value = 0.2538) because, despite providing solid technical support and necessary infrastructure, they only create favorable conditions and do not directly produce performance outcomes.

The actual impact on Employee Performance depends on how such support is translated into actionable practices, such as improving services or effectively utilizing technology. These findings are consistent with social influence as a key determinant of shaping technology use intentions and behavior. In the context of public organizations, superior support, peer norms, and institutional pressure encourage employees to adopt and utilize technology optimally, ultimately improving performance. These findings also align with research by Leso and Cortimiglia (2022);Rocha, Bewersdorff, and Nerdel (2024), which asserts that social norms have a strong influence, especially in the early stages of system implementation.

Table 9. Estimation Results

Variables	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation	T statistics (|o/stdev)	P values	Decision
Emotional Intelligent -> Employee Performance	H_{1a}	0.0058	0.0054	0.0296	0.1967	0.8441	H_o accepted
Emotional Intelligent -> Technology Adoption ->	H_{1b}	0.0528	0.0520	0.0120	4.3851	0.0000	H_a accepted

Employee Performance							
Emotional Intelligent -> Service Performance -> Employee Performance	H_{1c}	0.0681	0.0694	0.0228	2.9884	0.002 9	H_a accepted
Emotional intelligence -> Technology adoption -> Technology use -> Employee Pf.	H_{1d}	0.0014	0.0014	0.0010	1.4179	0.156 9	H_o accepted
Performance Expectancy -> Employee Performance	H_{2a}	0.3388	0.3390	0.0313	10.8359	0.000 0	H_a accepted
Performance Expectancy -> Technology Adoption -> Employee Performance	H_{2b}	0.0479	0.0475	0.0112	4.2602	0.000 0	H_a accepted
Performance Expectancy -> Service Performance -> Employee Performance	H_{2c}	0.0847	0.0837	0.0247	3.4224	0.000 7	H_a accepted
Performance Expectancy → Technology Adoption → Technology Use → Employee Pf.	H_{2d}	0.0013	0.0013	0.0009	1.4061	0.160 3	H_o accepted
Effort Expectancy -> Employee Performance	H_{3a}	0.1736	0.1731	0.0282	6.1458	0.000 0	H_a accepted
Effort Expectancy -> Technology Adoption -> Employee Performance	H_{3b}	0.0478	0.0474	0.0119	4.0151	0.000 1	H_a accepted

Effort Expectancy -> Service Performance -> Employee Performance	H_{3c}	0.0681	0.0694	0.0228	2.9884	0.002 9	H_a accepted
Effort expectancy → Technology adoption → Technology use → Employee Pf.	H_{3d}	0.0013	0.0013	0.0009	1.4148	0.157 8	H_o accepted
Social Expectancy -> Employee Performance	H_{4a}	0.2346	0.2334	0.0328	7.1507	0.000 0	H_a accepted
Social Expectancy -> Service Performance -> Employee Performance	H_{4b}	0.1483	0.1492	0.0252	5.8809	0.000 0	H_a accepted
Social Expectancy -> Technology Adoption -> Employee Performance	H_{4c}	0.0324	0.0324	0.0164	1.9721	0.049 2	H_a accepted
Social Expectancy → Technology Adoption → Technology Use → Employee Pf.	H_{4d}	0.0021	0.0021	0.0015	1.4653	0.143 5	H_o accepted
Facilitating Conditions -> Employee Performance	H_{5a}	0.0340	0.0325	0.0298	1.1424	0.253 8	H_o accepted
Facilitating Conditions -> Technology Adoption -> Employee Performance	H_{5b}	0.0222	0.0223	0.0117	1.9001	0.058 0	H_o accepted
Facilitating Conditions	H_{5c}	0.2219	0.2212	0.0287	7.7372	0.000 0	Ha accepted

-> Service Performance -> Employee Performance							
Facilitating Conditions → Technology Adoption → Technology Use → Employee Pf.	H_{5d}	0.0015	0.0015	0.0010	1.4608	0.1447	H_o accepted
Coordination Skills -> Employee Performance	H_{6a}	0.0526	0.0512	0.0343	1.5319	0.1262	H_o accepted
Coordination Skills -> Service Performance -> Employee Performance	H_{6b}	0.1971	0.1953	0.0266	7.3967	0.0000	H_a accepted
Coordination Skills -> Technology Adoption -> Employee Performance	H_{6c}	0.1108	0.1106	0.0206	5.3762	0.0000	H_a accepted
Coordination skills → Technology adoption → Technology use → Employee Pf.	H_{6d}	0.0030	0.0030	0.0021	1.4510	0.1474	H_o accepted
Technology Adoption -> Employee Performance	H_{7a}	0.2501	0.2496	0.0392	6.3866	0.0000	H_a accepted
Technology Adoption -> Technology Use -> Employee Performance	H_{7b}	0.0067	0.0067	0.0045	1.4963	0.1352	H_o accepted
Work Experience x Service Performance -> Employee Performance	H_{8b}	0.0070	0.0068	0.0247	0.2839	0.7766	H_o accepted

Education -> Employee Performance	H_{9a}	0.0961	0.0965	0.0287	3.3469	0.0009	H_a accepted
Education x Service Performance -> Employee Performance	H_{9b}	0.0610	0.0588	0.0273	2.2326	0.0260	H_a accepted

Without this implementation, the relationship between Supporting Conditions and Employee Performance weakens. Conversely, Supporting Conditions will support Employee Performance in relation to Public Services, offering infrastructure, training, and resources that improve the quality of public services (Service Performance). For example, robust technology systems, fast access to information, and technical support can significantly improve the efficiency and accuracy of service delivery (H_{5c}; P-value = 0.0000). While support and facilities may be sufficient to encourage the adoption or use of technology, their impact on Employee Performance is often more influenced by factors such as employee skills or motivation (H_{5d}; P-value = 0.1447). These findings align with the explanation that facilitating conditions function as supporting factors for system use, not as direct determinants of performance. Therefore, without effective utilization, infrastructure and technical support only create conducive conditions but do not produce performance output. Conversely, this study found that the Supporting Conditions significantly influenced Employee Performance through improved Service Performance (H_{5c}; p = 0.0000).

Adequate infrastructure, reliable technology systems, fast access to information, and technical support have been shown to improve the efficiency and accuracy of public services. This finding is consistent with the research by Celik and Ayaz (2022), which asserts that system and service quality increase net benefits, including improved organizational performance. However, when directly linked to Employee Performance without the mediation of service practices, the effect of Supporting Conditions was insignificant (H_{5d}; p = 0.1447). This suggests that the impact of organizational support is more influenced by internal factors, such as competence and motivation (Huang, 2025).

Coordination Skills did not show a significant relationship with Employee Performance, indicating that the development of coordination skills is not sufficient to directly influence the performance of Civil Service employees (H_{6a}; P-value = 0.1262). Coordination Skills can be seen as a facilitator rather than an end result. Their impact is not direct on Employee Performance but operates through the effective application of these skills in providing quality public services or utilizing technology effectively. The interaction between these factors yielded significant results when mediated by Service Performance (H_{6b}; P-value = 0.0000) and Technology Adoption (H_{6c}; P-value = 0.0000), which established a concrete mechanism for translating coordination skills into tangible effects on Employee Performance. Again, while support and facilities can adequately encourage the adoption or use of technology, the direct impact on Employee Performance may be more dependent on aspects such as employee expertise or motivation (H_{6d}; P-value = 0.1474).

These findings align with Kiggundu et al. (2025), who stated that interpersonal skills, including coordination, do not always directly impact individual performance without clear work systems and structures. Furthermore, these results support Fantozzi, Di Luozzo, and Schiraldi (2024) view that behavioral competencies (soft skills) will impact performance if integrated with job demands and the organizational environment. However, these results may differ from those of Sinkó and Salas-Lucia (2025), who asserted that coordination skills significantly influence team performance, particularly in dynamic teamwork contexts. This difference suggests that in a more individualized and structured bureaucratic environment, the influence of coordination on individual performance becomes less dominant (Alsheyadi, Baawain, & Shaukat, 2024). Thus, this research does not completely reject the importance of coordination skills but rather emphasizes that in the public sector context, these abilities are not a direct determinant of individual performance without the support of adequate work mechanisms and organizational systems (Virtanen & Jalonen, 2024).

Technology Adoption directly improves Employee Performance (H_{7a}; P-value = 0.0000) because it indicates the acceptance or introduction of new technology within an organization, although it does not guarantee that the technology is utilized to its full potential. If adopted, technology may not be implemented effectively because of inadequate training, knowledge gaps, or resistance to change. Furthermore, the benefits of technology adoption generally take time to realize. The initial implementation may not immediately result in improved Employee Performance due to the learning curve and adaptation phase. Technology Adoption significantly improves Employee Performance when mediated by Technology Use (H_{7b}; P-value = 0.2971). The findings indicate that Technology Adoption directly improves Employee Performance (H_{7a}), supporting the logic of the **UTAUT**, which states that acceptance of information systems increases performance expectancy and work efficiency. Previous studies Simmons, Burn, and McLeod (2022) similarly show that adopting digital systems accelerates task completion and reduces manual work, even though the benefits are not immediately optimal due to learning curves and adaptation phases (Mohr & van Rijn, 2024).

However, the results also confirmed that adoption alone does not guarantee effective performance improvement (Nascimento et al., 2022). The indirect effect through Technology Use suggests that technology only creates value when it is utilized in daily tasks. Prior research consistently explains that system availability represents potential value, whereas actual usage represents realized value. The weak mediation further implies that organizational factors, such as coordination, workflow adjustment, and training, are necessary to maximize performance outcomes. Thus, consistent with earlier studies, digital transformation should be viewed as an organizational change process rather than merely technology implementation (Mukroni & Sartika, 2025). Technology adoption and use are only the initial steps towards effective technology utilization. Without a well-planned approach, training, or organizational support, technology cannot serve as a direct catalyst for Employee Performance. This lack of a significant relationship highlights the need for additional factors, such as Service Performance, coordination, or updates in workplace processes, to optimize the impact of technology on Employee Performance (Fu, Moein, & Zami, 2024).

Work Experience does not have a direct impact on improving Employee Performance (H_{8a}; P-value = 0.8124). In a rapidly evolving work environment, the ability to learn and adapt is often more important than prior experience. Experienced employees may struggle to keep up with new technologies and procedures. The indirect effect indicates that Work Experience does not improve Employee Performance when mediated by the Service Performance variable (H_{8b}; P-value = 0.7766). The moderating term in this study is identified as Homologizer Moderation. This result contrasts with the traditional human capital assumptions proposed by Becker et al. (2022) and Fabian et al. (2020), who argue that accumulated experience increases skills and productivity. However, this finding supports more recent perspectives that emphasize competency relevance rather than tenure duration (Gilli, Nippa, & Knappstein, 2023). In dynamic organizations, especially those undergoing digital transformation, experience based on old routines may become less useful and even create rigidity in adapting to new work flows.

Several contemporary studies have also reported similar results, showing that experience only improves performance when accompanied by learning orientation, training, or adaptive capability (Arraya, 2022). Without continuous skill updating, experienced employees may rely on habitual practices that are inefficient (Quansah, Hartz, & Salipante, 2022). This explains why newer employees who quickly learn digital systems may achieve comparable or even better performance than senior employees do. Education directly influences employee performance improvement (H_{9a}; P-value = 0.0009). Education lays the theoretical and practical foundation that empowers employees to understand their responsibilities. Typically, employees with higher education possess superior critical thinking, analytical, and problem-solving skills that are essential for an efficient workflow. Those with higher levels of education are more adept at providing quality services. A solid Service Performance Framework can strengthen the positive effect of education on employee performance (H_{9b}; p = 0.0260). The moderating variable in this study is referred to as quasi-moderation.

This result is consistent with the Human Capital Theory proposed by Ibled (2025), which argues that education enhances knowledge, skills, and productivity. Employees with higher education levels tend to possess stronger analytical abilities, critical thinking skills, and structured problem-solving competence (PnevmatikosPnevmatikos (2025), all of which contribute to a more efficient workflow and better service outcomes (Mikram, El Kafhali, & Saadi, 2024). Empirical studies in public sector and organizational research similarly report that educational background positively affects job performance, particularly in knowledge-intensive and service-oriented settings. According to Breit, Andreassen, and Fossestøl (2024), education enables employees to better interpret regulations, manage complex tasks, and respond to citizens' needs with greater professionalism. This supports the argument that education provides not only technical competence but also the cognitive flexibility necessary in modern bureaucratic systems.

Furthermore, the significant moderating effect of the Service Performance Framework (H_{9b}) indicates a quasi-moderation relationship, meaning that the service system structure both directly affects performance and strengthens the influence of education on performance. This finding aligns with the socio-technical and performance management literature, which emphasizes that individual competencies yield optimal outcomes when supported by clear service standards, performance indicators, and process alignment. In other words, education creates potential capability, whereas a structured service framework ensures that this capability is translated into measurable performance. Therefore, consistent with prior research, this study confirms that education is a critical determinant of employee-performance. However, its impact becomes stronger when embedded within an effective service performance system, highlighting the importance of integrating human capital development with organizational performance.

5. Conclusions

5.1. Conclusion

This study concludes that digital adoption alone does not automatically improve public-sector performance. It will have a positive impact when supported by coordination capabilities and emotional intelligence, which serve as a translation mechanism that transforms technology into effective service outcomes. Therefore, digital transformation must be understood as a sociotechnical change, not simply a technology initiative. Public organizations must integrate human capability development, particularly in relation to collaborative coordination and interpersonal competencies. From a policy perspective, the government must balance technology investment with competency development to ensure performance improvements that impact government modernization and not simply digital procedures.

5.2. Research Limitations

This study focused on a single local government context, limiting its generalizability. Future research should compare multiple administrative levels and institutional settings to validate the model across governance systems

5.3 Suggestions and Directions for Future Research

Future studies should delve deeper into longitudinal and cross-institutional contexts to better capture the effects of sustainable digital transformation.

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Author Contributions

TYT conceived the study, designed the methodology, conducted the analysis, and drafted the manuscript. HW collected and validated the data and contributed to the manuscript revisions. AG performed the literature review, visualization, and technical support. MW supervised the project and provided critical revisions of the manuscript.

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