

Examining the Effect of Data-Driven Technology Adoption Factor Towards Smart Facilities Management in Public Sector

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Received Date: 15 May 2025

Accepted Date: 10 July 2025

Revised Date: 14 July 2025

Published Date: 31 July 2025

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ABSTRACT

Facilities Management (FM) in public sector involves overseeing large-scale, complex infrastructures that generate vast amounts of data especially. The integration of data-driven technologies (DDT), such as the Internet of Things (IoT), Cloud Computing, Big Data Analytics (BDA), and Artificial Intelligence (AI) could utilize data towards Smart FM practice. However, the adoption of these DDT in government FM practices are not fully realized due to individual and organizational challenges. Consequently, this study aims to investigate the key determinants factors influencing DDT adoption in FM from both individual and organizational perspective. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology-Organization-Environment (TOE) framework, this research employs a deductive approach, using a structured questionnaire survey. A total of 216 responses from Malaysian government FM practitioner were analysed by Structural Equation Modelling (SEM) technique. Findings reveal that performance expectancy, effort expectancy, social influence, facilitating conditions, technology readiness, and organizational support significantly influence DDT adoption towards Smart FM, while environmental factors do not. The results provide valuable insights for policymakers and FM practitioners seeking to enhance data-driven transformation in public sector facilities management.

Keywords: Data-driven technology, Data Analytic, Facilities Management, Government, UTAUT-TOE.

INTRODUCTION

We are witnessing the fast development of digital and data-based technologies (DDT), leading to changes in industries resulting in smarter decision-making, better operational efficiency and management of resources (Parviainen et al., 2017). Government Facilities Management (FM) is one such domain, dealing with large-scale, highly complex infrastructure that churns out tons of data on a daily basis (Ensafi et al., 2023). The implementation of Internet of Things (IoT), Cloud Computing, Big Data Analytics (BDA), Machine Learning (ML), Artificial Intelligence (AI) etc. offers a major potential to innovate FM process towards data-driven approach.

The adoption of DDT in FM can enhance performance by providing capability of real-time analytics, predictive maintenance and support based on evidence decision-making (D’Orazio et al., 2022). For example, Bouabdallaoui et al., (2021) highlight that by integrating IoT sensor with BDA and ML, facilities managers can undertake predictive maintenance before complete failure occurs and thereby extending the building assets using life and achieving long-term return on investment. Nevertheless, despite the benefits offered by DDT, its full advantages from being driven by data in FM especially in government sector have yet to be fully realized.

In the meantime, previous studies on technology adoption in FM is fragmented and heavily focus on IoT and Building Information Modelling (BIM) rather than examining adoption as a holistic ecosystem for data-driven decision making (Nortey et al., 2025). The technology adoption study also primarily focusing on the private sector usage, which contribute for less understanding of the technology adoption among the government FM practitioners’ (Nortey et al., 2025). It has also been reported that adoption of DDT in the operation and maintenance (O&M) phase is not being explored as much as in earlier phases of the facility lifecycle (Akbari et al., 2024). This is the gap that motivates additional research into more general technology adoption frameworks that may assist with the effectiveness and the efficiency of decision-making in FM.

While existing theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the Technology-Organization-Environment (TOE) (Tornatzky & Fleischer, 1990) framework have been widely applied to study technology acceptance, few studies have integrated these two theories to comprehensively investigate it from both individual and organization perspective. The intention of the current research, thus, is to fill this gap by proposing and testing a conceptual framework that explains DDT adoption in government FM.

Based on UTAUT and TOE as theoretical backgrounds, the study aims to identify the factors of paramount importance and its effect on FM performance. A quantitative research design is used to gather data from 216 government FM practitioners and the latter analysed using Structural Equation Modelling (SEM) in SmartPLS 4.0. The evidence will generate empirical knowledge on the drivers and barriers to adoption, enabling practical guidance for government FM policy makers, FM professionals and technology providers in progressing the Smart FM transformation in government FM.

LITERATURE REVIEW

Role of Data-Driven Technologies in Smart Facilities Management

Facilities Management (FM) is known as a multidisciplinary field that brings together people, places, and processes to help organizations meet their goals (Brian Atkin & Adrian Brooks, 2015; Gii Amaratunga, 2001; ISO, 2017). It’s a complex and evolving area that involves handling a wide range of data such as asset records, maintenance schedules, energy consumption and space planning. As a result, FM practices particularly in the government sector are being called upon to become smarter, more responsive, and data centric (Abu Bakar & Nizam Kamaruzzaman, 2023). This transformation has been largely driven by the integration of data-driven technologies, which are crucial to the development and implementation of Smart FM.

Smart FM refers to the digitization and automation of FM processes using interconnected systems, real-time data, and intelligent analytics to enhance decision-making, service delivery, and resource utilization (Hou, 2023; Olimat et al., 2023). As shown in Figure 1, Smart FM should consist of five essential characteristics which is intelligence (learning capability), responsive (automation, reactive), adaptability (flexible, scalability, interoperability), sustainability (energy efficiency, resource optimization) and connectivity (integration, real-time communication). Smart FM is rooted in data-driven technologies, which enable inform decision-making across all levels of FM function which is

operational, tactical and strategic (Akhlaghi & Then, 1992). The key enabling technologies involved in Smart FM include the IoT, Cloud Computing, BDA, BIM, Digital Twin (DT), AI).

The IoT forms the backbone of Smart FM by enabling real-time data capture through sensors and smart devices across physical assets (Zhuang et al., 2023). For instance, IoT sensor in building provide a solution for real-time monitoring on environmental conditions like temperature and humidity, track the performance of systems such as Heating, Ventilation and Air Conditioning (HVAC), and safety surveillance (Dahanayake & Sumanarathna, 2022; Sarkar, 2021). While cloud computing provides flexible storage for dynamic IoT sensor data and allows remote access and collaboration to scale smart systems as needed (Lau et al., 2013). BIM and DT provide virtual models of facilities that support diagnostics, simulations, and optimizations throughout a building's lifecycle (Chen et al., 2018). Meanwhile, big data analytics, machine learning, and artificial intelligence transform raw data into meaningful insights through processing large volumes of varied data to uncover inefficiencies and recommend improvements (Razali et al., 2020; Samatas et al., 2021). Together through integration, these approaches enable a proactive, data-driven approach to facilities management decision-making rather than relying on intuition alone (Yang & Bayapu, 2020).

Despite widespread reporting of such technological benefits, its adoption in FM especially within the public sector in Malaysia towards data-centric approach faces significant challenges. For example, current government FM practice still relies on legacy technology such as CMMS and BAS (Abu Bakar & Nizam Kamaruzzaman, 2023), which often contains incomplete data and lack of real-time updated for decision support (Razali et al., 2020). Similarly, while the government introduce Immovable Asset Management System (mySPATA) to facilitate asset and maintenance data collection, it cannot be fully used due to challenges with system integration, poor record management and non-centralized information (JPAK, 2018; Razali et al., 2020). Furthermore, outdated infrastructure, constrained budgets, regulatory barriers, limited digital skills, and low readiness to innovate becomes a challenge for the DDT adoption in FM (Abu Bakar & Nizam Kamaruzzaman, 2023; Zhan et al., 2023). Therefore, it is essential to identify the key drivers and barriers influencing DDT adoption in FM. These finding will play a critical role in supporting the development of strategic framework for integrating DDT into FM towards Smart FM practices in government sector.

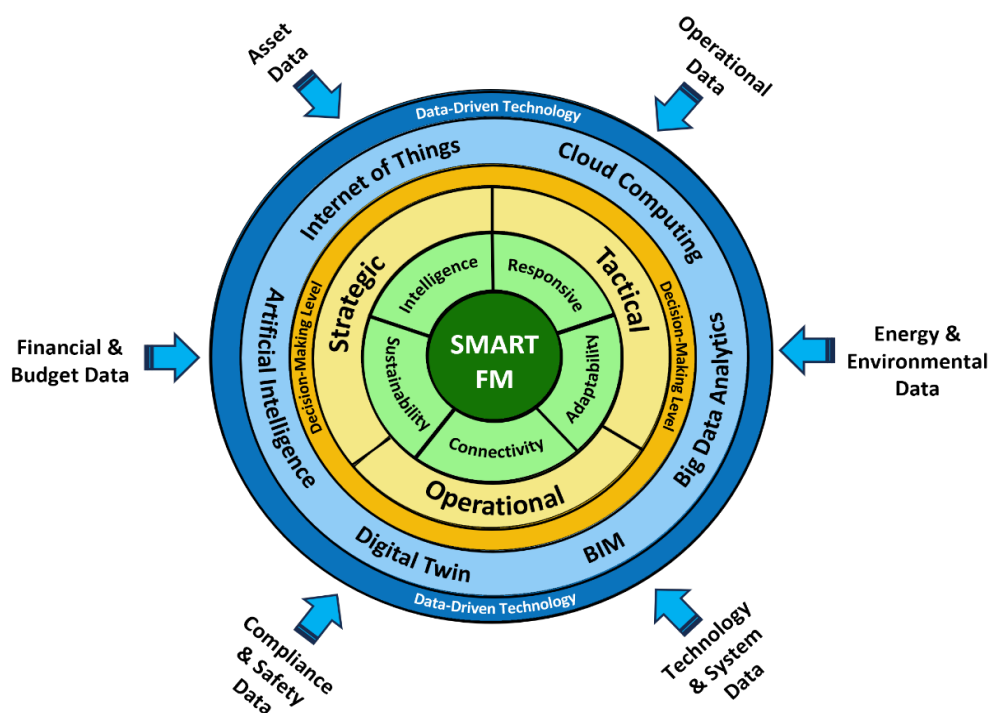


Figure 1: Concept of Smart FM Enable by Data-Driven Technology Adoption (Source: Author)

Theoretical Technology Adoption Review

To adopt the data-driven technology (DDT) in FM towards Smart FM practice in government, it is essential to understand on the key factors that influence both FM practitioner and organizations in accepting and utilizing technology. To fulfil this objective, this study suggests two widely recognized model which is the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology-Organization-Environment (TOE) framework as the underpinning theory in this study. UTAUT is introduced by Venkatesh et al., (2003), explain on how individual accept and use technology based on four core construct which is performance expectancy, effort expectancy, social influence, and facilitating conditions. It also consists of two outcome variables (behavioural intention and use behaviour) along with several moderating factors like gender, age, experience, and voluntariness of use (Venkatesh et al., 2003).

Despite offering valuable insight into user behaviour, UTAUT primarily focuses on individual acceptance rather than adequately take broader organizational context into consideration. (Xue et al., 2023). Due this limitation, this study proposed an integration of TOE framework to brings in an organizational lens for more comprehensive understanding. TOE is developed by Tornatzky and Fleischer in 1990 is a widely recognized and influential theoretical framework that seeks to explain the adoption and implementation of technology within organizations (Tornatzky & Fleischer, 1990). It considers three primary contexts that influence technological adoption at an organizational level: technological aspects such as complexity and compatibility; organizational factors like leadership support and resource availability; and external pressures from regulations and industry trends (Tornatzky & Fleischer, 1990). Alatawi et al., (2012) and Baker, (2012) also suggest the TOE framework should integrate other adoption theories to include individual contexts and thus enrich the theoretical perspectives.

Therefore, this research proposes integrating the UTAUT theory and the TOE framework to provide a robust and comprehensive theoretical foundation for studying this topic. A conceptual framework has been developed based on this integration, as shown in Figure 2. It comprises 28 attributes grouped under seven independent variables and 5 dependent variables related to Smart FM outcomes. Seven hypotheses (H1–H7) are formulated from this framework to examine how different factors influence the adoption of DDT in FM. This integrated approach offers a well-rounded view of the key influences on intention to adopt DDT in government contexts, supporting the transition towards more data-driven Smart FM practices.

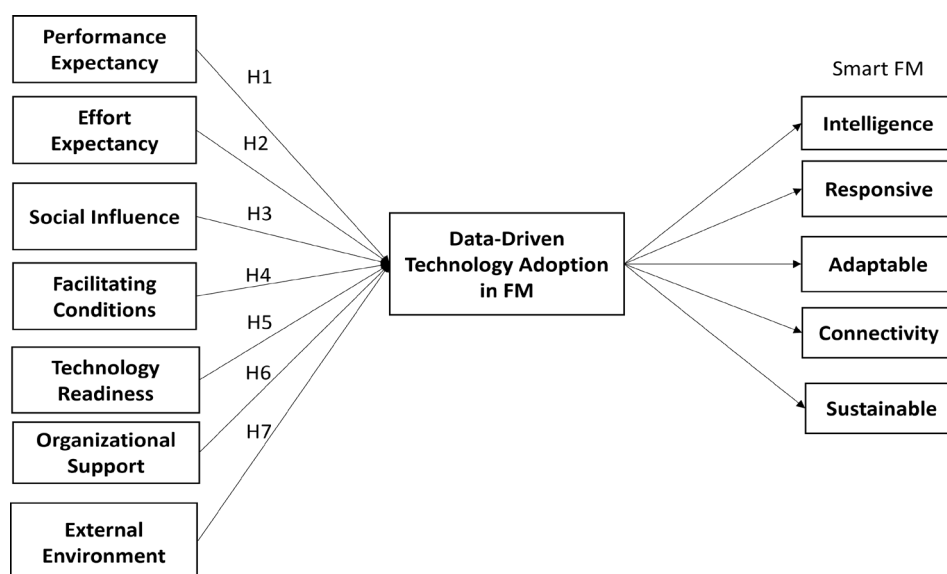


Figure 2: Conceptual Framework for Data-Driven Technology Adoption in FM

Table 1: Summary of Factors Affecting Data-Driven Adoption in FM

Theory/ Framework	Determinants Factor	Attributes	Source
UTAUT (Venkatesh et al., 2003)	Performance Expectancy: Degree to which individual believes that using a particular technology will help them enhance their job performance	Efficiency, reliability, functionality, effectiveness	(Adama & Michell, 2018; Dowelani & Ozumba, 2022; Ghayth Elghdban et al., 2020; Hassanain et al., 2024; Konanahalli et al., 2022; Nortey et al., 2025)
	Effort Expectancy: Degree of ease associated with the use of the system or technology	Ease of use, clarity, learnability, simplicity	(Adama & Michell, 2018; Dowelani & Ozumba, 2022; Ghayth Elghdban et al., 2020; Nortey et al., 2025)
	Social Influence: Degree to which an individual perceives that important others believe one should use the new technology.	Peer influence, perceived norms, organizational pressure, expert influence	(Adama & Michell, 2018; Baharetha et al., 2023; Dowelani & Ozumba, 2022; Ghayth Elghdban et al., 2020)
	Facilitating Conditions: Degree to which an individual believes that organizational and technical infrastructure exists to support the use of the system	Policies & guidelines, technical support, IT knowledge, training & education	(Adama & Michell, 2018; Ali et al., 2022; Brous et al., 2017; Dowelani & Ozumba, 2022; Hassanain et al., 2024)
TOE (Tornatzky & Fleischer, 1990)	Technology Context: Refers to both the internal and external technology relevant to an organization.	Interoperability, Data Quality & Security, cost, IT infrastructure	(Al Hadwer et al., 2021; Ghayth Elghdban et al., 2020; Hou, 2023; Konanahalli et al., 2022; Nortey et al., 2025)
	Organizational Context: Refers to internal characteristics and resources of the organizations that influence its technology adoption	Top management support, organization structure, financial & resources, innovation culture	(Ahmed et al., 2017; Ali et al., 2022; Ghayth Elghdban et al., 2020; Hassanain et al., 2024)
	Environment Context: Refers external factors related to an organization business ecosystem	Competitive pressure, stakeholder expectation, regulatory & compliance, government support	(Ahmed et al., 2017; Ali et al., 2022; Ghayth Elghdban et al., 2020; Hou, 2023)

Hypothesis 1: There is significant impact of the “Performance Expectancy” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as user efficiency improvement, reliability, functionality, and effectiveness.

Hypothesis 2: There is significant impact of the “Effort Expectancy” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as ease of use, clarity, learnability, and simplicity.

Hypothesis 3: There is significant impact of the “Social Influence” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as peer influence, perceived norms, organizational pressure, and expert influence.

Hypothesis 4: There is significant impact of the “Facilitating Conditions” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as policies & guidelines, technical support, IT knowledge, training & education.

Hypothesis 5: There is significant impact of the “Technology Readiness” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as interoperability, data quality & security, cost, IT infrastructure.

Hypothesis 6: There is significant impact of the “Organizational Support” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as top management support, organization structure, financial & resources, innovation culture.

Hypothesis 7: There is significant impact of the “External Environment” factor on DDT adoption for Smart FM practice in the government sector. This factor is defined by attributes such as competitive pressure, stakeholder expectation, regulatory & compliance, government support.

METHODOLOGY

This study adopts a quantitative research approach to explore the factors influencing DDT adoption in government FM. A purposive sampling method was employed by specifically targeting a respondent who are directly involved in government FM practices. Therefore, FM practitioner under Public Works Department (JKR) were selected, as this department is the biggest technical government agency in Malaysia responsible for managing government building maintenance through FM contract (JPA, 1974; Myeda & Pitt, 2014). Based on data provided by JKR’s Asset Management Department, the total population is estimated at 375 individuals, comprising both JKR officers (Grade J29 and above) and FM contractors actively engaged in government FM projects. To determine the appropriate sample size, the web-based Raosoft calculator was used with parameters set at a 5% margin of error, 95% confidence level, and 50% response distribution, resulting in a recommended minimum sample size of 191 respondents.

A structured questionnaire using a 5-point Likert scale was then developed based on conceptual framework as illustrated on Figure 2. Each construct such as Performance Expectancy or Technology Readiness was primarily adapted from established UTAUT (Venkatesh et al., 2003) and TOE (Tornatzky & Fleischer, 1990) frameworks. Based on these constructs, measurement items were identified through an extensive literature review on DDT adoption determinants in FM field and validated by 3 FM practitioner expert to finalise the research instrument. A pilot study involving 33 respondents was conducted to evaluate the clarity and reliability of the measurement items. By analysing using SPSS software, the internal consistency of the instrument was confirmed with a Cronbach’s Alpha of 0.951 which indicate excellent reliability. All items were retained, with slight wording modifications made for better understanding.

The final data collection was conducted and distributed online via Google Forms, resulting in 218 responses. A normality test revealed two outliers, which were subsequently removed, leaving 216 valid responses. As the data did not meet normality assumptions, Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed for analysis (J. F. Hair et al., 2017). PLS-SEM is suitable for non-normally distributed data and enables robust analysis of complex relationships (Chin, 1998), making it an appropriate method for examining the adoption of DDT in FM.

RESULT AND DISCUSSION

Respondent Demographic Profile

Table 2: Respondent Demographic Profile

Category		Frequency	Valid Percent	Cumulative Percent
Qualification	Certificate	14	6.5%	6.5%
	Diploma	28	13.0%	19.5%
	Bachelor's degree	119	55.1%	74.6%
	Master's degree	48	22.2%	96.8%
	Doctor of Philosophy (PhD)	7	3.2%	100.0%
	Total	216	100.0%	
Position	Facilities Manager	15	6.9%	6.9%
	Maintenance Supervisor/ Verifier	16	7.4%	14.3%
	Operation Manager	3	1.4%	15.7%
	Asset Manager	5	2.3%	18.0%
	Engineer (Civil/ Electrical/ Mechanical)	82	38.0%	56.0%
	Architect / Landscape Architect	8	3.7%	59.7%
	Surveyor (Quantity Sr./ Building Sr./ Land Sr.)	33	15.3%	75.0%
	Assistant or Technician (Engineer/ Architect/ Surveyor)	46	21.3%	96.3%
	Information Technology (IT) Officer	6	2.8%	99.1%
	Others	2	0.9%	100.0%
	Total	216	100%	
FM Experiences	Less than 1 year	44	20.4%	20.4%
	1 – 3 years	43	19.9%	40.3%
	4 – 6 years	38	17.6%	57.9%
	7 – 9 years	29	13.4%	71.3%
	More than 10 years	62	28.7%	100.0%
	Total	216	100	

A full overview the demographic profile of the respondents is shown in Table 1. It indicates a highly educated sample, with 55.1% holding at least a bachelor's degree (119 respondents), including 22.2% with master's degrees (48 respondents) and 3.2% (7 respondents) with PhDs. In terms of position, the majority of respondents (59.3%) occupy technical roles, such as engineers, technicians, and surveyors, while 6.9% and 7.4% hold managerial and supervisory positions, respectively. While for FM experience, it shows that the most common respondents experience level in facilities management or building maintenance field is more than 10 years, accounting for 28.7% (62 respondents). The second-largest group is less than 1 year, at 20.4% (44 respondent) and the group with the fewest respondents is 7 – 9 years, with only 13.4% (29 respondent). This indicates a relatively balanced distribution of experience levels across the categories. A significant portion (over a quarter) of respondents have more than 10 years of experience, indicating a highly experienced subset. This diverse and well-qualified sample provides a robust foundation for exploring the adoption of data-driven technologies across varying levels of expertise and roles within the FM in government sector.

Relationship Assessment by Structural Equation Modelling

To achieve the objective of this study which is to investigate the impacts of DDT adoption factor in improving the FM performance, PLS-SEM have been used as a technique to analyse complex relationships between observed and latent (unobserved) variables. It combines aspects of factor analysis and path analysis to test and estimate causal relationships among variables. The analysis was carried out in two stages which measurement model analysis and the structural model analysis. The results and findings can be discussed as follows:

Measurement Model Assessment

The measurement model evaluates how well the observed variables (indicators) measure the latent constructs (unobserved variables) (Bollen & Lennox, 1991). This stage focuses on assessing the reliability and validity of the constructs. To assess the reliability and internal consistency of the constructs in this study, Cronbach's Alpha (CA) and Composite Reliability (CR) have been tested, and the result is show as in Table 2 below.

Table 3: Internal Consistency Reliability

Determinant Factor	Cronbach's Alpha	Composite Reliability (rho_c)
Performance Expectancy	0.847	0.897
Effort Expectancy	0.841	0.893
Social Influence	0.812	0.877
Facilitating Condition	0.811	0.876
Technology Readiness	0.896	0.928
Organizational Support	0.915	0.940
External Environment	0.845	0.896

The results shows that all constructs exhibit strong reliability which above the recommended threshold of 0.70 for both CA and CR (J. Hair et al., 2010). High internal consistency across all constructs is shown by the Cronbach's Alpha values range from 0.811 to 0.915. Similarly, CR values exceeding the 0.70 threshold which range 0.876 to 0.940, confirms that the latent constructs are well-represented by their respective indicators (Fornell & Larcker, 1981). Organizational Support demonstrate the highest reliability ($\alpha = 0.915$, CR = 0.940), suggesting a strong consistency among the others constructs. Technology Readiness also exhibit an excellent reliability ($\alpha = 0.896$, CR = 0.928) which indicating robust measurement of the construct. Meanwhile, the lowest CA (0.811) and CR (0.876) is a Facilitating Condition factor, but the value still falls well within acceptable limits.

Table 4: Convergent Validity of Constructs

Determinant Factor	Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability (rho_c)
Performance Expectancy	0.685	0.847	0.897
Effort Expectancy	0.677	0.841	0.893
Social Influence	0.640	0.812	0.877
Facilitating Condition	0.639	0.811	0.876
Technology Readiness	0.762	0.896	0.928
Organizational Support	0.797	0.915	0.940
External Environment	0.683	0.845	0.896

For validity test, a convergent validity test has been carried out and the results shown on Table 4. The Average Variance (AVE) value indicates all determinant factors meet the AVE threshold of 0.50 (J. Hair et al., 2010). This confirming that the constructs explain more than 50% of the variance in their indicators. Organizational Support (AVE = 0.797, CR = 0.940) and Technology Readiness (AVE = 0.762, CR = 0.928) demonstrate the highest levels of convergent validity and reliability among the constructs, while Social Influence (AVE = 0.640, CR = 0.877) and Facilitating Condition (AVE = 0.639, CR = 0.876) show slightly lower but still acceptable validity. Overall, from the results, it indicates that the measurement model is well-constructed and effectively captures the underlying latent variables in the study. This confirms that the selected indicators reliably represent their respective constructs.

Table 5: Discriminant Validity of Constructs

Determinant Factors	AVE	PE	EE	SI	FC	TR	OS	EX
Performance Expectancy	0.685	0.828*						
Effort Expectancy	0.677		0.823*					
Social Influence	0.640			0.800*				
Facilitating Condition	0.639				0.799*			
Technology Readiness	0.762					0.873*		
Organizational Support	0.797						0.893*	
External Environment	0.683							0.826*

Construct validation was further conducted using a discriminant validity test and the results is shown on Table 4. Through the Fornell-Larcker Criterion method, it confirms that each construct in the study is distinct from the others (Fornell & Larcker, 1981). A result shows strong discriminant validity by the square root of the AVE for each determinant factor (bold diagonal values) is greater than its correlations with other constructs. For instance, Performance Expectancy has a square root AVE of 0.828, which is higher than its correlations with Effort Expectancy (0.823), and the same trend is observed across all constructs (FC, TR, OS, EX). This confirms that each construct is empirically distinct, ensuring that the model accurately captures the unique aspects of DDT adoption in government facilities management. Thus, the model demonstrates strong discriminant validity, supporting its reliability and robustness for further analysis.

Structural Model Assessment

After model measurement assessment have been caried out, this study proceeds a further step involves evaluating the path coefficients of all DDT adoption determinants by comparing their beta (β) values across different paths. The result of assessment is shown on Table 5 below:

Table 5: Results of Hypothesis Test

Hypothesis	Relationship	Path Coefficient, β	t-value	P-value	Interpretation
H1	Performance Expectancy -> DDT Adoption in FM	0.182	3.494	0.000	Supported
H2	Effort Expectancy -> DDT Adoption in FM	0.266	5.121	0.000	Supported
H3	Social Influence -> DDT Adoption in FM	0.107	2.700	0.003	Supported
H4	Facilitating Condition -> DDT Adoption in FM	0.131	2.609	0.005	Supported
H5	Technology Readiness-> DDT Adoption in FM	0.322	5.592	0.000	Supported
H6	Organizational Support -> DDT Adoption in FM	0.105	1.996	0.023	Supported
H7	External Environment -> DDT Adoption in FM	0.045	1.284	0.100	Not Supported

These values beta (β) values represent the hypothesized relationships between variables. A higher β value signifies a stronger impact of DDT adoption determinants (independent variables) towards Smart FM practice (dependent variable) (Chin, 1998). Hair et al (2010) suggest that path coefficients should exceed 0.10 to indicate a meaningful effect within the model (J. Hair et al., 2010). To ensure the robustness of the results, this study is conducted through a non-parametric bootstrapping technique, as recommended by (Chin, 1998). The path coefficient analysis revealed that six out of seven hypothesized relationships significantly influence the adoption of DDT in government FM. Technology Readiness ($\beta = 0.322$, $p < 0.001$) emerged as the strongest predictor, followed by Effort Expectancy ($\beta = 0.266$, $p < 0.001$), Performance Expectancy ($\beta = 0.182$, $p < 0.001$), Facilitating Conditions ($\beta = 0.131$, $p = 0.005$), Social Influence ($\beta = 0.107$, $p = 0.003$), and Organizational Support ($\beta = 0.105$, $p = 0.023$), all of which were statistically significant. These findings highlight that both personal and organizational elements such as how easy the technology is to use, the benefits it offers, the resources available, and the support from within the organization play a key role in encouraging the adoption of DDT. However, external factors like government policies or industry standards are found to be less impactful, as shown by the non-significant result for External Environment ($\beta = 0.045$, $p = 0.100$).

Hypothesis Results

A meaningful insight into what drives the adoption of DDT in government FM can be seen from the results of hypothesis testing. From out of the seven proposed hypotheses, six of them were supported with strong statistical evidence and showing significant relationships with p-values below 0.05. This means that these factors are important in shaping FM practitioners' willingness to embrace new technologies, and these findings are consistent with both the UTAUT and TOE models.

For example, Performance Expectancy (H1) had a positive and significant influence ($\beta = 0.182$, $p = 0.000$), indicating that when practitioners believe that using DDT will help them perform their jobs better, they are more inclined to adopt these tools. Effort Expectancy (H2) exhibited a stronger influence ($\beta = 0.266$, $p = 0.000$), emphasizing that the perceived ease of using DDT significantly contributes to its acceptance. These findings reflect that perceived usefulness and user-friendliness are critical in driving individual acceptance, consistent with the foundational constructs of UTAUT.

Social Influence (H3) also showed a significant but weaker effect ($\beta = 0.107$, $p = 0.003$), indicating that peer and managerial support moderately encourages practitioners to adopt DDT. Facilitating Conditions (H4), with a path coefficient of 0.131 ($p = 0.005$), further highlight the importance of accessible resources, infrastructure, and technical support in enabling adoption. These results demonstrate that both social and organizational enablers contribute meaningfully to technology acceptance.

Technology Readiness proved to be the most influential factor, underscoring how critical technological infrastructure and preparedness within organizations are for fostering adoption. Similarly, Organizational Support significantly impacts adoption as well, demonstrating that encouragement from leadership as well as committed resources and assistance mechanisms are important catalysts. These results align nicely with the organizational and technological dimensions of the TOE framework, specifically within public sector contexts.

Surprisingly, the External Environment was found to be an insignificant determinant, indicating that external elements like regulations, customer expectations, or industry trends have minimal bearing on DDT adoption among government facilities management. This is consistent with previous research on analogous public sector settings. It may reflect how centralized decision-making is within government agencies where internal policies and priorities often outweigh outside pressures. Overall, the conclusions emphasize focusing on internal preparedness and organizational backing to successfully propel data-driven transformation within government facilities management practices.

CONCLUSION

This study sheds light on several pivotal determinants that greatly encourage the adoption of digital design technologies in facilities management organizations within the public sector. Out of the seven proposed hypotheses, six received empirical support, demonstrating that elements such as expected performance improvements, minimal effort requirements, social motivators, facilitating conditions, technological preparedness, and organizational backing all positively affect facilities professionals' willingness to embrace digital design technologies. Technological readiness emerged as the leading factor which emphasizing the necessity of robust tech infrastructure, skilled workers, and comprehensive preparedness within FM groups. Expected effort and expected performance also surfaced as strong drivers, suggesting practitioners are more prone to adopt such technologies when they are user-friendly and evidently boost job output.

Conversely, the external environment variable lacked statistical significance, proposing that exterior pressures like regulatory demands, client requirements, or industry developments may have less immediate influence on government FM practitioners' adoption choices compared to internal organizational and individual factors. These results emphasize the need for policymakers and FM leaders to prioritize internal enablers such as providing technical training, strengthening organizational support, and demonstrating tangible performance benefits to drive successful adoption of data-driven technologies in public sector FM practices. Future research could explore additional contextual factors and conduct longitudinal studies to assess long-term adoption trends.

ACKNOWLEDGEMENTS

The authors would like to thank College of Built Environment, Universiti Teknologi MARA (UiTM), Shah Alam and Perak Branch for their guidance, technical and moral support in completing this research paper. Special thanks to the Jabatan Kerja Raya Malaysia for the opportunity and providing resource of data for these studies.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.”

AUTHORS' CONTRIBUTION

Mohd Rahimi A. Rahman conducted the primary research, including data collection, analysis, and manuscript drafting under the guidance of the supervisory team. Irwan Mohammad Ali provided overall academic direction, critical revisions, and validation of the research methodology. Wan Samsul Zamani Wan Hamdan contributed technical expertise, assisted in research design, and reviewed findings. Mohd Najib Abdul Rashid supported theoretical framework development and manuscript refinement. Each author offered valuable critiques and participated in shaping the research, analysis, and drafting process of this manuscript.

CONFLICT OF INTEREST DECLARATION

This manuscript is the original work of the authors and co-authors. It has not been published previously and is not under consideration for publication elsewhere. The study has not been submitted, either in whole or in part, to any other journal or publication. We affirm that all listed authors have made

substantial contributions to the research, including the accuracy and interpretation of the data, and collectively approve its submission to Jurnal Intelek.

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