Influences on Public Sector Employees' Embrace of Open Government Data: A Step Forward in Data-based Administration

By

HWANG, Seula

IRP-THESIS

Submitted to

KDI School of Public Policy and Management

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For the Degree of

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Abstract

This study explores the strategic utilization of open government data as a pivotal resource for advancing data-based administration, which is a key mechanism for harnessing digital power. The research involved surveying 700 government and public sector employees and extending the UTAUT model by integrating data literacy, self-efficacy, and personal innovativeness as precedents of user characteristics and abilities. The findings indicate that data literacy and self-efficacy boost anticipated job performance and reduce the effort necessary for data use, indirectly influencing the behavioral intention to use. However, personal innovativeness significantly impacts only performance expectations. The intention to adopt a behavior is strongly affected by the expected performance outcomes, the anticipated effort involved, and the degree of social influence.. Interestingly, no relationship is found between facilitating conditions, including expectations of organizational and technological support, and the behavioral intention to use. The research emphasizes the importance of systematically evaluating data literacy levels, strengthening weak competencies, and enhancing data competency training. Additionally, it advocates for encouraging data use and innovation in the public sector through organizational culture flexibility and cooperative activities with the private sector, ultimately stimulating data-based innovative actions at the societal level.

Key words : Open Government Data, Data-based Administration, Public sector workers, UTAUT, Data Utilization, PLS Structural Equation

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LIST OF CONTENTS

List of Tables

List of Figures

Chapter 1: Introduction

In this era of profound digital evolution, the global economy and business sectors are experiencing transformative shifts. Emerging digital technologies, like cloud computing and artificial intelligence, intertwined with a shifting international landscape, make this digital upheaval not only a technological challenge but also a determinant with consequences for industry, trade, diplomacy, and security. This transition has profound implications for national competitiveness (National Information Society Agency, 2022). Recognising the gravity of these changes, the Korean government has identified the establishment of digital platform government as a key national agenda. The goal is to establish a premier digital governance model that integrates data cohesively. This is intended to enhance the public sector's operational efficiency, transparency, dependability, and accountability. The government aims to expand data-driven services for its citizens, encourage private sector participation, and promote the continuous evolution of services through the interaction of various stakeholders(National Information Society Agency, 2022).

Central to the success of digital platform government is data-driven administration, which uses data generated or managed by public institutions for evidence-based policy-making and decision-making. This data-centric approach serves as the foundation for innovation across economic and social sectors, leveraging comprehensive government data to create new industrial value and ultimately realise a digital powerhouse. The government's aspirations include leveraging OGD as a strategic asset, providing integrated, predictive and tailored data services to citizens, fostering new opportunities for businesses and building public trust through data-centric governance.

Despite the country's proactive Data openness policy, which has propelled South Korea to the top of the OECD's OURdata Index (Open Useful Reusable Data Index) on parameters such as accessibility, availability, and government support for data reuse(with a score of 0.93 in 2019), significant concerns remain. Chief among them is the limited availability of high-quality data and its suboptimal utilisation (Han, 2018). In particular, while active user participation and engagement are essential to revitalise OGD, existing policies and services often fail to realise this potential, drawing criticism (Hwang, 2020). The discourse is now shifting from the mere 'openness' of data to improving its 'utility'. Civil servants, as the main facilitators of public services, must utilize OGD to bolster predictive and adaptive policy strategies. This is crucial for the success of a data-based administration and the broader framework of a digital platform government..

This research seeks to identify the factors that affect the willingness of government and public sector workers to utilize OGD in their professional capacities. The primary goal is to develop strategies that enable these stakeholders to implement data-driven administration effectively.

Chapter 2: Literature Review and hypothesize

2.1 Open Government Data

2.1.1 Concept and Characteristics

Open government data(OGD) encompasses the diverse array of information and resources generated, overseen, and stored by federal and local government bodies as well as public institutions. This vast realm of data spans domains such as architecture, traffic incidents, public health, municipal governance, fiscal management, real estate, fisheries, and commercial zones. The unique value proposition of this public data is its accessibility and customizability. This means that anyone can access it, and it can be reused and repurposed. In addition, this data exists in a variety of formats, including text, images, and audio.

With the recent digital transformation of the public sector, there has been a focus on increasing the accessibility of public data, not only to government employees, but also to the general public. In response, governments around the world are increasingly providing platforms or portals through which users can conveniently access and download this treasure trove of data. South Korea, for example, has unveiled its public data portal, DATA.GO.KR, which serves as a hub for the country's most important public sector data.

The OECD understands OGD as both a philosophy and a policy ensemble. This approach is rooted in the belief that data from government sources should be universally accessible. Such access can enhance transparency, accountability and value creation. The OECD underscores the pivotal role of governments in promoting data utilization to cultivate innovative businesses and services centered on citizens.

From the perspective of reusability, it is imperative that public data be made more widely available. This requires strengthening its accessibility in a way that is cost-effective and user-friendly(Hong, 2014). Furthermore, for data-driven decisions to be actionable, the data must be provided in a timely manner and embody accuracy. This ensures that such decisions are underpinned by trust and reliability. In addition, Robert J. Shapiro(2017) has highlighted attributes such as standardization, quality, and security of OGD. According to him, data should be standardized for easy comparison and analysis. Maintaining a consistent level of data quality is essential for its accuracy and trustworthiness. Last but not least, improving data security, especially with regard to protecting sensitive information and preventing data misuse, is of paramount importance.

2.1.2 Utilization of Open Government Data

OGD represents a significant asset, offering insights from public institutions that can fuel both governmental and private sector decision-making. Tapping into this resource has the potential to spur technological advancements and data analytics, fostering the creation of novel services and products. Furthermore, in academic research, such data provides an invaluable lens to explore diverse socio-economic and political phenomena.

In South Korea, various sectors, including transportation, health, and urban development, are witnessing a flurry of innovative activities driven by the joint efforts of public and private entities using OGD. These best practices and innovative efforts are showcased and shared through the OGD portal, strengthening their sustainability by encouraging widespread innovation.

For example, South Korea's Ministry of the Interior and Security has incorporated big data analytics into its operations to preemptively predict potential tax payment capabilities. This novel system was instrumental in developing strategies to collect overdue local taxes. Not only did it significantly reduce time and costs, but it also helped foster a culture of fair tax payment. In addition, the Korean Coast Guard has implemented a data-driven, scientific approach to management. By leveraging OGD, they've been able to predict coastal risks and formulate tailored safety management strategies for various maritime zones. Recognizing the potential of such efforts, the government is promoting them as exemplary cases of public sector data analysis and use. The goal is to encourage similar applications in various fields, including public administration, healthcare, industrial employment, education, welfare, and disaster safety.

2.1.3 Open Government Data Policy

Following a commitment to transparency and accountability, South Korea unveiled its Basic Plan for Activating the Provision and Use of OGD, in alignment with the "Act On Promotion Of The Provision And Use Of Public Data". The most recent version of this plan, from 2022, not only reviews the accomplishments of previous open data policies but also charts a strategic course for 2023 to 2025. At this juncture, the government, in tandem with various public entities, has released close to 74,000 public data records. Special emphasis has been placed on making data available from 168 critical national sectors, pivotal for driving innovation and fostering societal benefits. Nevertheless, despite these commendable strides in data transparency, there's a growing sentiment, as indicated by Cha (2017), that the practical application and tangible outcomes of this OGD haven't fully met expectations.

The Fourth Basic Plan covers not only the quantitative aspects of data openness, but also emphasizes data quality management. Going beyond mere data openness, the government aims to build a platform for data integration and analysis accessible to citizens. The strategy underscores enhancing bespoke assistance for enterprises utilizing OGD, tailored to their individual capabilities and stages of development. It also aims to improve the usability of data by forging partnerships with local communities and the private sector. From the perspective of consolidating a data-centric foundation, the government is refining regulations and laws related to OGD. At the same time, there's a concerted effort to increase public literacy in understanding and using this data. The overarching goal is to manifest a digital platform government model. To this end, the plan aims to provide citizens with proactive, integrated, and customized data, provide businesses with new opportunities through data, and achieve a governance model based on data-driven science, thereby realizing a trusted society. The overarching framework of the Fourth Basic Plan emphasizes the principles of OGD.

[Table 1] Vision Framework of the 4th Open Government Data Basic Plan

Vision	Open and connect all data for a Digital Platform Government
Goal	(People) Provide integrated, proactive, and personalized data (Businesses) Provide new opportunities through data (Government) Realize data-driven scientific administration and a trusted society
Driving Strategy	(Openness) Establishment of a system to open all unopened data in a negative manner (Quality) Strengthen quality management and standard application to improve practical utilization, such as connecting and converging all data (Utilization) Leveraging OGD can significantly drive the achievement of national objectives and address social challenges when paired with effective public-private partnerships (Foundation) Strengthening the foundation for revitalizing the ecosystem from production to utilization of OGD

2.1.4 Data-Based Administration

Per the 2020 proposal titled 'Act On The Promotion Of Data-based Administration', data-based Administration refers to a system wherein public institutions actively gather, maintain, handle, study, and showcase data—originating either internally or sourced from other governmental bodies, corporations, or entities—with the aim of formulating policy decisions grounded in objective and scientific insights.. Guided by the vision of improving citizens' lives through data-driven, scientific administration, as manifested in the First Basic Plan for Activating Data-based Administration(2021), the government is making comprehensive efforts.

Key among these is the establishment of a platform to integrate and share data across government sectors. This aligns with the overarching objective of updating and refining laws and regulations to foster data-based administration and implement an efficient governance system. Public sector institutions are increasingly embracing data-based administration by investing in targeted training, recognizing and implementing best practices, and benefiting from advisory panels that offer expertise in data analysis and strategies for ensuring analytical data integrity. Significantly, the entire policymaking process-from formulation to implementation to evaluation-is being transformed through the use of data for innovative workflows. The government is using data analysis to design tailored policies, while also using data, including citizen feedback, to monitor and manage the impact of policies. The evaluation phase uses data to validate the effectiveness of policy outcomes. Complementing these initiatives, the Ministry of Internal Affairs and Security will conduct regular assessments of the current state of data-based administration under the 'Act On The Promotion Of Data-based Administration' from 2021, ensuring a feedback loop in policymaking and accelerating the establishment of a solid foundation for data-based administrative practices.

[Table 2] Inspection Content by Indicators for the Current State of Data-based Administration

Fields	Inspection Contents
Establishment of data-based administration promotion system	① Establishment of data-based administration management system ○ Hold discussions chaired by deputy agency heads or above ○ Securing the data-based administration budget ○ Expansion of data-based administration personnel ○ Appointment of a data-based administration officer ○ Organize internal and external consultative bodies such as committees
Promoting joint data utilization among administrative and public agencies	① Registration rate for jointly utilized data ○ Registration rate for designated registration data requested by the Ministry of the Interior and Safety
	② Registration and provision of jointly utilized data ○ Efforts and achievements in data research, discovery, processing, and registration for voluntary registration ○ Request and provide data directly between administrative and public agencies

Fields	Inspection Contents
Administrative innovation based on data	① Data analysis and utilization performance ○ Performance in discovering tasks for utilizing data analysis, conducting analysis of the discovered tasks, and utilizing policies for the performed tasks
	② Best practices in data-based administration ○ Best cases of analysis to improve internal administration and public service ○ Best practices for utilizing analyzed results for policy
Data Literacy Strengthening and creating a culture	① Diagnosis of data utilization capabilities and establishment of improvement plans ○ Track record of diagnosing data utilization capabilities of institutional members and establishing improvement plans
	② Participation in data utilization competency training ○ Participation in data utilization training for all employees of the institution ○ Participation in data utilization training(for managers) at the department head level and above ○ Participation in specialized training for data-based administrators
	③ Creating a culture to activate data-based administration ○ Inspection of measures promoted by the agency to spread data-based administration * Contests, best practices publications, internships, campaigns, etc

Public sector decision-making demands rigorous data-driven precision from the outset due to its wide-ranging impact on diverse stakeholders, especially amidst the complexities and uncertainties of modern societal shifts(Moon, 2002). OGD plays a key role in modern data-based administration. The effectiveness of such governance hinges on the accuracy, quality, and relevance of the data used. Informed decisions, underpinned by reliable data, have a direct impact on policy outcomes. Furthermore, when public officials hone their skills in interpreting and leveraging this data, they can better discern citizens′ needs, leading to the development and enhancement of tailored public services. Fundamentally, the effective utilization of OGD by public officials is crucial for achieving a modern, data-based administration framework. This research delves into the determinants that shape how public servants and institutional employees leverage OGD.

2.1.5 Preceding Studies on Open Government Data

While numerous studies have delved into the economic and social ramifications of OGD, as well as the conditions facilitating or hindering its use, the focus has predominantly been on its utilization by citizens and private entities. Research on its adoption by public officials and institutions, on the other hand, remains notably limited.

2.1.5.1 Studies in Korea

Seong-Uk Joon(2016) used the Analytic Hierarchy Process(AHP) to assess the enhancement of big data policies in the public domain.

The research aimed to determine the significance and immediacy of various policy tasks, spanning technological, infrastructural, legal, institutional, and cultural dimensions. Results from the AHP analysis pinpointed legal reforms as the foremost and most pressing concern. The study also underscored the necessity of cultivating a data-driven culture and refining organizational frameworks.

The study by Seo & Myung(2014) delved into strategies for leveraging OGD in the private sector, with an emphasis on the perspectives of IT managers. By surveying actual stakeholders in the private sector, the study shed light on data utilization challenges from four perspectives: the government's provision of public information, the technical environment, the information climate, and socioeconomic factors. The study found that environmental factors, such as data quality and insular government culture, need to be improved to increase the usefulness of OGD.

Song & Hwang(2014) conducted group interviews with OGD providers in Seoul. Their findings indicated that the main barriers to data disclosure and use in the private sector were insufficient awareness and passive, evasive attitudes of relevant public officials. They emphasized the need for dedicated personnel with a proper understanding of OGD to carry out data dissemination tasks.

2.1.5.2 International Studies

Janssen et al.(2012) embarked on a study to find the factors that hinder the utilization of OGD. Their findings emphasized that promoting open data increases transparency, improves public service delivery, and strengthens civic engagement, which in turn promotes innovation and contributes to economic growth. The research highlighted technical challenges, such as data quality and interoperability, and regulatory issues, including privacy concerns, as key barriers.

Similarly, a research endeavor by Zuiderwijk et al. (2015) in the Netherlands pinpointed key elements that bolster the propagation and adoption of OGD by relevant stakeholders. Their insights underscored the significance of well-defined policies, consistent financial and technical backing, unwavering support from senior management, and a solid technical foundation for successful data dissemination. As for promoting data usage, the determinants of data quality, seamless accessibility, intuitive guidance, and a conducive infrastructure stood out as pivotal.

Wirtz et al.(2016) delved into the resistance factors encountered by public officials in relation to OGD. Their study identified cognitive barriers such as perceived threats to job security, fears of loss of control, and fears of negative consequences. The study underscored that factors such as age, work experience, and rank significantly influence attitudes towards OGD. It further emphasized the critical role of education and communication in mitigating these concerns.

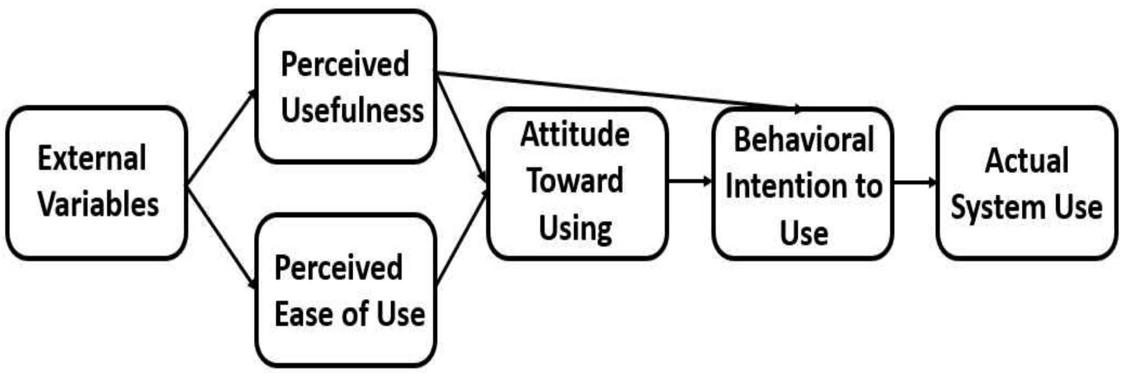
In a study based in China, Yupan Zhao et al.(2022)examined factors affecting the success of OGD, considering both internal resources and external pressures. The research showed that the efficiency of OGD was significantly influenced by organizational strategies, such as resource distribution and coordination efforts. Moreover, the competitive dynamics with neighboring governments at the same administrative level were also identified as crucial contributors.

2.2 Unified Theory of Acceptance and Use of Technology

2.2.1. Technology Acceptance Model

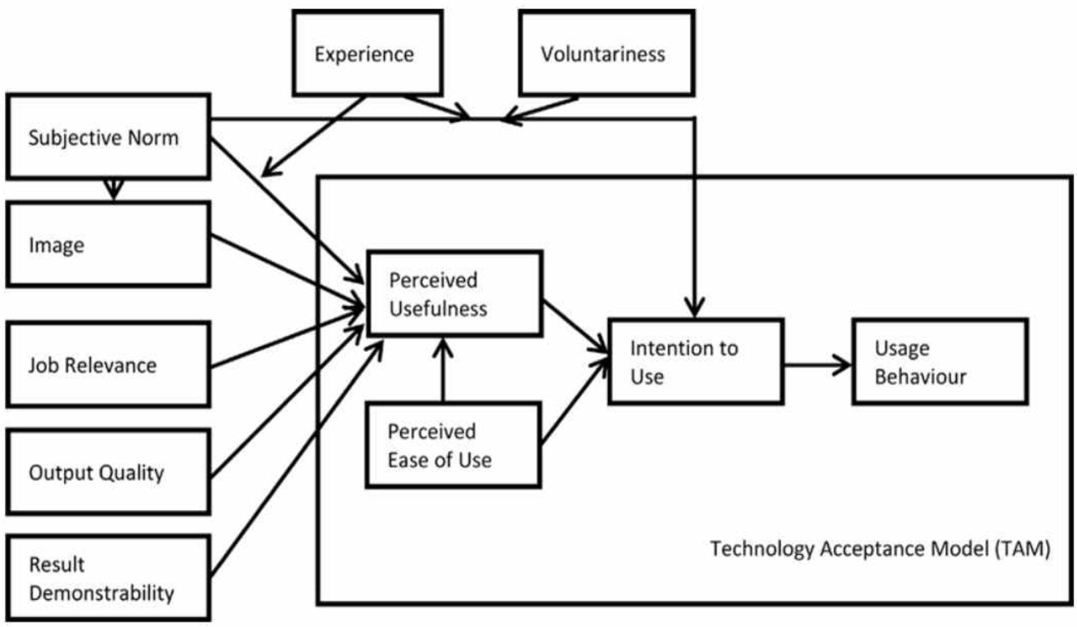
As technology evolves rapidly, understanding how individuals perceive and adopt new information systems becomes crucial in emergent technology research(Swanson, 1987). Rooted in the Theory of Reasoned Action, the Technology Acceptance Model(TAM) offers insights into the behavior patterns of tech users, shedding light on their motivations to embrace or reject new systems(Davis, 1989). Central to TAM are two determinants: perceived usefulness, which gauges a user's belief in the technology's capacity to enhance efficiency and productivity; and perceived ease of use, which assesses whether a user feels the technology is user-friendly. Empirical research affirms the significant role both factors play in influencing an individual's intention to adopt technologies.

[Figure 1] TAM



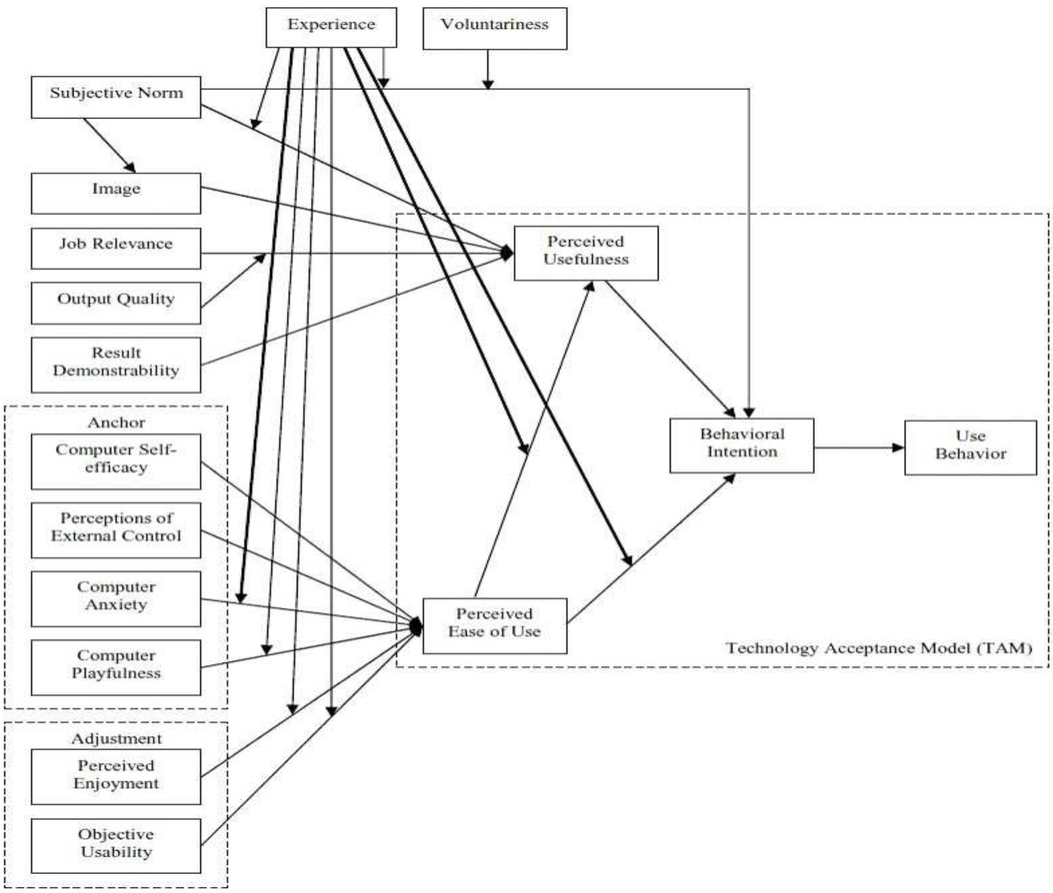
While the TAM shows a foundational framework for understanding technology adoption, it has faced criticism for not fully capturing the dynamic nature of the modern technological landscape and for neglecting certain external factors that play a role in technology adoption. To address these shortcomings, researchers have endeavored to enhance the TAM by incorporating additional external variables. For instance, Venkatesh and Davis(2000) broadened the model by integrating antecedents of perceived usefulness such as subjective norms tied to influences from peers, organizations, and society at large. They also integrated individual cognitive perceptions of technology, like its job relevance, output quality, and the demonstrability of results. The addition of experience and voluntariness as potential moderating variables gave rise to what is now known as the Extended TAM, or TAM2.

[Figure 2] TAM2



Venkatesh and Bala's TAM3, introduced in 2008, builds upon the foundational TAM2 by offering a more detailed examination of the determinants that shape perceived ease of use in technology adoption. This revised model emphasizes the significance of various external factors including computer self-efficacy, perceptions of external control, and objective usability. Importantly, TAM3 provides a balanced perspective by accounting for both positive influences like enjoyment and playfulness, as well as potential barriers such as computer anxiety. This holistic approach gives a nuanced insight into users' motivations and hesitations in adopting technology.

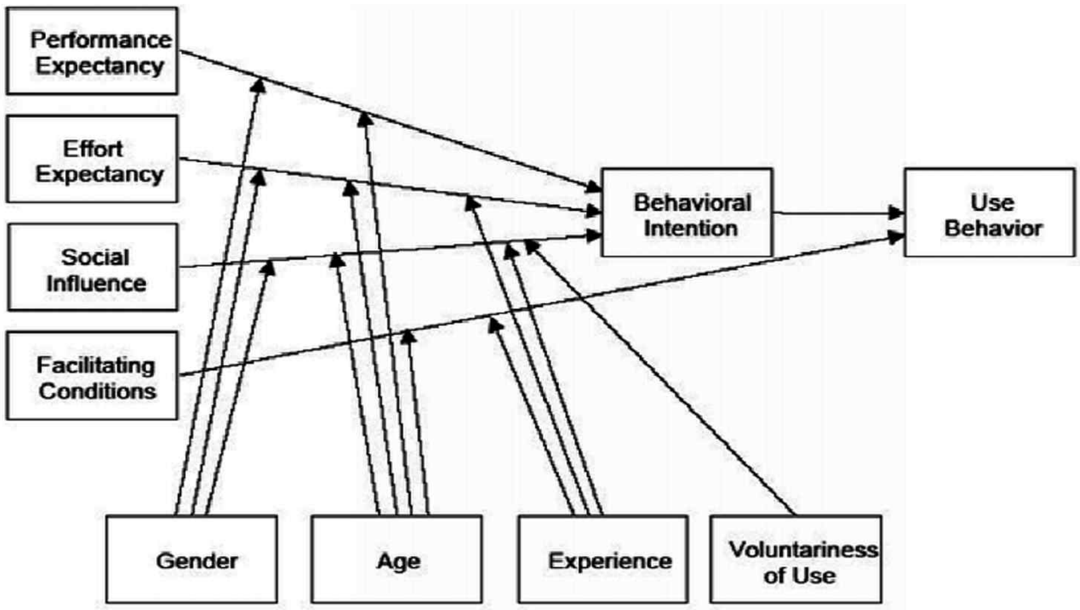
[Figure 3] TAM3



2.2.2. Unified Theory of Acceptance and Use of Technology

Venkatesh(2003) presented the Unified Theory of Acceptance and Use of Technology(UTAUT) by merging insights from various models such as the TAM, the Theory of Reasoned Action, and certain motivational models. The UTAUT highlighted four primary determinants for the intention to use technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. It also shed light on how factors like gender, age, experience, and volition could moderate these determinants. Although previous models, like TAM, emphasized perceived usefulness and ease of use, they often missed capturing the broader sociocultural and infrastructural nuances of technology adoption. Hence, the more comprehensive UTAUT framework has gained prominence for its enhanced explanatory capacity. Drawing inspiration from recent studies like that of Yang Seungho et al.(2016), this study uses the UTAUT model to delve into the factors influencing public officials′ willingness to adopt OGD.

[Figure 4] UTAUT



Performance expectancy refers to an individual's belief that adopting a particular technology will enhance their achievement or improve their job performance (Venkatesh et al., 2003). This notion aligns closely with the TAM's concept of perceived usefulness, implying that using a novel technology can elevate one's job performance(Kim, 2011; Venkatesh et al., 2003). It's widely recognized within the UTAUT framework that performance expectancy plays a pivotal role in technology acceptance. In similar lines, the TAM model asserts that perceived usefulness directly affects behavioral intention (Davis et al., 1989).

Effort expectancy denotes the simplicity associated with using a given technology(Venkatesh et al., 2003), mirroring TAM's idea of perceived ease of use. While empirical research often links this perceived ease with positive behavioral intention, some arguments propose that the linkage might not always hold true(Lee, 2021).

Social influence is understood as the degree to which an individual perceives that key figures in their life, such as colleagues or managers, deem it essential to adopt a specific technology (Venkatesh et al., 2003). Elements of this concept find resonance in several models, including TAM, PC Utilization Model, Diffusion of Innovations Theory, and Theory of Planned Behavior. Notably, the weight of social influence is more pronounced when the utilization of a technology becomes obligatory.

Facilitating conditions encompass an individual's trust in the technical and organizational support available for technologies (Venkatesh et al., 2003). The UTAUT construct blends elements from various models, and factors such as compatibility, technical assistance, and training are subsumed under this concept. These conditions influence behavioral intention, though their significance may wane post initial adoption(Marikyan, D. & Papagiannidis, S., 2021).

The UTAUT model serves as a valuable framework in diverse arenas for examining the intent to adopt and utilize emerging technologies and services(Lee, 2021). For example, Merchant et al.(2015) applied the UTAUT model to understand the adoption and utilization of an Internet-based virtual world program for chemical education. They found that factors representing perceived usefulness for chemical learning(performance expectancy), ease of use(effort expectancy), and the influence of peers and teachers on students' attitudes toward the technology(social influence) influenced behavioral intention. In addition, Lee & Kim(2015) conducted an empirical study to identify enterprises′ perceptions of social media and found that performance expectancy, social influence, and facilitating conditions were critical determinants of behavioral intention and actual use of social media. They also highlighted the moderating effects of firm size, as indicated by parameters such as revenue, number of employees, and sales force size, on behavioral intention. Numerous other studies have used the UTAUT model in different areas such as mobile internet(Venkatesh, Thong & Xu), mobile banking applications(Zhou, Lu & Wang, 2010; Mütterlein, Kunz & Baier, 2019), and e-government(Gupta, Dasgupta & Gupta, 2008).

2.2.3 External Factors of UTAUT

While the UTAUT is known for its explanatory power, it has limitations in adequately accounting for factors related to individual use. Consequently, previous studies have introduced external factors into the UTAUT model in an effort to expand and refine it. In this study, data literacy, personal innovativeness, and self-efficacy were adopted as external variables to the UTAUT with the goal of incorporating individual psychological traits and capabilities, thereby influencing subjective perceptions such as performance expectancy and effort expectancy. In examining the application of the UTAUT model in academic research, several external factors consistently emerge as significant. Hwang et al.(2017) analyzed 69 articles from the KCI and highlighted safety, innovativeness, trust, self-efficacy, and perceived value as the most recurrent external factors. In a similar vein, Williams et al.(2015) in their review of 174 articles, underscored self-efficacy, attitude, personal innovativeness, and trust as paramount. It is noteworthy that self-efficacy and personal innovativeness are not only predominant in UTAUT research but also prominently featured in studies using the TAM model

As the public sector increasingly prioritizes digital transformation, there is a growing imperative for data literacy. The OECD and EU(2017) have highlighted data literacy as a critical competency for maximizing open government outcomes and fostering sustainable innovation in public governance. The UK government has emphasized the importance of the ability to use data-driven evidence and knowledge for effective decision-making as a core competency for civil servants(Civil Service & The Rt Hon Lord Maude of Horsham, 2012). Therefore, this study strategically selected personal innovativeness, self-efficacy, which has been universally applied in previous UTAUT research, and data literacy, a critical competency in data-based administraion, as external variables.

2.2.3.1 Data literacy

In today's evolving information and communication landscape, digital literacy has taken center stage as an essential competency. It encapsulates not just the technical skills to use communication technologies, but also the cognitive ability to understand, assess, and produce relevant information using these platforms(ALA, 2013). Especially with the accelerated shift to a data-centric society, data literacy, which emphasizes the importance of decision making through the appropriate use of data and data analysis, has emerged as one of the most important human competencies globally(Lee, 2019). Data literacy refers not only to reading, writing, and communicating with data, but also to the ability to think critically about data(Tuladhar, 2014). It represents a holistic understanding of data sets rather than a fragmented understanding.

Past research has highlighted the role of the TAM in understanding the adoption of new technologies, often emphasizing the significance of skills and abilities needed to harness digital platforms. Notably, Jang et al.(2021) enriched the UTAUT model by considering digital and information literacy in the context of students' intent to use digital learning tools. Their findings reinforced the idea that both types of literacy bolster expectations of performance and effort. Similarly, Samuel et al.(2020) adapted the TAM framework by integrating digital literacy while exploring e-government adoption in India. Their study underscored the pivotal role of digital literacy in shaping preferences for e-government offerings and, consequently, its adoption. These studies collectively spotlight the indispensable role of digital literacy across different contexts.

Jang, C., & Sung, W.(2022) investigated the behavioral intention AI-based public services and found that higher levels of digital literacy correlate with both increased perceived usefulness and decreased perceived effort to use AI systems. Empirical studies have corroborated that digital literacy serves as an intermediary, shaping perceptions about the usefulness and ease of use of AI technologies.

Specifically, as individuals become more digitally literate, they tend to view AI technologies as not only beneficial for their work outcomes but also straightforward to use. This positively sways their intention to adopt these technologies. These findings highlight the significance of factoring in individual digital and data-related competencies when considering technology acceptance models. They also affirm the pivotal role of perceived usefulness and ease of use in determining adoption intentions.

2.2.3.2 Personal innovativeness

Personal innovativeness is characterized by an individual's inclination to seek novel and varied experiences, as described by Hirschman(1980). This trait reveals the extent of one's receptivity to trying or encountering new things. Within the realm of information technology, Prasad(1998) characterized personal innovativeness as the propensity to experiment with emerging information technologies. Numerous studies have subsequently highlighted its pivotal role in influencing technology adoption.

Cha et al.(2017) used TAM to analyze the influences on private sector intentions to use public data. Their study included factors such as system and information quality, information security, social impact, and support from public organizations, while also considering innovativeness as a significant variable. In addition to the importance of system and information quality and security, they emphasized the importance of improving innovativeness at both the organizational and individual levels.

Lu, J. et al.(2005) expanded on the TAM by integrating components like personal innovativeness, social influence, and cost to explore the factors that affect the adoption of mobile-based Internet services. Their findings indicate a positive relationship between personal innovativeness and the intention to use wireless Internet services. Similarly, Agarwal and Karahanna(2000) presented "cognitive absorption" as a multidimensional concept that potentially impacts perceived utility and ease of use in technology. A pivotal component of this absorption is personal innovativeness, which they highlighted as influential in technology adoption. Past studies consistently suggest that those who score high on innovativeness tend to be more inclined to embrace new technologies and actively seek related information. Given that individual adoption tendencies significantly shape the outcome of technological innovations (Agarwal and Prasad, 1998), it's clear why personal innovativeness has gained prominence in studies and models pertaining to technology adoption and innovation in services.

2.2.3.3 Self-efficacy

Bandura(1982) assertedtofhdns that self-efficacy is rooted in an individual's confidence regarding their capacity to undertake specific tasks or realize set goals. He asserted that such self-belief plays a pivotal role in shaping motivation, guiding behavior, and determining outcomes. Given its capacity to augment the propensity to embrace and employ new technologies, self-efficacy garners significant interest among prospective technology users(Susan Lew et al., 2020). Research expanding on the UTAUT frequently integrates self-efficacy as an influential determinant in the adoption of new technologies and services.

Cheng-Min Chao(2019) examined the adoption of mobile learning through a modified UTAUT framework, incorporating variables like enjoyment, self-efficacy, satisfaction, perceived risk, and trust. This research substantiated the role of self-efficacy in enhancing enjoyment levels. Drawing from the positive correlation between enjoyment and both effort and performance expectancies, the study emphasized the pivotal position of self-efficacy in determining intentions towards mobile learning.

In a similar vein, a study by Karrar Al-Saedi and his team in 2020, which aimed to discern factors affecting the adoption of mobile payment systems, enriched the UTAUT model by introducing elements such as trust, self-efficacy, perceived risk, and personal innovativeness. Their findings corroborated the constructive impact of self-efficacy on mobile payment utilization, implying that self-efficacy-centric strategies could potentially bolster the uptake of these systems. In a nutshell, self-efficacy can be viewed as a precursor to UTAUT's foundational variables, thereby indirectly swaying user inclinations.

2.3 Research Objectives and Hypothesis Setting

2.3.1. Research Objectives

Investigating the personal and societal determinants affecting the inclination to utilize OGD, a survey of 700 government and public agency employees was used. The study applied the UTAUT, an evolved model derived from the seminal TAM, which focuses on the efficient diffusion of new technologies and services. The objective was to examine the interplay between factors that drive the behavioral intentions to utilize OGD. This would assist in formulating strategies to enhance the data use intentions among employees of governmental and public institutions.

The study delves into the influence of principal UTAUT elements —performance expectancy, effort expectancy, facilitating conditions, and social influence—on the inclination to utilize OGD. Furthermore, it explores how user attributes, including data literacy, self-efficacy, and personal innovativeness, interrelate with their perceived performance and effort in harnessing OGD.

The research also presents strategies to motivate public sector professionals to adopt OGD, addressing contemporary hurdles such as the evolution in digital transformation approaches, societal quandaries, and the myriad expectations of citizens.

2.3.2. Hypothesis Setting

2.3.2.1 Relationship between facilitating conditions, expected performance, expected effort, social impact, and behavioral intention

"Facilitating conditions" is a belief that organizational and technological infrastructures are available to support the use of OGD. While some studies, such as those by Zuiderwijk et al.(2015) and Rana et al.(2012), indicate that these conditions may not significantly influence usage intentions of e-government services, other research suggests otherwise. For instance, Ryu(2011) emphasizes the need for bolstering legal and institutional measures to enhance OGD use. This divergence in findings underscores the ongoing debate in the literature; while some scholars believe facilitating conditions have minimal effect on use intentions, others contend they play a pivotal role and advocate for robust OGD policies and support (Marikyan, D. & Papagiannidis, S., 2021; Saxena & Mahomed, 2018).

Performance expectancy has been identified in numerous previous studies as a variable that plays a pivotal role in driving technology adoption.. Mahomed et al.(2017) demonstrated that how the anticipated benefits and usefulness of a technology can influence the intention to adopt services like e-government in Mauritius. Applying the technology acceptance model, Talukder et al.(2019) showed that perceived usefulness, a concept similar to performance expectancy, is a critical determinant of user acceptance of OGD in Bangladesh. In addition, Kim & Lee(2021), in their study on the influence of big data policy adoption among civil servants, showed that perceived usefulness directly affects adoption intentions. The belief that new technologies can maximize work efficiency in the work environment increases big data policy adoption as perceived usefulness increases.

Effort expectancy, highlighting the user-friendliness and learnability of a technology, has also been found to be a positive determinant of adoption intentions. This is evident in research focused on OGD, where the ease of use emerges as a significant factor(Zuiderwijk et al., 2015; Cha et al., 2017; Talukder et al., 2019).

The role of social influence, reflecting the weight of opinions from significant peers or superiors, cannot be understated either. It suggests that the broader perception within an individual's social network can sway their inclination to embrace a new technology (Venkatesh et al., 2003). The importance of social influence in OGD activation has been confirmed in various previous studies(Talukder et al., 2019; Zuiderwijk et al., 2015). In addition, research in fields such as education and media using UTAUT confirms the impact of social influence from peers and stakeholders on technology and service acceptance intentions(Merchant et al., 2015; Lee & Kim, 2015)

2.3.2.2 Relationship between data literacy and performance expectations and effort expectations

The significance of data literacy becomes paramount in the context of OGD policies. Lim & Ki (2017) conducted a perception survey on public officials in central and metropolitan self-governing bodies, who handle data-related tasks. The study highlighted the need for specialized personnel and dedicated departments in the big data ecosystem of public agencies. In line with this, a 2018 survey conducted by the Korean Institute of Informatics Promotion among domestic companies highlighted the lack of data specialists as the most significant obstacle to big data adoption. These insights underscore the importance of data literacy for data assimilation and vitality. Furthering the discourse, Jang & Sung(2022) delved into the intent of public service policy acceptance based on artificial intelligence(AI). The study examined the relationship between an individual's digital literacy and their perceptions of AI-driven public services. It was found that higher digital literacy correlated with a perception of greater ease of use and utility in these services, leading to increased user intent to adopt. High digital literacy correlated with increased beliefs in the potential of AI technologies to improve job performance, while simultaneously perceiving less effort required to use such systems. Jang et al.(2021), in their application of the UTAUT model, validated the positive influence between digital literacy and performance and effort expectancies.

2.3.2.3 Relationship between personal innovativeness and performance and effort expectations

Personal innovativeness represents an individual's willingness to explore and embrace new experiences and ideas. Although not inherently included in the basic UTAUT model, personal innovativeness has been accepted as a critical predictor of the adoption of new services across various domains(Agarwal & Prasad, 1998; Lu et al., 2005; Patil et al., 2020). In particular, previous research has identified a significant direct effect of personal innovativeness on performance expectancy and effort expectancy(Talukder et al., 2019; Lee, 2021). Song(2014) identified limited awareness and passive attitudes toward the openness of OGD as the main barriers to promoting its use, suggesting the importance of personal innovativeness. Meanwhile, Cha (2015) demonstrated the positive influence of personal innovativeness on perceived ease of use and usefulness, particularly in the realm of public data application services. Individuals with high innovativeness tend to perceive technological complexity as less cumbersome and can better identify potential benefits associated with innovation(Mun et al., 2006; Yi et al., 2006).

2.3.2.4 Relationship between self-efficacy and performance expectancies and effort expectancies

Individuals with a strong sense of self-efficacy tend to actively engage in challenging situations, positively influencing their task performance(Bandura, 1986). Several studies have supported the relationship between self-efficacy and perceived ease of use(Davis, 1989; DOAN, 2021; Venkatesh & Davis, 2000). Abdullah and Ward(2016), after reviewing 107 studies, identified self-efficacy as a important determinant of perceived ease of use. According to social cognitive theory, an individual's self-efficacy in performing certain actions directly affects their performance expectations(Bandura, 1978; Compeau & Higgins, 1995b). Stajkovic & Luthans(1998) concluded that self-efficacy has the strongest positive correlation among individual characteristics explaining job performance. Moreover, within the public sector, it has been consistently observed that officials with higher levels of self-efficacy tend to have stronger beliefs in and produce more effective task outcomes(Kim & Park, 2011). Given the theoretical discussions and prior research, this study proposed following hypotheses.

H1. Data literacy is positively correlated with performance expectancy
H2. A higher level of data literacy results in increased effort expectancy
H3. Individuals with greater personal innovativeness are likely to have enhanced performance expectancy
H4. Personal innovativeness positively correlates with effort expectancy
H5. Greater self-efficacy is associated with heightened performance expectancy.
H6. There's a positive relationship between self-efficacy and effort expectancy
H7. Facilitating conditions positively influence the intent to use OGD
H8. As performance expectancy increases, so does the intention to

use OGD

H9. There's a positive correlation between effort expectancy and the intent to adopt OGD

H10. The behavioral intent to use OGD is positively impacted by social influence

H11. Data literacy indirectly boosts the intent to use OGD via performance expectancy

H12. Through effort expectancy, data literacy has a positive bearing on the intention to use OGD

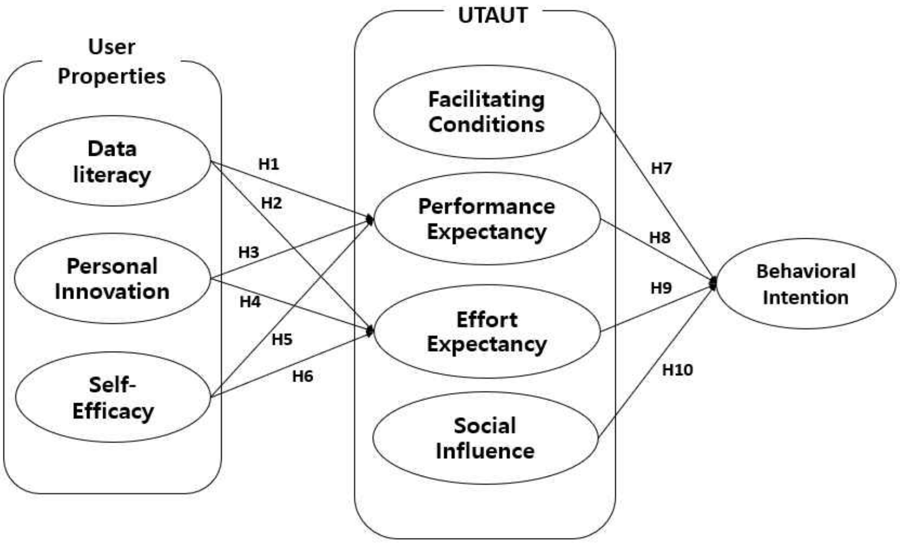
H13. The relationship between personal innovativeness and the intent to use OGD is mediated by performance expectancy

H14. Personal innovativeness indirectly fosters a greater intention to use OGD through effort expectancy

H15. Performance expectancy mediates the positive relationship between self-efficacy and the intention to use OGD

H16. The intent to adopt OGD, driven by self-efficacy, is mediated by effort expectancy

[Figure 5] Research Model



Chapter 3: Research Methodology

3.1 Variable Measurement

3.1.1 Facilitating Conditions

"Facilitating Conditions" concern the technical infrastructure and compatibility that support the use of OGD. This study define it as "the perception of a conducive technical environment for OGD use." In addition, a 5-point Likert scale was used to measure all variables.

[Table 3] Questions: Facilitating Condition

No	Questions
1	I have access to the technical guidance needed to utilize OGD.
2	I have the technical infrastructure (equipment, software) to utilize OGD.
3	I have access to expert technical support in utilizing OGD.
4	The devices and technologies I use are directly related to my use of OGD.
5	I have a network of people I can turn to for help when I encounter difficulties in utilizing OGD.
6	I will be able to leverage the experience of others to solve problems when using OGD.
7	I have access to the educational support I need to utilize OGD.

3.1.2 Performance Expectancy

"Performance Expectancy" encapsulates an individual's forecast of obtaining either time or economic advantages in work efficiency and productivity by adopting new tech tools. In this context, this study delineate it as "the belief that OGD adoption will bolster work results."

[Table 4] Questions: Performance Expectancy

No	Questions
1	Utilizing OGD improves my work performance.
2	Utilizing OGD improves my work effectiveness.
3	Utilizing OGD will increase my chances of achieving important goals.

3.1.3 Effort Expectancy

"Effort expectancy" refers to users' perception of how easily they can utilize a specific technology, encompassing both the ease of using OGD and the simplicity of mastering the methods and technologies for its utilization. For this research, it's "how straightforward individuals find using OGD."

[Table 5] Questions: Effort Expectancy

No	Questions
1	Utilizing OGD is easy.
2	Becoming proficient with OGD is not difficult for me.
3	I can clearly utilize and understand OGD.
4	Utilizing OGD is simple.

3.1.4 Social influence

"Social Influence" is articulated as "the level to which peers and superiors believe I should adopt OGD." In this study, social influence encompasses both horizontal and vertical relationships with surrounding individuals.

[Table 6] Questions: Social Influence

No	Questions
1	People who matter to me think I should use OGD (friends, coworkers, etc.)
2	People who influence my behavior think I should use OGD (friends, coworkers, etc.)
3	People I frequently ask for advice favor my use of OGD. (Friends, coworkers, etc.)

3.1.5 Behavioral intention

"Behavioral Intention" denotes an individual's disposition towards the adoption of a new technological tool, being a primary determinant influencing actual use (as proposed by Venkatesh, 2003; Venkatesh & Davis, 2000; Bhattacherjee, 2001). In this study, it represents "the predisposition to use OGD," capturing both direct and nuanced intentions.

[Table 7] Questions: Behavioral intention

No	Questions
1	I intend to continue utilizing OGD in the future.
2	I plan to use OGD frequently*. (①: Never, ②: Once or twice a year, ③: At least once a month, ④: At least once a week, ⑤: Several times a day)
3	I would recommend others to use OGD when they are planning to use it.
4	I think it is beneficial to utilize OGD.
5	I support the use of OGD in my work.
6	I will cooperate in utilizing OGD.

3.1.6 Data Literacy

Data literacy was operationally defined as “the degree to which an individual possesses the skills necessary to collect, utilize, analyze, and interpret data”. This study, inspired by the framework established by Park & Jo(2021), encompassed various aspects of data literacy, including data collection, management, analysis, visualization, and result interpretation.

[Table 8] Questions: Data Literacy

No	Questions
1	I know how to collect data for a purpose.
2	I have the ability to manage data for its intended use.
3	I have the ability to analyze data for a purpose.
4	I have the ability to visualize data.
5	I can explain the results of my data analysis to others.

3.1.7 Personal Innovativeness

Personal innovativeness was operationalized as "willingness to try new technologies," which is related to willingness to use OGD. To gauge this variable, this study used the following questions.

[Table 9] Questions: Personal Innovativeness

No	Questions
1	If I learn about a new technology, I will find a way to try it.
2	I am usually the first person around me to try a new technology.
3	I enjoy learning new skills.
4	In general, I don't hesitate to try new technologies.

3.1.8 Self-Efficacy

"Self-Efficacy," based on Bandura's 1982 conception, signifies an individual's conviction in their capability to perform a task or realize an objective. Here, it pertains to "the assurance in one's capacity to integrate OGD into their repertoire."

[Table 10] Questions: Self-Efficacy

No	Questions
1	I have the ability to work through difficult situations.
2	I can find a way to get what I want, even if someone disagrees with me.
3	I am confident that I can handle unexpected events effectively.
4	I can solve most problems if I try.
5	I can stay calm when faced with difficulties because I believe in my ability to cope.
6	When faced with a challenge, I can find multiple solutions.
7	I can usually handle anything that is within my control.

3.2 Data Collection and Analysis

3.2.1. Data Collection

To analyze the intention to utilize OGD, this study uses the results of an online survey of 700 government and public sector employees conducted by the KDI SCHOOL study "Civil Service Communication Competency Assessment Study". The survey was conducted for one week from April 7 to 13, 2022, to develop digital innovation capacity and explore ways to utilize OGD.

3.2.2. Analysis Method

This study utilizes the Partial Least Squares Structural Equation Modeling(PLS-SEM) to scrutinize the interplay between the intention to use OGD, factors from the UTAUT, and individual characteristics. SEM stands out as a multivariate analytical technique that merges elements of factor and regression analysis. It offers more flexibility than regression analysis, particularly in dealing with multicollinearity issues. The PLS approach to structural equation modeling is rooted in principal component analysis, unlike traditional SEM tools such as AMOS and LISREL, which are based on common factors. PLS-SEM is advantageous in that it has fewer restrictions on data distribution and sample size, and it does not share the assumptions prevalent in multiple regression analysis(Oh, 2018). The PLS-SEM methodology bifurcates into two components: the outer model, which pertains to the measurement, and the inner model, which relates to the structural relationships. The validity of our PLS-SEM approach was established through a combination of reflective and formative assessments for both these models. To enhance the robustness of our findings, bootstrapping techniques were employed. For the analytical procedures, we utilized SMART PLS 4.0 for PLS-SEM and STATA 17.0 for descriptive statistics."

Chapter 4: Analysis Results

4.1 Demographic Characteristics

The demographic characteristics used were determined through descriptive statistics based on the data collected, and the results are as follows:

Out of 700 respondents working in government and public institutions, 490(70%) were male and 210(30%) were female. The age distribution was as follows: 5.29% were in their 20s, 23.86% in their 30s, 40.71% in their 40s, and 30.14% in their 50s.

When examining the distribution by occupation, 126(18%) were national government officials, 151(21.57%) were local government officials, 265(37.86%) worked in public corporations or public institutions, 38(5.43%) were affiliated with national universities or government-sponsored research institutes, 15(2.14%) were from national schools, 72(10.29%) were in social welfare/services, and 33(4.71%) belonged to other categories.

In terms of tenure, 169(24.14%) had been employed for less than 5 years, 126(18%) for 5 to less than 10 years, 124(17.71%) for 10 to less than 15 years, 102(14.57%) for 15 to less than 20 years, 75(10.71%) for 20 to less than 25 years, 61(8.71%) for 25 to less than 30 years, and 43(6.14%) for 30 years or more.

In terms of individual monthly income, 1(0.14%) earned less than 1 million won, 20(2.86%) earned between 1 million and less than 2 million won, 90(12.86%) earned between 2 million and less than 3 million won, 105(15%) earned between 3 million and less than 4 illion won, 107(15. 29%) earned between 4 million and less than 5 million won, 114(16.29%) earned between 5 million and less than 6 million won, 93(13.29%) earned between 6 million and less than 7 million won, 64(9.14%) earned between 7 million and less than 8 million won, and 106(15.14%) earned 8 million won or more.

Finally, regarding educational background, 6.14% had attained a high school diploma or less, 65.43% had either attended or completed a university degree, and 28.43% were engaged in or had finished graduate school studies."

[Table 11] Respondent Characteristics(N=700)

		respondents	Ratio(%)
Sex	Male	490	70.00
	Female	210	30.00
Age	19 - 29	37	5.29
	30 - 39	167	23.86
	40 - 49	285	40.71
	50 - 59	211	30.14
Occupation	National government	126	18.00
	Local government	151	21.57
	Public corporations or Public institutions	265	37.86
	National universities or government-sponsored research institutes	38	5.43
	National schools	15	2.14
	Social welfare/Services	72	10.29
	Other	33	4.71
Tenure (years)	< 5	169	24.14
	5 - 10	126	18.00
	10 - 15	124	17.71
	15 - 20	102	14.57
	20 - 25	75	10.71
	25 - 30	61	8.71
	30+	43	6.14

		respondents	Ratio(%)
Monthly income (₩)	< 1 million	1	0.14
	1 million – 2 million	20	2.86
	2 million – 3 million	90	12.86
	3 million – 4 million	105	15.00
	4 million – 5 million	107	15.29
	5 million – 6 million	114	16.29
	6 million – 7 million	93	13.29
	7 million – 8 million	64	9.14
	8 million+	106	15.14
Education	High school diploma or less	43	6.14
	Attending or had graduated from a university	458	65.43
	Attending or had graduated from a graduate school	199	28.43

4.2 Descriptive Statistics of Variables

Before analyzing the research model, the characteristics and trends of the variables in this study were examined by checking the means, standard deviations, maximum values, and minimum values of the measurement items using STATA 17.0.

[Table 12] Descriptive Statistics (N=700)

Variables		Questions	range	Mean	SD
Independent variables	Data Literacy	Q_01	1~5	3.39	.852
		Q_02		3.38	.863
		Q_03		3.34	.900
		Q_04		3.15	.932
		Q_05		3.39	.876
	Personal Innovativeness	Q_01	1~5	3.59	.789
		Q_02		3.07	.971
		Q_03		3.38	.912
		Q_04		3.37	.889
	Self-Efficacy	Q_01	1~5	3.57	.782
		Q_02		3.42	.770
		Q_03		3.36	.829
		Q_04		3.56	.824
		Q_05		3.41	.771
		Q_06		3.51	.778
		Q_07		3.54	.771

Variables		Questions	range	Mean	SD
Intervening variables	Facilitating Condition	Q_01	1~5	3.03	.906
		Q_02		2.88	.928
		Q_03		2.80	.924
		Q_04		2.85	.936
		Q_05		2.95	.947
		Q_06		3.14	.857
		Q_07		3.06	.908
	Performance Expectancy	Q_01	1~5	3.39	.859
		Q_02		3.39	.887
		Q_03		3.32	.918
	Effort Expectancy	Q_01	1~5	2.88	.894
		Q_02		3.17	.887
		Q_03		3.11	.885
		Q_04		2.92	.912
	Social Influence	Q_01	1~5	3.17	.913
		Q_02		3.14	.916
		Q_03		3.12	.948
Dependent variables	Behavioral intention	Q_01	1~5	3.63	.784
		Q_02		3.63	.790
		Q_03		3.33	.891
		Q_04		3.47	.853
		Q_05		3.66	.809
		Q_06		3.64	.874

4.3 Reliability and Validity Verification

Through PLS-SEM analysis, the study validated the reliability and validity to verify the relationships among the variables in the research model. First, the study employed Cronbach's α, Composite Reliability(CR), and Average Variance Extracted(AVE) values to estimate the reliability. Additionally, the study examined Convergent Validity, which relates to the correlation between scales measuring the same construct, and Discriminant Validity, which analyzes the differences between scales measuring distinct constructs.

4.3.1 Reliability

Internal consistency, a method used to assess the intercorrelation among items when a concept is gauged through multiple parameters, is pivotal for determining reliability. The stronger the correlation among these items, the greater the internal consistency. One prominent measure to evaluate this consistency is Cronbach's alpha(α), where values range between 0 and 1. A higher value, particularly those above 0.7, signals satisfactory reliability(Kim, 2010). In this study, all the derived

Cronbach's alpha figures for each parameter surpassed 0.8, reflecting a strong reliability. Moreover, with rho_A values ranging from 0.862 to 0.908 and Composite Reliability(CR) values between 0.898 and 0.938, both metrics exceed the standard 0.7 threshold, solidifying their internal consistency.

[Table 13] Cronbach's α Verification

<table>
<tr><th colspan="2">Variables</th><th>Criteria</th><th>Cronbach's alpha</th><th>Number of questions</th></tr>
<tr><td rowspan="3">Independent variables</td><td>Data Literacy</td><td rowspan="8">0.8~0.9 : Good
0.6~0.7 : Normal
< 0.6 : Not reliable</td><td>0.909</td><td>5</td></tr>
<tr><td>Personal Innovativeness</td><td>0.863</td><td>4</td></tr>
<tr><td>Self-Efficacy</td><td>0.906</td><td>7</td></tr>
<tr><td rowspan="4">Intervening variables</td><td>Facilitating Conditions</td><td>0.893</td><td>7</td></tr>
<tr><td>Performance Expectancy</td><td>0.894</td><td>3</td></tr>
<tr><td>Effort Expectancy</td><td>0.862</td><td>4</td></tr>
<tr><td>Social Influence</td><td>0.888</td><td>3</td></tr>
<tr><td>Dependent variables</td><td>Behavioral intention</td><td>0.901</td><td>6</td></tr>
</table>

4.3.2 Validity

Validity represents the extent to which latent variables align with the items used for measurement in a survey. The core objective is to ensure the latent variables are accurately represented by the measurement items. Focusing on convergent validity, this study analyzed the uniformity among items that measure identical latent variables. Convergent validity is ascertained when measurements of a singular latent variable, conducted in varied ways, produce closely correlated outcomes. An item is deemed trustworthy if its factor loading surpasses 0.7 and its AVE is 0.5 or more (Hair Jr et al., 2016; Mikalef & Pateli, 2017). In our findings, the standardized factor loadings for the items linked to latent variables varied between 0.726 and 0.925, all surpassing the set 0.7 benchmark. This suggests a commendable validity. Similarly, AVE values fluctuating between 0.609 and 0.825 surpassed the advocated 0.5 benchmark, showcasing robust convergent validity

[Table 14] Results of CFA for Measurement Model

Variables		Questions	λ	CR	AVE	rho_a
Independent variables	Data Literacy	Q_01	0.865	0.932	0.734	0.911
		Q_02	0.869			
		Q_03	0.871			
		Q_04	0.834			
		Q_05	0.844			
	Personal Innovativeness	Q_01	0.827	0.907	0.709	0.866
		Q_02	0.798			
		Q_03	0.872			
		Q_04	0.868			
	Self-Efficacy	Q_01	0.822	0.926	0.641	0.911
		Q_02	0.748			
		Q_03	0.827			
		Q_04	0.776			
		Q_05	0.819			
		Q_06	0.855			
		Q_07	0.752			
Intervening variables	Facilitating Condition	Q_01	0.758	0.916	0.609	0.896
		Q_02	0.783			
		Q_03	0.793			
		Q_04	0.759			
		Q_05	0.791			
		Q_06	0.792			
		Q_07	0.784			
	Performance Expectancy	Q_01	0.923	0.934	0.825	0.894
		Q_02	0.912			
		Q_03	0.890			
	Effort Expectancy	Q_01	0.829	0.906	0.706	0.874
		Q_02	0.825			
		Q_03	0.878			
		Q_04	0.827			
	Social Influence	Q_01	0.913	0.930	0.817	0.888
		Q_02	0.913			
		Q_03	0.885			

Variables		Questions	λ	CR	AVE	rho_a
Dependent variables	Behavioral intention	Q_01	0.857	0.924	0.671	0.903
		Q_02	0.806			
		Q_03	0.730			
		Q_04	0.846			
		Q_05	0.829			
		Q_06	0.840			

* CR: Composite Reliability

Discriminant validity assesses the degree to which distinct latent variables can be differentiated. Essentially, it underscores the independence of these latent variables, positing that measurements of different latent variables using identical methods should exhibit low correlations. When examining the relationships between these latent variables, a substantial correlation indicates potential overlap or insufficient differentiation between constructs, thereby questioning the discriminant validity. A widely adopted method to verify discriminant validity is through contrasting the AVE with the square of the correlation coefficients between latent variables. A situation where the AVE exceeds this squared correlation suggests the presence of discriminant validity. In this study, utilizing the Fornell & Larcker criterion, the data consistently met the required thresholds, thereby affirming strong discriminant validity.

[Table 15] Discriminant Validity of Model

	DL	EE	FC	PE	PI	SE	SI	BI
DL	.856							
EE	.439	.840						
FC	.323	.622	.780					
PE	.327	.442	.498	.908				
PI	.594	.349	.288	.320	.842			
SE	.577	.391	.330	.307	.635	.801		
SI	.201	.434	.477	.570	.209	.237	.904	
BI	.392	.410	.389	.650	.425	.423	.541	.819

* The diagonal values represent the square root of the AVE, while the values beneath the diagonal depict the correlation coefficients between distinct constructs

** DL(Data Literacy), EE(Effort Expectancy), FC(Facilitating Conditions), PE(Performance Expectancy), PI(Personal Innovativeness), SE(Self-Efficacy), SI(Social Influence), BI(Behavioral intention)

4.4 Analysis and Hypothesis Testing

4.4.1 Model Fit

The model fit can be checked using the Standardized Root Mean square Residual(SRMR) and Normed Fit Index(NFI) values. The model fit is considered satisfactory if the SRMR is less than or equal to 0.08 or if the NFI is 0.9 or greater. In this model, the SRMR was measured to be 0.046, which meets the threshold($\leq$0.08) and indicates an excellent model fit as it is less than 0.06.

4.4.2 Hypothesis Testing

This study employed bootstrapping, a resampling technique, to evaluate our research hypotheses. Bootstrapping provides estimates of statistics by repeatedly sampling from a dataset. To test hypotheses, the study set the resampling iterations to 1,000. The results of hypothesis testing are as follows.

4.4.2.1 How data literacy, personal innovativeness, and self-efficacy affect performance expectancy and effort expectancy

[Table 16] Analysis Results Between Data Literacy and Performance Expectancy, Effort Expectancy

Endogenous variable	Exgenous variable	Path coefficients	Std. dev.	t	p	Test	
DL	PE	0.176	0.061	2.874	0.004*	Accept	H1
	EE	0.302	0.059	5.102	0.000**	Accept	H2

* P<0.05, **P<0.01, ***P<0.001

Evaluating significance through path coefficients and t-values, it is evident that individual data literacy significantly and positively influences performance expectancy(t=2.874, $p<0.01$) and effort expectancy(t=5.102, $p<0.01$). Notably, the effect on effort expectancy is relatively more pronounced. Thus, the hypotheses regarding the relationship between data literacy and performance expectancy and effort expectancy were accepted.

[Table 17] Analysis Results Between Personal Innovativeness and Performance Expectancy, Effort Expectancy

Endogenous variable	Exgenous variable	Path coefficients	Std. dev.	t	p	Test	
DL	PE	0.141	0.052	2.702	0.007**	Accept	H3
	EE	0.054	0.053	1.023	0.307	Reject	H4

* P<0.05, **P<0.01, ***P<0.001

Investigation into the relationship between personal innovativeness and performance expectancy revealed a notable positive impact, with a t-value of 2.702 and a significance level (p-value) less than 0.01. This supports the proposed hypothesis. On the contrary, when assessing the effect of personal innovativeness on effort expectancy, the data yielded a t-value of 1.023. Since this value is below the threshold of ±1.96 and the p-value stands at 0.307(surpassing the 0.05 significance level), it suggests that personal innovativeness doesn't significantly influence effort expectancy

[Table 18] Analysis Results Between Self-Efficacy and Performance Expectancy, Effort Expectancy

Endogenous variable	Exgenous variable	Path coefficients	Std. dev.	t	p	Test	
SE	PE	0.116	0.056	2.096	0.036*	Accept	H5
	EE	0.183	0.052	3.501	0.000**	Accept	H6

* P<0.05, **P<0.01, ***P<0.001

When analyzing the influence of individual self-efficacy on performance expectancy, a t-value of 2.096, greater than ±1.96, and a p-value of 0.036 were observed, confirming a positive effect. Furthermore, the relationship between self-efficacy and effort expectancy also showed a significant positive effect ($t=3.250$, $p<0.05$), leading to the acceptance of the hypothesis.

4.4.2.2 How data UTAUT Key Variables affect Behavioral Intention

[Table 19] Analysis Results Between UTAUT Key Variables and Behavioral Intention

Endogenous variable	Exgenous variable	Path coefficients	Std. dev.	t	p	Test	
FC	BI	-0.036	0.043	0.847	0.397	Reject	H7
PE		0.485	0.040	11.995	0.000**	Accept	H8
EE		0.118	0.041	2.909	0.004**	Accept	H9
SI		0.231	0.041	5.599	0.000**	Accept	H10

* P<0.05, **P<0.01, ***P<0.001

Analyzing the relationship between facilitating conditions, which represent the technical environment and related requirements for using OGD, and behavioral intention, the results showed a t-value of 0.847, which is less than ±1.96, and a p-value of 0.397. Therefore, the hypothesis was rejected.

Performance expectancy, which reflects the expected job outcomes of using OGD, significantly and positively influenced behavioral intention ($t=11.995$, $p<0.01$). It had the highest path coefficient, indicating that its influence on behavioral intention is stronger than the other variables. Therefore, the hypothesis regarding the relationship between effort expectancy and behavioral intention was accepted. In addition, effort expectancy regarding the use of OGD had a positive effect on behavioral intention($t=2.909$, $p<0.01$). Social influence, which means the influence of peers, friends, etc. on the use of OGD, had a positive and significant effect on behavioral intention ($t=5.599$, $p<0.01$), leading to the acceptance of all related hypotheses.

4.4.3 Mediation Effect Analysis

The study indicated that data literacy, personal innovativeness, and self-efficacy are significant predictors of the UTAUT model's main components: performance expectancy and effort expectancy. Data literacy impacts both performance and effort expectancies, whereas personal innovativeness notably affects performance expectancy. In contrast, self-efficacy predominantly influences effort expectancy. Both of these expectancies are significant determinants of behavioral intentions. It's evident from this study that performance and effort expectancies mediate the relationship between public officials' data literacy, innovativeness, self-efficacy, and their propensity to use OGD. This mediating role was subsequently verified empirically.

For quantifying the mediating effects, we employed a bootstrapping technique with 1,000 iterations set at a 95% confidence interval. Using the PLS method, bootstrapping is especially beneficial in assessing mediation outcomes. The results, as detailed in [Table 20], highlight that both data literacy and self-efficacy have a marked effect on behavioral intentions through the mediation of performance and effort expectancies. Conversely, while personal innovativeness steered behavioral intentions via performance expectancy, no mediating influence was discerned via effort expectancy.

[Table 20] Results of Mediation Effect Analysis

Path	Path coefficients	Std. dev.	t	p	Confidence interval (95%)	Test	
DL → PE → BI	0.085	0.031	2.775	0.006**	0.021, 0.141	Accept	H11
DL → EE → BI	0.036	0.014	2.573	0.010*	0.011 0.064	Accept	H12
PI → PE → BI	0.069	0.026	2.600	0.009**	0.020, 0.123	Accept	H13
PI → EE → BI	0.006	0.007	0.867	0.386	-0.004 0.024	Reject	H14
SE → PE → BI	0.056	0.028	2.049	0.041*	0.006 0.115	Accept	H15
SE → EE → BI	0.022	0.010	2.105	0.036*	0.005, 0.044	Accept	H16

* P<0.05, **P<0.01, ***P<0.001

Chapter 5: Conclusion

5.1 Research Findings

This research focuses on the factors that affect the inclination of public officials and staff members of public entities to utilize OGD during the digital transition within the public sector. The study examines how individual traits influence the UTAUT parameters and, subsequently, their willingness to adopt the technology.

First, higher levels of data literacy, which represents an individual's ability to collect, use, analyze, and interpret data, corresponded with a stronger belief that using OGD would improve work outcomes and that using data would not be challenging. This supports previous research suggesting that data literacy positively influences the adoption of new technologies and services(Jang et al., 2021; Jang, C., & Sung, W., 2022). As public servants are at the forefront of data-based administration, this underscores the importance of improving their data literacy. Comparing the direct effects of data literacy on performance expectancy and effort expectancy, the influence on effort expectancy was found to be more substantial. This suggests the critical role of data literacy in mitigating challenges such as inadequate data literacy and fear of adopting new technologies faced by public officials and employees of public institutions.

Second, individuals with higher innovativeness, which indicates their openness to novel experiences and endeavors, positively influenced their performance expectations when using OGD. This is consistent with numerous studies suggesting that more innovative individuals are better able to identify potential benefits associated with innovations(Mun et al., 2006; Yi et al., 2006; Talukder et al., 2019; Lee Hyuk-Jun, 2021). In this study, personal innovativeness emerged as an antecedent that positively influenced performance expectancy, which in turn significantly influenced behavioral intention. However, personal innovativeness did not significantly influence effort expectancy. Thus, in order to increase the primary determinants of intention, such as effort expectancy, efforts to strengthen other competencies, such as data literacy and self-efficacy, should accompany the cultivation of personal innovativeness.

Third, users with higher self-efficacy regarding their ability to adapt to OGD use exhibited higher effort and performance expectations. This is consistent with previous studies suggesting that self-efficacy positively influences perceived ease of use and expected outcomes. Essentially, individuals who are more confident in their ability to proactively engage in new situations tend to find technology adoption relatively effortless and expect greater outcomes from its use. This suggests that an overarching belief in one's abilities plays a key role in shaping expectations about the outcomes and effort required to integrate OGD into work processes.

Fourth, Facilitating Conditions, which represent the level of belief in the existence of organizational and technical infrastructure for using OGD, did not significantly affect intentions to use data. This confirms previous studies suggesting that when facilitating conditions are already at a satisfactory level, their impact on technology adoption becomes marginal(Venkatesh, V et al., 2003). Given South Korea's status as a global IT powerhouse, this analysis suggests that civil servants and employees of public institutions may not be strongly influenced by technical and organizational infrastructure when seeking to use OGD.

Fifth, performance expectancy, which is the belief that using OGD will improve task outcomes, emerged as a critical determinant of behavioral intentions to use data. Among the core variables of the UTAUT, performance expectancy exerted the strongest influence on behavioral intention to use OGD, a finding consistent with previous research. Civil servants and employees of public institutions showed increased intentions to use OGD when they anticipated that doing so would lead to improved work efficiency and goal attainment. Notably, the study found that data literacy indirectly increased intention to use through its significant influence on performance expectancy.

Sixth, effort expectancy, which refers to the belief that using OGD is not challenging, positively influenced behavioral intention to use. The analysis suggests that if OGD can be easily integrated into job functions, it could significantly contribute to data-driven policy decisions. Among the antecedent variables influencing behavioral intention to use through effort expectancy, data literacy had the most significant indirect effect.

Finally, social influence, which refers to the perceived level of belief by peers and colleagues in one's own use of OGD, positively influenced intention to use. The results highlight that, in addition to individual capabilities, environmental factors also influence intentions to use OGD. Notably, social influence, coupled with performance expectancy, emerges as a critical determinant of the behavioral intention towards OGD utilization. This emphasizes the necessity to not only bolster individual perceptions of OGD's efficiency and user-friendliness but also to cultivate a wider societal culture that values its significance.

5.2 Policy Implications

Given the significant statistical relevance of data literacy in increasing the intention to use OGD through the path of performance expectations, policy implications focusing on the importance of data literacy in improving data-based administration are drawn as follows:

First, First, it is necessary to systematically diagnose the level of data literacy among public servants and public institutions and prepare a strategy for strengthening data literacy based on this. Historically, public sector assessments of data literacy levels have been limited to those with direct or indirect job relevance to data analysis or those who have received data-related training. Combined with a lack of standardized benchmarks and procedures, these assessments have fallen short of a comprehensive, government-wide diagnosis of data skills. Recent government efforts, such as the establishment of a government-wide Data Analysis and Utilization Capability Assessment Model(Department of

Homeland Security, 2023), aim to holistically diagnose individual and organizational capabilities, including policy/analysis planning, data collection and analysis capabilities, and broader organizational metrics such as data vision, leadership, governance, and performance management. Going forward, public organizations should use this model as a benchmark to assess their capabilities, prioritize based on urgency and feasibility, and tailor strategies to strengthen weak competencies at both the organizational and individual levels. While organizations can identify technical gaps and develop data-driven workforce plans, individuals can identify their data literacy deficits and develop plans to improve them through networking, training, and self-development.

Second, data competency training programs as part of a strategy to strengthen data literacy should be considered by expanding the focus from practical exercises applicable to data-driven policy making and enforcement processes to individual-level motivation measures such as personal innovativeness and self-efficacy. The Ministry of the Interior and Security's "Basic Plan for OGD (2023-2025)" underscores the importance of restructuring the educational framework for data literacy among public sector employees, emphasizing both online and offline training that includes specialized knowledge and real-world applications. The agenda also seeks to move towards a hands-on approach to training that is linked to the practical use of OGD in the performance of tasks. However, future training efforts should go beyond curricular offerings. They should integrate action science approaches to maximize educational outcomes, emphasize the internalization, actualization, and habitualization of innovative capacity skills, and infuse innovative leadership based on self-efficacy. As the public sector continues to embrace new changes and innovations, including data-based administration, public servants will inevitably face ongoing challenges that require new skills and techniques. As a result, training programs that foster a positive, innovative mindset and build individual self-efficacy are essential.

Third, the importance of societal impacts on the behavioral intention to use OGD suggests an urgent need to improve the culture of data use in the public sector. This can be achieved by promoting flexibility in the organizational culture of the public sector and innovative shifts in public data-based working methods. The Ministry of the Interior and Security has emphasized organizational flexibility and a move away from formalism in its "2023 Government Innovation Master Plan". Achieving this requires moving away from the rigid decision-making processes of the past and encouraging proactive engagement, creativity, and positive work outcomes(chang & Jin, 2006). In addition, the creation of an integrated platform that facilitates the sharing and analysis of data held by government and public institutions across agencies can increase the efficiency of workflows. It's imperative to build inclusive data use services, even for those with limited data analysis skills, and to assign tasks that match individuals' digital competencies to increase their experience with public data-driven tasks.

In particular, leadership support is critical to creating a positive perception of OGD use in public organizations. The level of active support and encouragement from leaders or senior managers plays a critical role in fostering a data-friendly organizational culture and emphasizing the importance of data-based administration. Thus, in addition to training on the practicalities of using OGD, it is possible to raise awareness of the importance of using OGD by providing leadership training in this area. Strengthening administrative collaboration within public organizations, building on efforts such as the “OGD Strategy Committee”, can pave the way for innovation in the public sector and raise expectations and recognition of the value of OGD.

This study included individual innovation and self-efficacy as antecedents, highlighting their influence on OGD use intentions.

Thus, long-term initiatives must aim to strengthen these positive personal attributes and motivations. Fourth, there's a need to increase feedback and incentives for government and public agency employees who implement data-based administration. While the current administration promotes the use of OGD by showcasing exemplary cases and rewarding advances in digital government, it is essential to diversify these recognitions, taking into account external reinforcement and encouragement, as emphasized by Bandura(1997). There's a call for broader institutional rewards, including promotions, training opportunities, and performance-based bonuses.

Fifth, to foster individual innovation, public organizations must shift from control-centered leadership to one that empowers, shares authority, and ignites intrinsic motivation among members. Choi et al.(2023) confirmed the positive impact of empowering leadership on innovative behavior in public organizations, emphasizing the centrality of empowerment in organizational culture. Methods such as mentorship programs can be used to share expertise, establish regular communication channels between leaders and members, and evaluate progress and results. Appropriate interaction between leaders and members can effectively harness empowerment, strengthen members' innovativeness, and achieve desired outcomes(Choi et al., 2023).

This research has focused primarily on policy considerations for revitalizing data-based administration in public organizations. However, achieving digital transformation and societal innovation through the use of OGD requires significant participation from civilians and the private sector. As a result, future efforts must extend beyond the public sector to promote a laudable culture of data use in the private sector. This can be achieved by sharing exemplary solutions to societal problems using OGD, and by strengthening consistent frameworks for OGD use. In particular, to address complex societal challenges, the establishment of a tri-sector(public-private-academic) collaborative platform for OGD can uncover more creative and effective solutions. For example, creating spaces, both online and offline, where experts from the public sector, business, and academia come together to discuss different perspectives on OGD analysis and applications can be invaluable.

5.3 Limitations and Further Research

A limitation of this study is the challenge of making comparisons across demographic characteristics. The UTAUT model posits that the effects of pathways may be moderated by factors such as gender, age, experience, and voluntary use. In future research, it will be beneficial to elucidate moderating effects based on variables such as occupation, job rank, and tenure. By doing so, this study can analyze differences in pathways at both the individual and group levels, thereby facilitating tailored policy design. In addition, this study did not clarify the relationships between the external factors presented, namely data literacy, personal innovativeness, and self-efficacy. Therefore, there's a need to further develop models that analyze the relationships between individual characteristics, such as the influence of inherent traits like innovativeness and self-efficacy on competency-related characteristics like data literacy. Moreover, beyond the three selected external factors highlighted in this study, there are other important attributes that could strongly influence the use of OGD. Subsequent studies that address these gaps will accelerate the transition to data-based administration on a broader scale and contribute to the effective dissemination of a data culture within the public sector.

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