International Journal of Innovative Research and Scientific Studies, 8(6) 2025, pages: 2064-2082

IJIRSS International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Open government data in Vietnam: The integrated toe and trust theory model

Dang Thi Viet Duc[1], Ngo Mai Phuong[2*], Luan-Thanh Nguyen[3], Tri-Quan Dang[4]

[1]*Faculty of Finance and Accounting, Posts and Telecommunications Institute of Technology, Hanoi, Vietnam.*
[2]*Faculty of Economics and Administration, Thai Nguyen University of Information and Communication Technology, Vietnam.*
[3,4]*Faculty of Business Administration, Ho Chi Minh City University of Foreign Languages-Information Technology, Ho Chi Minh City, Vietnam.*

Corresponding author: Ngo Mai Phuong (*Email: nmphuong@ictu.edu.vn*)

Abstract

This study investigates the continuous usage intention and satisfaction dynamics of Open Government Data (OGD) initiatives by employing the Technology-Organization-Environment (TOE) framework and Trust theory. The proliferation of OGD platforms presents significant opportunities for government agencies to enhance transparency, collaboration, and data-driven decision-making. Comparatively, less attention has been given to the impact factors influencing the continuous usage intention and satisfaction dynamics of OGD among business employees. Data were collected in Vietnam. The Neural Network Model was employed to rank relatively significant predictors obtained from structural equation modeling (SEM). This study contributes to the growing literature on using OGD to increase competitive advantages for businesses. Its new methodology and findings will significantly contribute to the existing literature on technology adoption and OGD usage intention. Additionally, the findings can be helpful for practitioners interested in fostering OGD adoption, continuous usage intention, and satisfaction.

Keywords: Open government data, PLS-SEM-ANN, TOE, Trust theory, Vietnam.

DOI: 10.53894/ijirss.v8i6.10079
Funding: This study received no specific financial support.
History: Received: 13 June 2025 / **Revised:** 17 July 2025 / **Accepted:** 21 July 2025 / **Published:** 19 September 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

The expansion of information and communication technologies (ICTs) has accelerated the production of diverse governmental data that is easily accessible to the public. The data encompasses information regarding transportation, weather, finance, health, education, policies, and additional topics. Open government data (OGD) refers to "data open to and available in the public domain in various (including machine-readable) formats and normally licensed for all to access, use, modify, and share" [1]. The hypothesis posits that OGD will produce "intrinsic effects" that enhance democracy by enabling the public to more effectively monitor government actions or performance [2]. Moreover, it can be argued that open government data (OGDs) provided in a machine-readable and reusable format yield "instrumental effects" that diminish information disparity, improve individual quality of life, foster public service development, stimulate economic growth, and facilitate innovative applications in the private sector [3]. Moreover, OGD is regarded as a policy instrument that fosters innovation via the citizen source project, which "enables public organizations to engage with voluntary citizens seeking innovative ideas and solutions via online intermediary platforms" to assist with tasks or decision-making that have traditionally been the responsibility of public employees [4]. Despite acknowledging the advantages of OGD, its implementation and adoption remain limited, leading to a decline in the e-participation index (EPI) in some developing countries, such as Phillipines, from ranking 57 in 2020 to 80 in 2022 and Vietnam, from ranking 70 in 2020 to 72 in 2022, as reported by the United Nations [5]. It is crucial to examine the elements contributing to adopting and continuously using OGD in developing nations in response to Tai [6] request. Analyzing the motivations behind individual utilization of Open Government Data (OGD) will enhance the development of OGD and elevate the Electronic Government Development Index (EGDI) [7].

The literature concerning the acceptability and application of OGD is still in its infancy, particularly in developing nations, as OGD is an evolving field [4]. Reviewing the prior literature, the study identified some research gaps. First, existing literature has focused primarily on behavioral intention and attitude by using the unified theory of acceptance and use of technology (UTAUT) [8, 9] the technology acceptance model (TAM) [10] providing limited perspective on continuous intention to use and satisfaction of OGD. While intention is a starting point, it does not guarantee continuous intention or actual usage and satisfaction of new technological services [11]. Additionally, the limitations of TAM when focused on characteristics of technology, ignoring context factor [12] and inadequate in explaining OGD adoption of UTAUT [13] require the proposition of a model that fully represents the OGD contexts which include technological, organizational, and external environment [14]. Therefore, the development of a unified model tailored to OGD is imperative. Second, there is a scarcity of research that has examined the adoption of OGD as perceived by its users, such as employees in organizations [15, 16]. The studies have been carried out in developed nations, leaving a dearth of scientific literature concerning adopting and utilizing OGD in developing countries such as Vietnam. To gain a greater understanding of the distinct difficulties and opportunities in developing nations, it is essential to research the elements that determine continuous intention to use and satisfaction of OGD in such regions. Third, the close relationship between trust and the effect of users with satisfaction and continuous intention to use has been demonstrated in information system (IS)/ information technology (IT) literature [17, 18]. Specifically, users will continuously use and be satisfied with items or services when they trust them and feel satisfied once their quality expectations align with their perception [19]. When discussing the relationship between quality factors with trust, most scholars believe that perceived quality and perceived value of products and services are related to quality factors [15, 19] while ignoring the preparation of products and services. In terms of OGD, well-prepared data improves OGD credibility, user confidence, and evidence-based decision-making [15]. This study will analyze how government preparation and perceived data value influence user trust and satisfaction, likely impacting users' continuous usage of Open Government Data (OGD). Moreover, based on the existing literature analysis, most studies have utilized conventional statistical approaches to predict user behavior, focusing primarily on linear relationships between variables [9]. In this study, artificial neural networks (ANN) will be utilized to identify the relative importance of key variables by modeling complex non-linear interactions [20, 21]. The goal is to help OGD providers create efficient OGD portals by considering the significant criteria for users.

Our research fills these gaps by investigating how employee cognitive and affective trust when using OGD in conjunction with data-related, organizational, technological, and external environmental aspects impact employee satisfaction and intention to use OGD. In order to investigate users' satisfaction and intention to continue using in the OGD domain, this study presents the first integration of trust theory with Technology-Organization-Environment (TOE), a commonly used theoretical framework for understanding the adoption and assimilation of information technology within organizations. Furthermore, it is the first time that three dimensions of OGD are utilized as antecedents of trust in the context of OGD. By doing so, this research not only contributes to the existing body of knowledge but also advances the field of OGD. By illustrating the impact of each trust and effect factor on OGD, the research findings assist OGD providers in determining which user dimensions are most important and in enhancing the quality of OGD. Furthermore, the factors encompassed in the TOE assist organizations in evaluating the extent to which their technological capabilities correspond to the demands of utilizing OGD, the way their organizational structure either supports or obstructs the incorporation of OGD into the decision-making process and how they react to the expanding trend of opening up OGD.

The rest of this paper is organized as follows. Section 2 contains a literature review, while section 3 gives a theoretical framework and the creation of hypotheses. Section 4 outlines the research approach. Sections 5 and 6 provide an overview of the data analysis and discuss the findings, including theoretical contributions and practical consequences. Section 7 presents the conclusion, limits, and suggestions for future research.

2. Literature Review

2.1. Technology-Organization-Environment Framework (TOE)

The TOE framework highlights the contextual factors influencing organizational behavior. This framework emphasizes the influence of technology application scenarios at different levels on its impact. The scenarios include organizational requirements, technological characteristics, application contexts, and the alignment of technology with organizational policies [22]. The application of technology is influenced by technological, organizational, and environmental conditions within the TOE analysis framework. Technical conditions relate to the characteristics of the technology and the interaction between the technology and the organization. The assessment focuses on the degree of alignment between the technology and the organizational structure, as well as its synchronization with the organization's application capabilities [23]. characterizes organizational conditions by factors such as organizational size, business scope, formal and informal institutional structures, communication mechanisms, and inactive resources [24].

Environmental conditions refer to the comprehensive context in which an organization engages with its various stakeholders during business operations. The behavior and structure of an organization are shaped by both internal and external pressures [25]. The application scenarios and connotations of the TOE framework have been expanded through its extensive use in information management [22, 26, 27]. While TOE frameworks offer a robust analytical standpoint and theoretical underpinning for comprehending the performance and implementation of OGD, they have their limitations. Initially, the TOE framework is an overarching theory that fails to delineate and specify variables; it merely identifies sources of influential factors [28]. Secondly, while TOE acknowledges the importance of technology infrastructure, it may not explicitly address issues related to data quality and standardization, which are crucial for ensuring the usefulness and reliability of OGD [25]. Thirdly, OGD involves not only the release of data but also considerations of data quality, privacy, security, and the development of data ecosystems. The TOE framework may need to be more concise with these intricate relationships. Therefore, integrating data-related factors such as government preparation, perceived data value, and perceived data quality will overcome the limitations when investigating the satisfaction and continuous usage intention of OGD from business employees' perspectives.

2.2. Trust Theory

Trust is calculative, personal, and institutional for economic transactions under transaction cost theory [29]. Personal trust might be entity or virtual in the network environment. Bart, et al. [30] describe virtual trust as trust in the online world. While scholars in many domains have varying perspectives on online trust [31, 32] earlier studies have outlined its characteristics. First, online trusts have a consumer or user trustee and a website or Internet trustor [33]. Second, the Internet's complexity makes online trust weak and hard to create. Trust in persons or organizations creates offline trust [34].

Future studies on virtual trust can build on the foundation laid by entity trust research. Risks associated with online transactions, such as identity and quality verification, make trust all the more important for lowering transaction costs and increasing customer purchase rates [35]. Virtual trust is important. To improve online purchase intentions, retailers should reduce ambiguity and risk for customers. Lee and Turban [36] emphasized the importance of trust in uncertain and risky situations. The OGD website is a central platform for government data resource services [37-39]. While some websites have privacy policies, which serve as an agreement between the government and consumers, there are still issues with personal privacy and privacy protection rules [12].

Cognitive and affective trust are two dimensions that play a significant role in understanding employees' trust toward Open Government Data (OGD) initiatives [12]. Cognitive trust refers to a rational and logic-based trust, often grounded in an individual's assessment of the source's reliability, competence, and consistency, in this case, the government providing the data. On the other hand, affective trust is more emotional. It relies on personal feelings, emotional bonds, and the belief that the entity, in this case, the government, genuinely cares about the employees' well-being. In the context of OGD, cognitive trust is likely influenced by factors such as the data's accuracy, completeness, and relevance. Employees may develop cognitive trust if they perceive that the government provides reliable and valuable information through open datasets [40]. This trust can be strengthened by transparent communication about data sources, methodologies, and updates, fostering a sense of credibility and dependability. On the other hand, affective trust may be influenced by the government's commitment to openness, transparency, and responsiveness to feedback [41]. If employees feel that the government genuinely values their input and concerns and is actively working to improve the accessibility and quality of OGD, affective trust may develop. Additionally, fostering a positive organizational culture that promotes openness and collaboration can contribute to affective trust among employees.

In summary, the Technology-Organization-Environment (TOE) framework, while valuable for assessing technological adoption, may fall short in capturing the nuanced and emotional dimensions of trust from employees using Open Government Data (OGD). A more comprehensive understanding can be achieved by integrating cognitive trust, focusing on rational evaluations of data reliability and affective trust, addressing emotional connections and perceptions of government commitment. By doing so, the investigation gains depth, offering a holistic perspective on trust factors that influence employee satisfaction and continued usage of OGD beyond the scope of the TOE framework.

3. Theoretical Framework and Hypotheses Development

3.1. Data-Related Factors

Value can be described as the level of regard, importance, value, or usefulness that anything is considered to possess [42]. Usefulness or utility is key to determining economic value [43]. Perceived value encompasses the different advantages that a product or service might offer, such as emotional, social, quality/performance, and price/value for money considerations [44]. In the context of Open Government Data (OGD), perceived value refers to the advantages that individuals can have by utilizing specific data. These advantages include academic benefits, functional benefits, and opportunities for public participation. Trust is determined by the value they derive from a service or agreement. In knowledge sharing, employees' perceived value of knowledge sharing is a positive antecedent of affective trust [45]. In IS research, the perceived value of information directly influences users' cognitive and affective trust [46]. Thus, the study proposes the hypotheses:

H_{1a}: Perceived data value positively influences cognitive trust of employees.

H_{1b}: Perceived data value positively influences affective trust of employees.

The product and service provider can enhance quality in numerous ways, including establishing a quality policy and deploying a quality management system [47]. The enhancement of the quality of OGD necessitates increased government preparation, including the provision of well-structured data and high-quality metadata [48] the development of user-friendly systems and websites, the formulation of effective OGD plans and policies, the solicitation of broader publicity the clear delineation of responsibilities and their implementation, and the integration of the OGD platform into pre-existing content management systems [49]. According to Wang, et al. [15] in order for OGD to be practical, it must be implemented and interpreted, contrasted and analyzed, interconnected and combined, visualized and explained through intermediaries. One of the important antecedents for trust relating data is users' usability [50]. The term "usability," which refers to the assessment of how well a product fulfills particular standards [51] is frequently applied to the evaluation of the interaction quality between a user and a system [52]. The study revealed that the level of trust is significantly impacted by the efficacy of websites [51]. Complaints are common for website portals not designed with nontechnical users in mind [51-53]. In order to enhance trust, including cognitive and affective trust, Kimiagari and Malafe [54] recommended the incorporation of digital watermarks, visualization, and local download capabilities into a data platform, as determined by a usability test. Cognitive and affective trust can be enhanced if employees feel at ease with usability from well-preparation data. Thus, the study proposes the hypotheses:

H_{2a}: Government preparation positively influences cognitive trust of employees.

H_{2b}: Government preparation positively influences affective trust of employees.

3.2. TOE Frameworks

Perceived risk refers to an individual's assessment of probable negative repercussions of adopting a technology [21]. According to Alimamy and Gnoth [55] people's willingness to accept technology is influenced by uncertainty because of insufficient knowledge and the inability to forecast. Other studies have found that risk perception is a substantial barrier to adopting new technologies and trust developments [56, 57]. According to Chen, et al. [58] perceived risk has a significant role in consumers' acceptance and trust of the value of new technologies. Risks to be utilized during the life cycle of data employing prefabricated methods must be identified, analyzed, and managed [59]. Risk factors may also be attributed to the use of OGD in the decision-making of organizations, including unanticipated decisions during project planning or business expansion and may affect the cognitive and affective trust of users. Consequently, regarding the relationship between the perceived risk of using OGD and the trust constructs from the employee perspectives, the following hypotheses can be formulated:

H_{3a}: Perceived risk negatively influences cognitive trust of employees.

H_{3b}: Perceived risk negatively influences affective trust of employees.

Compatibility refers to the degree to which an innovation aligns with the pre-existing values, prior experiences, and requirements of technology adopters Tweneboah-Koduah, et al. [23]. Lei, et al. [60] argues that environments more compatible with existing processes are more receptive to innovations and new data technologies. Certain scholars in the field of information systems failed to identify a precise correlation between the implementation of these technologies and compatibility [61]. Nevertheless, many studies have substantiated an enormous and robust correlation between compatibility and the acceptability of technology[62]. Moreover, introducing a wholly novel approach incompatible with prior methods increases the probability that individuals will lose comprehension of the effectiveness of the emerging technology such as OGD [14] and then reduce users' trust. Access to open government data empowers employees to make informed decisions and contribute meaningfully to organizational goals [49]. If the data is accurate and comprehensive, cognitive trust can be developed. Additionally, OGD initiatives signal the government's commitment to integrity and accountability. When employees perceive that their organization is open and honest in its operations, it enhances affective trust. They feel a sense of pride and loyalty to an organization that prioritizes transparency and accountability. Therefore, the compatibility of using OGD can positively impact cognitive and affective trust from an employee perspective by promoting transparency, empowerment, and perceived integrity. The subsequent hypotheses are formulated in congruence:

H_{4a}: Compatibility positively influences cognitive trust of employees.

H_{4b}: Compatibility positively influences affective trust of employees.

Multiple studies have demonstrated that the cost of a technology directly influences an individual's inclination to employ that technology [63-65] identified the expense of technology implementation as a significant impediment to technology adoption. A correlation exists between technology hazards and individuals' perceptions of technology cost, according to a study by Yan, et al. [66] on OGD. Wu and Wang [67] identified a cost-benefit analysis as a significant determinant in assessing the utility and user-friendliness of mobile commerce technologies. In an organization, if the cost of accessing and utilizing technology is perceived as prohibitive or inefficient, it may undermine cognitive trust [68]. Employees may question the organization's ability to effectively leverage available resources and may doubt the reliability of the data obtained. In terms of affective trust, high costs without tangible benefits can lead to feelings of disillusionment and disengagement among employees [49]. They may perceive the organization as wasteful or shortsighted in resource allocation, which can negatively impact affective trust. Therefore, the study proposed hypotheses as follows:

$H5_a$: Cost negatively influences cognitive trust of employees.

H_{5b}: Cost negatively influences affective trust of employees.

Organizational readiness pertains to the extent to which the organization possesses the necessary financial resources and personnel to implement new technologies Nguyen and DANG [69]. Maroufkhani, et al. [70] posit that larger organizations are more inclined to embrace innovation and novel technologies because of the accessibility of technical specialists, in contrast to smaller organizations. Additional research has demonstrated that an organization's inclination to adopt novel technologies is influenced by the presence of proficient personnel. Transparent communication regarding the organization's preparedness to leverage open data fosters cognitive trust by demonstrating a commitment to data-driven decision-making aligned with organizational objectives. Adequate training and support enhance cognitive trust by equipping employees with the skills and knowledge to navigate and analyze data effectively [26]. Additionally, a robust technology infrastructure instills confidence in data security and reliability, further reinforcing cognitive trust among employees. Haffar, et al. [71] confirm that an organizational culture that values data-driven decision-making and fosters collaboration promotes cognitive and affective trust by creating an environment where employees feel supported, valued, and included in the decision-making process. In light of the concerns, the subsequent hypotheses may be contemplated:

$H_{6a:}$ Organizational readiness positively influences cognitive trust of employees.

$H_{6b:}$ Organizational readiness positively influences affective trust of employees.

Punyatoya [72] defines trust as a consumer's belief that a trustee will follow accepted business standards and deliver promised items or services, even if there is a risk of loss during the transaction process. Punyatoya [72] defines cognitive trust as trusting views that consider a user's cognitive perspective [72]. Affective trust is how consumer emotions, such as intuition and attachment, influence trust decisions [72].

3.3.1.Trust Cognitive Trust

When employees have confidence in the accuracy and reliability of the data, they feel empowered to make informed decisions, leading to increased job satisfaction and enhanced performance [72, 73]. This sense of empowerment reduces uncertainty and stress associated with decision-making processes, fostering a positive organizational perception and strengthening employees' commitment to their workplace. Moreover, trusting in the organization's ability to use open government data effectively enhances perceptions of innovation and transparency, further contributing to job satisfaction. Additionally, when employees trust in the value of the data provided, they are more likely to continue using it in their work, seeking out opportunities for its utilization. Considering the concerns indicated before, the following hypotheses can be considered:

$H_{7a:}$ Cognitive trust positively influences satisfaction of employees.

$H_{7b:}$ Cognitive trust positively influences continuous usage intention of employees.

3.3.2. Affective Trust

When employees feel emotionally connected to the organization and trust its commitment to utilizing open data, it fosters a sense of belonging, loyalty, and support. This positive emotional bond enhances overall job satisfaction as users feel valued and recognized for their contributions [46]. Moreover, affective trust promotes a collaborative culture where employees feel comfortable sharing ideas and working together towards common goals, boosting job satisfaction [45]. Importantly, when employees perceive the organization as supportive and trustworthy, they are more likely to intend to continue utilizing open data in their work, seeking out opportunities for its integration and application [74]. Therefore, nurturing affective trust in the organization's approach to open government data is essential for fostering employee satisfaction and sustaining its usage over time. Considering the given issues, the following hypotheses could be examined:

$H_{8a:}$ Affective trust positively influences satisfaction of employees.

$H_{8b:}$ Affective trust positively influences continuous usage intention of employees.

3.4. Theoretical Framework

In accordance with the hypotheses, Figure 1 illustrates the theoretical framework for this research.

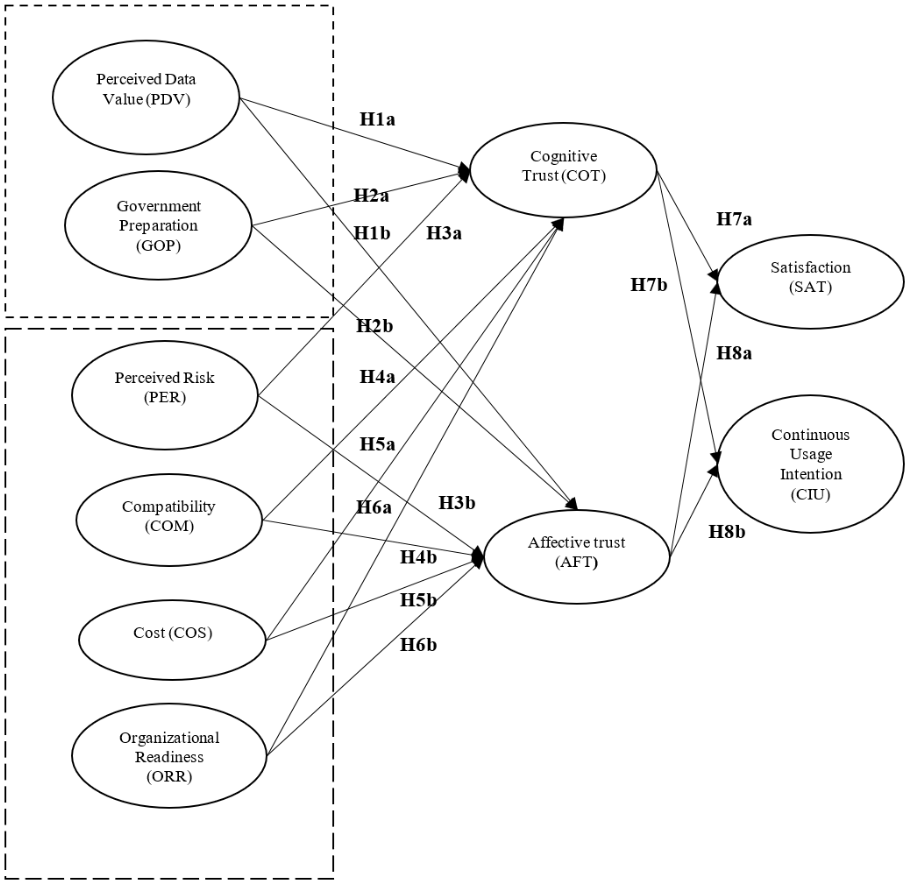

Figure 1.
Theoretical Framework.

4. Methodology

4.1. Sampling Method and Sample Size

This study's target population consists of employees working in Vietnamese firms. As a result, the research sample was purposely chosen utilizing non-probability judgmental sampling procedures to meet the study's criteria. The requirement is to include respondents who work in Vietnamese firms and are familiar with open data. This strategy is appropriate for the objectives of this study and was used in past research in relevant fields. This study's target population consists of employees working in Vietnamese firms. As a result, the research sample was purposely chosen utilizing non-probability judgmental sampling procedures to meet the study's criteria. The requirement is to include respondents who work in Vietnamese firms and are familiar with open data [75]. This strategy is appropriate for the purposes of this investigation. Furthermore, we conducted a power analysis with the G-Power 3.1 program to determine the sample size required to identify the effects of the adjustments on flow experience. Many reputable authors and articles use this approach to calculating sample size [21, 44, 75-77]. With effect size f2= 0.15, power (1-β) =90%, and a number of predictors = 8, power analysis findings suggest that the current investigation requires a total sample size of 115. Additionally, this sample size exceeds the 50-fold rule of thumb for PLS-SEM combined ANN analysis [78-81] which states that the hybrid PLS-SEM-ANN model requires a sample size of at least 50 times the maximum number of arrows pointing toward an endogenous component (6 x 50=300). Thus, 329 qualified samples were gathered, exceeding the required number.

4.2. Questionnaire Design

We evaluated our conceptual framework using a survey methodology, incorporating measurements from earlier studies that were later incorporated into the survey instrument. These measurements were carefully modified to fit the unique context of the OGD context, ensuring that a useful questionnaire was created. The survey was conducted using the Google Forms platform and was primarily directed at people living in Ho Chi Minh City (Southern) and Ha Noi (Northern). The participants received thorough explanations about the study's goals and the protection of respondent confidentiality. Numerous investigations on open government data views served as the basis for the measurement scales employed in this study. Government preparation and perceived OGD value are adapted from Wang and Lo [49] TOE framework's construct adapted from Zhu, et al. [26] cognitive trust and affective trust adapted from Dang Quan, et al. [46] and satisfaction, continuous usage intention are adapted from Nguyen, et al. [82]. On a seven-point Likert scale, each item receives a rating of 1 (strongly disagree) and 7 (strongly agree). Since the majority of respondents are Vietnamese, for ease of comprehension by Vietnamese people, before conducting the official survey, the questionnaire is written in both English and Vietnamese to ensure that the respondents understand it clearly. Data collection for this study was carried out from January to April 2024. From Table 1 of the respondents, it can be seen that the majority of the sample was female, 53.80%, male sample accounted for 42.60%. The study mainly surveyed three types of companies, including foreign-invested enterprises (1.82%), private companies (70.52%), and public companies (27.66%). The majority are Joint-stock companies, with 39.51%, followed by Limited Liability Companies, Sole Proprietorship, and General partnerships, with 34.95%, 19.45%, and 6.08%, respectively. In this survey, companies come from two main regions of Vietnam. Northern accounted for 69.60%, and Southern accounted for 30.40%. More than three-fourths of the companies in this survey have been established for 2 to 23 years (reaching 79.33%). Lastly, for the position in the company, the staff reaches 37.08%, the low manager reaches 34.35%, the middle manager reaches 22.19%, and the top manager 6.38%.

Table 1.
Demographics (N=329).

Demographic Characteristics		**Frequency**	**Percentage**
Gender	Male	152	46.20%
	Female	177	53.80%
Types of fund	Foreign Invested Enterprise	6	1.82%
	Private Company	232	70.52%
	Public Company	91	27.66%
Types of Company	General partnership	20	6.08%
	Joint Stock Company	130	39.51%
	Limited Liability Company	115	34.95%
	Sole Proprietorship	64	19.45%
Headquarters	Northern Vietnam	229	69.60%
	Southern Vietnam	100	30.40%
Company Age	2-12	122	37.08%
	13-23	139	42.25%
	24-34	40	12.16%
	35-45	10	3.04%
	46-56	5	1.52%
	57-67	8	2.43%
	68-79	5	1.52%
Position in the company	Staff	122	37.08%
	Low Manager	113	34.35%
	Middle Manager	73	22.19%
	Top Manager	21	6.38%

4.3.Common Method Bias (CMB)

Common method bias (CMB) is a concern when a single instrument is used to measure both exogenous and endogenous constructs [20, 83]. We employed procedural and statistical measures to mitigate this issue. Leong, et al. [84] incorporated contextual details, clear language, explanations of unfamiliar terms, and assurances of respondent anonymity. As a statistical check, the Harmon's single factor test revealed that the leading factor explained 44.104 percent of the variance, below the 50 percent threshold [85-89]. In addition, Table 3 displays the results of the comprehensive collinearity assessment used to determine if the model is free of common method bias (CMB). VIF readings should be below the 3.3 criterion [90]. The findings indicate that all items have VIF values of <3.3. The results can be read as indicating that the model is not bound by the CMB.

5. Data Analysis Results

5.1. Assessing the Outer Measurement Model

The study used the average variance extracted (AVE) and individual factor loading (FL) to test the convergent validity. According to the basic rule of thumb, external loading should be at least 0.7, while AVE should be greater than 0.5 to be deemed [90]. Following the rule after excluding the item CIU4 and GOT1 because the FL is less than 0.7, it shows that all factor loadings are greater than 0.7 and AVE values exceeded thresholds of 0.5. Next, Cronbach's alpha coefficient and the Composite Reliability (CR) index were used to measure construct reliability. The index of all variables is higher than 0.70, which shows that the constructs were reliable in Table 2. Additionally, the study examined discriminant validity using the Fornell-Larcker and cross-loading test [91, 92]. Table 3 shows discriminant validity in which the square root of AVE for all constructs on the diagonal was higher than the correlation coefficients with other constructs [93]. In addition, according to the cross-loadings test, each item loading should be larger than its associated construct; item loadings are also regarded as a threshold [90]. Table 4 displays the item loadings and cross-loadings for all related values. Since the item loadings of the factors are greater than the cross-loading values of the other latent factors, the cross-loading conditions are satisfied [93]. As a result, all measures show strong internal consistency, convergent validity, reliability, and discriminant validity.

Table 2.
Reliability and convergent validity.

Constructs	Item	FL	VIF	CA	CR	AVE
AFT	AFT1	0.844	1.800	0.845	0.847	0.764
	AFT2	0.898	2.365			
	AFT3	0.880	2.154			
CIU	CIU1	0.858	1.907	0.849	0.849	0.768
	CIU2	0.899	2.382			
	CIU3	0.872	2.066			
COM	COM1	0.855	2.259	0.86	0.861	0.705
	COM2	0.863	2.454			
	COM3	0.828	2.019			
	COM4	0.810	1.698			
COS	COS1	0.820	1.484	0.716	0.717	0.638
	COS2	0.800	1.433			
	COS3	0.776	1.33			
COT	COT1	0.870	1.945	0.833	0.836	0.749
	COT2	0.887	2.121			
	COT3	0.838	1.790			
GOP	GOP2	0.773	2.144	0.884	0.917	0.587
	GOP3	0.716	2.005			
	GOP4	0.805	2.187			
	GOP5	0.762	2.034			
	GOP6	0.749	1.807			
	GOP7	0.804	2.608			
	GOP8	0.748	2.199			
ORR	ORR1	0.865	1.821	0.778	0.781	0.693
	ORR2	0.835	1.746			
	ORR3	0.795	1.430			
PDV	PDV1	0.846	1.849	0.821	0.822	0.737
	PDV2	0.891	2.199			
	PDV3	0.837	1.702			
PER	PER1	0.831	1.685	0.822	0.824	0.738
	PER2	0.874	1.984			
	PER3	0.870	1.951			
SAT	SAT1	0.870	2.046	0.850	0.850	0.770
	SAT2	0.900	2.410			
	SAT3	0.861	1.942			

Note(s): FL= Factor loading, CA = Crobach's alpha, CR = Composite reliability, AVE = Average variance extracted.

Table 3.
Fornell and Larcker [93].

	AFT	CIU	COM	COS	COT	GOP	ORR	PDV	PER	SAT
AFT	**0.874**									
CIU	0.739	**0.876**								
COM	0.815	0.750	**0.839**							
COS	0.650	0.517	0.598	**0.899**						
COT	0.837	0.736	0.808	0.623	**0.866**					
GOP	-0.073	-0.084	-0.066	0.021	-0.066	**0.766**				
ORR	0.769	0.619	0.717	0.829	0.742	-0.022	**0.832**			
PDV	0.824	0.721	0.79	0.635	0.774	-0.062	0.778	**0.858**		
PER	-0.920	-0.701	-0.772	-0.71	-0.796	0.044	-0.736	-0.750	**0.859**	
SAT	0.742	0.778	0.768	0.523	0.753	-0.078	0.622	0.726	-0.699	**0.877**

Table 4.
Cross-loading

	AFT	CIU	COM	COS	COT	GOP	ORR	PDV	PER	SAT
AFT1	**0.844**	0.644	0.700	0.533	0.695	-0.027	0.610	0.740	-0.721	0.651
AFT2	**0.898**	0.653	0.731	0.583	0.748	-0.090	0.687	0.724	-0.831	0.662
AFT3	**0.880**	0.643	0.708	0.588	0.751	-0.074	0.716	0.699	-0.857	0.635
CIU1	0.644	**0.858**	0.838	0.457	0.639	-0.063	0.533	0.625	-0.607	0.846
CIU2	0.641	**0.899**	0.846	0.432	0.667	-0.084	0.541	0.649	-0.611	0.847
CIU3	0.659	**0.872**	0.814	0.471	0.630	-0.075	0.555	0.622	-0.624	0.838
COM1	0.657	0.859	**0.855**	0.447	0.654	-0.045	0.546	0.645	-0.621	0.830
COM2	0.642	0.873	**0.863**	0.440	0.683	-0.071	0.538	0.645	-0.613	0.821
COM3	0.655	0.842	**0.828**	0.490	0.645	-0.089	0.552	0.621	-0.607	0.824
COM4	0.769	0.634	**0.810**	0.613	0.721	-0.021	0.749	0.727	-0.736	0.636
COS1	0.525	0.422	0.501	**0.820**	0.510	0.012	0.692	0.528	-0.544	0.428
COS2	0.515	0.407	0.463	**0.800**	0.491	-0.010	0.703	0.507	-0.591	0.408
COS3	0.519	0.409	0.469	**0.776**	0.493	0.049	0.592	0.487	-0.567	0.417
COT1	0.769	0.661	0.717	0.589	**0.870**	-0.026	0.682	0.699	-0.714	0.665
COT2	0.740	0.656	0.733	0.534	**0.887**	-0.064	0.669	0.690	-0.703	0.681
COT3	0.659	0.592	0.644	0.493	**0.838**	-0.084	0.569	0.617	-0.647	0.606
GOP2	-0.057	-0.051	-0.057	-0.028	-0.015	**0.773**	-0.072	-0.051	0.035	-0.055
GOP3	-0.051	-0.027	-0.025	0.021	-0.004	**0.776**	-0.037	-0.015	0.029	-0.028
GOP4	-0.084	-0.080	-0.086	-0.017	-0.072	**0.805**	-0.057	-0.082	0.060	-0.088
GOP5	-0.035	-0.058	-0.039	0.033	-0.078	**0.762**	0.011	-0.015	0.004	-0.057
GOP6	-0.044	-0.089	-0.058	0.005	-0.059	**0.749**	0.002	-0.028	0.015	-0.069
GOP7	-0.057	-0.048	-0.028	0.049	-0.052	**0.804**	0.004	-0.065	0.044	-0.040
GOP8	-0.054	-0.077	-0.036	0.064	-0.029	**0.748**	0.030	-0.049	0.037	-0.054
ORR1	0.669	0.578	0.658	0.693	0.665	-0.025	**0.865**	0.692	-0.619	0.574
ORR2	0.601	0.462	0.539	0.734	0.584	0.007	**0.835**	0.600	-0.601	0.461
ORR3	0.646	0.499	0.587	0.646	0.598	-0.036	**0.795**	0.646	-0.618	0.510
PDV1	0.679	0.608	0.674	0.518	0.655	-0.072	0.691	**0.846**	-0.654	0.610
PDV2	0.725	0.677	0.722	0.561	0.677	-0.030	0.654	**0.891**	-0.668	0.679
PDV3	0.717	0.570	0.636	0.555	0.660	-0.058	0.659	**0.837**	-0.608	0.580
PER1	-0.738	-0.586	-0.650	-0.578	-0.675	-0.015	-0.607	-0.659	**0.831**	-0.587
PER2	-0.805	-0.623	-0.690	-0.615	-0.702	0.062	-0.625	-0.637	**0.874**	-0.629
PER3	-0.825	-0.596	-0.649	-0.634	-0.674	0.063	-0.665	-0.637	**0.870**	-0.585
SAT1	0.657	0.859	0.855	0.447	0.654	-0.045	0.546	0.645	-0.621	**0.870**
SAT2	0.642	0.843	0.863	0.440	0.683	-0.071	0.538	0.645	-0.613	**0.900**
SAT3	0.655	0.842	0.828	0.490	0.645	-0.089	0.552	0.621	-0.607	**0.861**

5.2. Structure Model Testing

Before determining the significance of the association, we followed Hair, et al. [94] approach and examined the VIF values among the predictor constructs. The maximum VIF value reported was 2.357, which is lower than the conservative criterion of 3.3, indicating that collinearity is unlikely to be an issue in this dataset.

Next, we used the bootstrapping process with 5,000 samples to propose correlations among the constructs. Table 5 shows that PDV had a beneficial impact on both AFT (β=0.202, p_value<0.05) and COT (β=0.157, p_value<0.05). The same as COM had a positive effect on AFT (β=0.110, p_value<0.05) and COT (β=0.330, p_value<0.05). PER had a negative impact on both AFT (β=-0.671, p_value<0.05) and COT (β=-0.324, p_value<0.05). COS had a negative effect on AFT (β=-0.163, p_value<0.05) and COT (β=-0.123, p_value<0.05). Thus, H3 through H10 are confirmed. In addition, COT had positive effects on SAT (β=0.392, p_value<0.05) and CIU (β=0.440, p_value<0.05). AFT had a positive effect on SAT (β=411, p_value<0.05) and CIU (β=0.374, p_value<0.05). Therefore, H1a,b; H3a,b; H4a,b; H5a,b; H7a,b; and H8a,b are supported. However, the effect of GOP and ORR on AFT and COT was not significant (p_value > 0.05). Therefore, H2a,b and H6a,b were not supported.

Additionally, Table 5 presents all values with 95% confidence intervals whose lower and upper limits consistently fall below the threshold value of 1 [95]. This compelling consistency demonstrates that all hypotheses are supported robustly within the specified confidence intervals. Notably, the confidence intervals exclude the value 1, indicating that the estimated parameters have been reliably estimated [76]. Such a result indicates that the hypothesized relationships between variables have been confirmed, as the confidence intervals provide strong evidence that the true parameters of the population lie within the established limits. This result lends substantial empirical support to the validity of the established hypotheses, validating their importance in the context of the study.

Table 5.
Result for hypothesis testing.

Hypothesis	Pathway	Original sample	T statistics	CI [5%-95%]	P_values	Remark
H1a	PDV -> COT	0.157	2.406	[0.049; 0.263]	0.008	Supported
H1b	PDV -> AFT	0.202	3.037	[0.083; 0.306]	0.001	Supported
H2a	GOP -> COT	-0.014	0.347	[-0.077; 0.055]	0.364	Unsupported
H2b	GOP -> AFT	-0.017	1.249	[-0.038; 0.006]	0.106	Unsupported
H3a	PER -> COT	-0.324	5.233	[-0.424; -0.222]	0.000	Supported
H3b	PER -> AFT	-0.671	9.353	[-0.799; -0.563]	0.000	Supported
H4a	COM -> COT	0.330	4.445	[0.214; 0.460]	0.000	Supported
H4b	COM -> AFT	0.110	2.321	[0.034; 0.190]	0.010	Supported
H5a	COS -> COT	-0.123	1.985	[-0.175; -0.088]	0.018	Supported
H5b	COS -> AFT	-0.163	2.173	[-0.269; -0.022]	0.015	Supported
H6a	ORR -> COT	0.204	1.596	[-0.028; 0.388]	0.055	Unsupported
H6b	ORR -> AFT	0.173	1.633	[-0.019; 0.326]	0.051	Unsupported
H7a	COT -> SAT	0.440	6.358	[0.327; 0.554]	0.000	Supported
H7b	COT -> CIU	0.392	5.669	[0.276; 0.505]	0.000	Supported
H8a	AFT -> SAT	0.374	5.442	[0.258; 0.483]	0.000	Supported
H8b	AFT -> CIU	0.411	5.976	[0.295; 0.521]	0.000	Supported

The PLS_predict approach was used to determine the Q^2 value, representing the structural model's predictive accuracy. In Table 6 the result revealed Q2 values greater than 0 for the key of the dependent variable (i.e. SAT, CIU), indicating the predictive relevance of the model [94]. Additionally, the R^2 values must be high enough to guarantee that the model has at least some explanatory power [96]. R^2 should be larger than or equal to 0.1 in order to variance. The minimal R^2 value in this situation is 0.591 (higher than 0.1), which is a significant value [96]. As a result, it can help explain why a certain dependent variable is regarded as sufficient.

Table 6.
Predictive Relevance (Q^2) and R^2.

Dependent variable	Q^2	Predictive Relevant	R^2
AFT	0.887	$Q^2 > 0$	0.900
CIU	0.668	$Q^2 > 0$	0.591
COT	0.732	$Q^2 > 0$	0.749
SAT	0.681	$Q^2 > 0$	0.607

5.3. Post-Hoc Exploratory Analysis: Moderating Effect of Gender Through Multigroup Analysis

"Men are from Mars, and women are from Venus" is a metaphor used by Dang Quan, et al. [46] to illustrate the myriad of psychological distinctions between the sexes, encompassing perception, emotion, and values. In the literature, gender differences in information processing and decision making are well-documented and extensively studied Dang Quan, et al. [46]. In particular, this difference is also shown through their use of new technologies that have also been researched. In keeping with this line of research about open data, we went a step further and investigated gender as a potential observed variation in the model.

Before considering the moderating effect of gender, we examined the models using the MICOM (measurement invariance of composite models) procedure to ensure measurement invariance [97] (Table 7). To begin with, configuration invariance was attained by ensuring each group had an identical model setup. Secondly, the results of a comparison between the 5% quantile and the correlation coefficient c revealed that c is greater than or equal to the 5% quantile for all constructs, especially, this conclusion is further supported by a permutation p-value greater than 0.05. Thirdly, the mean value and variance of the equal composite were evaluated across groups, and it was discovered that full measurement invariance has been established, permitting the subsequent implementation of multigroup analysis. As indicated in Table 8, perceived risk's negative effect on affective and cognitive trust is stronger for females. A similar finding was identified in the relationship between COS and affective trust. On the contrary, the effect of PDV on cognitive trust is stronger for males.

Table 7.
Result of partial invariance measurement testing.

Constructs	Configural invariance	Compositional invariance (Correlation =1)		Equal Mean		Equal Variances		FMI
		C=1	5% quantile	Dif	CI [2.5%; 97.5%]	Dif	CI [2.5%; 97.5%]	
AFT	Yes	1.000	1.000	0.170	[-0.207; 0.206]	0.045	[-0.339; 0.349]	Yes
CIU	Yes	1.000	0.999	0.112	[-0.209; 0.218]	0.109	[-0.423; 0.388]	Yes
COM	Yes	0.999	0.999	0.152	[-0.216; 0.219]	0.121	[-0.399; 0.376]	Yes
COS	Yes	0.998	0.993	0.158	[-0.224; 0.209]	-0.019	[-0.32; 0.358]	Yes
COT	Yes	1.000	0.999	0.098	[-0.213; 0.209]	0.111	[-0.389; 0.378]	Yes
GOP	Yes	0.828	0.194	-0.121	[-0.228; 0.216]	-0.178	[-0.322; 0.338]	Yes
ORR	Yes	1.000	0.998	0.093	[-0.209; 0.225]	0.089	[-0.402; 0.43]	Yes
PDV	Yes	1.000	0.999	0.114	[-0.218; 0.212]	0.120	[-0.393; 0.366]	Yes
PER	Yes	1.000	0.999	-0.190	[-0.209; 0.207]	0.053	[-0.28; 0.292]	Yes
SAT	Yes	1.000	0.999	0.152	[-0.209; 0.22]	0.105	[-0.439; 0.409]	Yes

Table 8.
Result of PLS-MGA for gender.

Relationship	Path coefficient (male)	Path coefficient (female)	CIs (bias corrected) male	CIs (bias corrected) female	Path coefficient difference	2 tail-p_value (Male - Female)
AFT -> CIU	0.490	0.332	[0.314; 0.667]	[0.146; 0.491]	0.158	0.146^{ns}
AFT -> SAT	0.459	0.285	[0.285; 0.642]	[0.095; 0.447]	0.174	0.124^{ns}
COM -> AFT	0.155	0.072	[0.066; 0.25]	[-0.038; 0.187]	0.083	0.177^{ns}
COM -> COT	0.390	0.277	[0.226; 0.567]	[0.117; 0.415]	0.112	0.211^{ns}
COS -> AFT	-0.149	-0.166	[-0.248; 0.013]	[-0.427; 0.18]	0.016	0.040^{*}
COS -> COT	-0.054	-0.105	[-0.168; 0.139]	[-0.337; 0.248]	0.050	0.366^{ns}
COT -> CIU	0.375	0.384	[0.179; 0.554]	[0.215; 0.517]	-0.008	0.479^{ns}
COT -> SAT	0.413	0.446	[0.208; 0.591]	[0.274; 0.582]	-0.033	0.414^{ns}
GOP -> AFT	-0.005	-0.037	[-0.039; 0.025]	[-0.082; -0.003]	0.032	0.148^{ns}
GOP -> COT	-0.033	0.015	[-0.095; 0.09]	[-0.06; 0.118]	-0.048	0.245^{ns}
ORR -> AFT	0.142	0.202	[-0.049; 0.267]	[-0.304; 0.543]	-0.060	0.399^{ns}
ORR -> COT	0.088	0.368	[-0.184; 0.295]	[-0.167; 0.626]	-0.280	0.200^{ns}
PDV -> AFT	0.210	0.189	[0.089; 0.339]	[0.012; 0.394]	0.021	0.433^{ns}
PDV -> COT	0.282	0.135	[0.048; 0.334]	[-0.007; 0.305]	0.147	0.049^{*}
PER -> AFT	-0.652	-0.785	[-0.774; -0.524]	[-0.88; -0.434]	0.133	0.042^{*}
PER -> COT	-0.338	-0.462	[-0.48; -0.209]	[-0.42; -0.100]	0.124	0.028^{*}

Note(s): p < 0.05*, n.s = not significant

5.4. Results of Neural Network Modeling

SPSS 25, a widely recognized statistical software, was utilized to analyze the neural network model. The model was provided with the statistically significant predictors obtained from the SEM analysis at this juncture. Four parameters have been determined to be significant through SEM analysis. As depicted in Figure 2 and Figure 3, four variables (04) were therefore provided as input variables in the input layers; these variables were represented as covariates by significant predictors: PDV, PER, COM, and COS. The dependent variables in the current case were COT and AFT for OGD in the output layer. Furthermore, to address the issue of overfitting in the neural network model, the cross-validation tool was implemented [21, 44]. Nevertheless, determining the exact quantity of concealed neurons remains an unresolved issue in the current body of research. According to Wang and Elhag [98] concealed neurons or nodes in an ANN model should fall within the range of 1–10. 10% of data points were utilized for experiments during the analysis phase, while 90% of data points were utilized for training. Tables 9 and 10 contain the root mean square error (RMSE) values and the mean and standard deviation for the testing and training data points. According to the outputs, model A's mean RMSE values for training and assessment are 0.634 and 0.622, respectively. Similarly, the values for training and assessment in model B are 0.350 and 0.339, respectively. The relatively small average RMSE values and extremely low standard deviations suggest that the statistical results are of a higher order of accuracy [82].

Furthermore, the outcomes demonstrate that the extracted models are exceptionally reliable at capturing the connections between the significant predictors and the output variables. Furthermore, to compute the sensitivity analysis, the mean significance of every predictor in relation to a critical outcome variable was utilized. In order to calculate the normalized relative significance of each predictor in the model, its relative importance was divided by the predictor with the highest importance. The average and normalized importance of every predictor is presented in Table 11. The results obtained from the neural network model analysis indicate that COM is, in comparison, the least significant predictor of COT for OGD, with PDV, PER, and COS following suit. However, in comparison, COS exhibits the highest predictive power for AFT, with PER, PDV, and COM following suit.

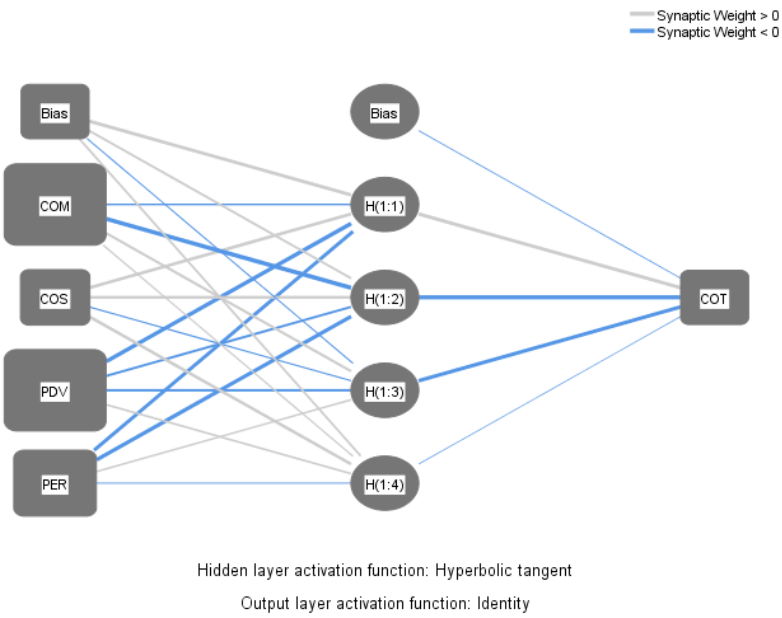

Figure 2.
ANN network for Model A.

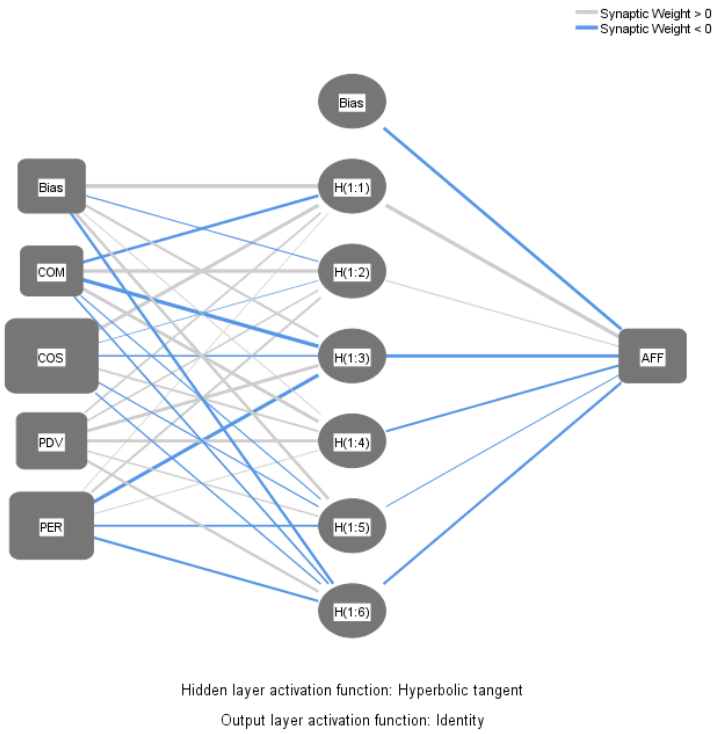

Figure 3.
ANN network for Model B.

Table 9.
RMSE values of ANN for Model A (Input: PDV, PER, COM, COS, Output: COT).

		TRAINING			TESTING		
Neural Network	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**TOTAL**
1	291	389.589	0.598	38	51.769	0.526	329
2	299	445.769	0.632	30	38.854	0.600	329
3	297	435.468	0.630	32	41.051	0.656	329
4	288	422.661	0.613	41	51.347	0.603	329
5	289	341.348	0.628	40	44.410	0.625	329
6	300	348.019	0.631	29	39.149	0.656	329
7	290	346.149	0.653	39	43.241	0.608	329
8	298	331.747	0.621	31	32.147	0.655	329
9	285	320.882	0.694	44	45.059	0.621	329
10	292	369.059	0.636	37	40.089	0.667	329
Means		375.069	0.634		42.712	0.622	
SD		43.217	0.024		5.604	0.040	

Table 10.
RMSE values of ANN for Model B (Input: PDV, PER, COM, COS, Output: AFT).

		TRAINING			TESTING		
Neural Network	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**	**TOTAL**
1	289	312.555	0.359	40	46.203	0.300	329
2	288	336.598	0.305	41	49.339	0.340	329
3	281	335.475	0.312	48	47.809	0.417	329
4	272	318.961	0.379	57	45.434	0.386	329
5	288	346.170	0.345	41	47.072	0.366	329
6	272	300.768	0.317	57	48.947	0.389	329
7	281	311.598	0.380	48	48.152	0.333	329
8	279	321.801	0.382	50	48.774	0.241	329
9	277	312.145	0.360	52	48.204	0.323	329
10	274	317.291	0.365	55	44.288	0.291	329
Means		321.336	0.350		47.422	0.339	
SD		13.233	0.028		1.565	0.050	

Table 11.
Sensitivity analyses: normalized importance of constructs for Model A and Model B.

Neural Network	**Model A**				**NN**	**Model B**			
	PDV	**PER**	**COM**	**COS**		**PDV**	**PER**	**COM**	**COS**
1	0.246	0.311	0.207	0.236	1	0.261	0.289	0.191	0.259
2	0.198	0.175	0.297	0.330	2	0.298	0.273	0.105	0.324
3	0.102	0.246	0.205	0.447	3	0.241	0.324	0.121	0.314
4	0.192	0.335	0.198	0.275	4	0.184	0.304	0.108	0.404
5	0.329	0.117	0.263	0.291	5	0.261	0.341	0.105	0.293
6	0.249	0.167	0.432	0.152	6	0.249	0.297	0.131	0.323
7	0.202	0.298	0.370	0.130	7	0.202	0.332	0.142	0.324
8	0.200	0.241	0.342	0.217	8	0.200	0.270	0.185	0.345
9	0.311	0.184	0.382	0.123	9	0.311	0.222	0.223	0.244
10	0.279	0.201	0.315	0.205	10	0.278	0.282	0.116	0.324
Average relative importance	0.231	0.228	0.301	0.241		0.249	0.293	0.143	0.315
Normalized relative importance (%)	88.35%	71.60%	100.00%	52.20%		56.20%	82.30%	40.50%	100.00%

6. Discussions

The purpose of this study was to investigate employee perceptions of trust and affect when using OGD, as well as data-related, organizational, technological, and external environmental aspects that influence satisfaction and intention to continue using OGD. This study verified the integration model of Technology-Organization-Environment (TOE) and Trust Theory in examining employee satisfaction and desire to continue using OGD. The study also makes two significant contributions: (1) From the standpoint of an employee, the study offered a conceptual framework for measuring OGD satisfaction and intention to use by incorporating data-related, organizational, technological, and external environmental aspects. (2) Rate these elements by neural network analysis, something previous research has not done[9].

First, according to the findings, perceived data value, perceived risk, compatibility, and cost are essential drivers for affective trust and cognitive trust of OGD when evaluating satisfaction and the intention to continue using OGD. These results align with previous studies in other contexts [4]. The results indicate that when users believe that the data offered by the government is valuable and reliable for their needs, they are more likely to trust the source and feel satisfied with its usage. Moreover, if the data provided by OGD is compatible with users' requirements and can be easily integrated into their workflows or applications, they are more likely to trust and continue using the platform [99]. However, in terms of the cost of using OGD, if the costs associated with using OGD are perceived as reasonable and justifiable in comparison to the benefits gained, users are more likely to trust the platform and continue using it. The same issue is with risk; following the result, risks could include concerns about data accuracy, privacy, security, or misuse, which affect the trust of users. Government agencies need to address these concerns by ensuring data accuracy, implementing robust security measures, and being transparent about data collection and usage practices.

Second, there are insignificant correlations between compatibility, government preparation and trust. These results contradict the findings presented by the literature in other research contexts [62]. The contradiction could be explained by diverse user needs and expectations. Users accessing OGD may have diverse needs, goals, and levels of technical proficiency. Compatibility, which refers to aligning OGD with users' needs and existing systems, may vary greatly among user groups. Similarly, government preparation, which encompasses the readiness and capability of government agencies to provide and manage OGD effectively, may not directly influence users' perceptions of trust if they are primarily concerned with the relevance and reliability of the data itself.

Hypotheses H7a, H7b, H8a, and H8b are supported by statistical evidence that validates research findings in different contexts. For example, the path between cognitive trust, affective trust, and satisfaction toward OGD is affirmed by Alimamy and Gnoth [55] while the path between cognitive trust, affective trust, and intention to continue using OGD are endorsed by Bhuiyan, et al. [74]. These paths highlight the sequential relationships between cognitive trust, affective trust, satisfaction, and intention to continue using OGD. They underscore the importance of building rational and emotional trust among users to enhance satisfaction and foster continued usage of OGD platforms. By understanding these pathways, government agencies and policymakers can develop strategies to cultivate trust, satisfaction, and user loyalty toward OGD initiatives.

7. Contributions

7.1. Theoretical Contributions

The theoretical feedback loop can emphasize the theoretical contributions when the theory is implemented in novel contexts. This suggests that scholars require further comprehension of novel facets of the theory within a recently embraced framework [100]. It is emphasized that prior analogies must be modified to challenge established rationales while endorsing accepted theories when they are applied to a new context. This provides a comprehensive examination of established perspectives on the conceptualization of theories and organizational, technological, data-related, and external factors. Thus, the research contributions of this study are demonstrated by the value added to the adopted theories and prior literature, as well as by providing an overview of the OGD context.

To begin, this study utilizes the TOE model to investigate the satisfaction levels of users and their intention to continue utilizing OGD. By utilizing non-traditional theoretical frameworks, this study investigates the impact of cognitive and affective trust on the outcome of OGD utilization. Further developing the TOE perspective, technological, organizational, data-related, and external environmental factors can influence trust, which, if implemented strategically, can impact OGD utilization and satisfaction. This perspective supplements the existing body of theoretical literature in the domains of management and organizations, which is grounded in research. Due to its inside-outside perspective, the TOE theory generally allocates its resources toward examining the internal structure of organizations, while contextual factors receive comparatively less attention. Our research overcomes this constraint by conducting an analysis of the external environment and integrating data-related variables alongside internal organizational factors. This provides contextual validation for the significance of attaining congruence between organizational resources, OGD capabilities, and the external environment. Furthermore, this study expands upon current knowledge by investigating the impact of four dimensions (data-related, organizational, technological, and external environmental factors) on adopting Open Government Data (OGD) from employees' perspective. The prior literature has examined these dimensions across many disciplines by adding different aspects to each dimension [32]. This study employs the Theory of Reasoned Action (TOE) and Trust theory to assess the impact of data-related, organizational, technological, and external environmental factors on cognitive and emotional trust, as well as their influence on the intention to use and satisfaction with Open Government Data (OGD) consumption. This study highlights the crucial importance of trust as a mediator in the interaction between several aspects (such as data-related, organizational, technological, and external environmental factors) and the utilization of Open Government Data (OGD).

The research model contributes to the existing theories of Technology-Organization-Environment (TOE) and Trust theory by investigating the influence of trust on the adoption of Open Government Data (OGD) and the intention to use it. This study also contributes to the limited but growing body of literature that explores this issue in the industry context. Furthermore, the research investigates the adoption of Open Government Data (OGD) in an underexplored setting, specifically focusing on developing nations such as Vietnam. While the subject of this study is becoming more popular, it is examined from a comprehensive perspective [15] with limited emphasis on offering empirical evidence for the suggested methods. We contend that in the specific circumstances of Vietnam, the adoption of Open Government Data (OGD) by enterprises empowers them to take the lead in the market and effectively tackle the growing issues they encounter.

Lastly, An artificial neural network (ANN) was used in combination with partial least square structural equation modeling (PLS-SEM) to rank the normalized importance of the variables and identify any potential nonlinear and non-compensatory relationships that may have gone undetected with PLS-SEM analysis alone. This is a significant aspect of the study's methodology, which aims to validate the model.

7.2. Managerial Contributions

Examining the use and satisfaction of Open Government Data (OGD) poses complex issues and opportunities for government organizations and policymakers. By utilizing the Technology-Organization-Environment (TOE) framework and Trust theory, we may identify management implications that help guide strategic decision-making in this field. From a technological standpoint, it is important to undertake assessments to evaluate the usability, quality, accessibility, and interoperability of Open Government Data (OGD) platforms. Additionally, smart resource allocation should be implemented to ensure scalability and reliability. Creating a culture that values transparency, collaboration, and making decisions based on facts is essential for the business. To overcome resistance inside the organization, it is important to implement change management tactics and have strong leadership support. Moreover, environmental considerations require the synchronization of policy frameworks, active involvement of stakeholders, and formation of strategic alliances to effectively negotiate regulatory obstacles and expand the influence of open government data projects. Trust theory emphasizes the significance of transparency, ensuring data quality, and empowering users to develop trust among stakeholders. This, in turn, improves the adoption and satisfaction with Open Government Data (OGD). Government agencies can establish comprehensive plans to tackle technological, organizational, and environmental obstacles, as well as build trust and maximize the effectiveness of Open Government Data (OGD) projects by incorporating lessons from these frameworks.

8. Conclusions, Limitations, and Future Research Directions

8.1. Limitations and Future Research Directions

There are some limitations to this study that ought to be considered in future research. Initially, while the research model's design is predicated on the involvement of specialists and considers four dimensions, the factors representing each dimension could be expanded to encompass broader aspects of the evaluation procedure, such as the organization's structure and size. Additional significant attributes of the organization that warrant consideration include its risk tolerance, cultural disposition, and economic standing. Furthermore, it is possible to enhance the research model by including additional research variables that may provide industry decision-makers with practical guidance. Furthermore, since the study focuses on decision-makers in Vietnam, particular attention must be paid to the generalizability of the results. A comparative analysis of OGD adopters and non-adopters could ultimately offer a more comprehensive understanding of the viewpoints of industry performance decision-makers regarding the advantages of OGD implementation.

8.2. Conclusions

This paper introduces the first combination of the Technology-Organization-Environment (TOE) framework, a commonly used theoretical framework for understanding the adoption and integration of information technology in organizations, with trust theory. The purpose is to investigate users' satisfaction and intention to continue using the domain of OGD. Moreover, this is the initial instance where all three dimensions of OGD are employed as precursors of trust and affect inside the OGD framework. This research not only adds to the current understanding but also pushes forward the field of OGD. Moreover, the research findings help OGD providers assess the significance of each trust and its effect on OGD. This enables them to prioritize user dimensions and improve the overall quality of OGD. Moreover, the elements included in the TOE framework help organizations assess the degree to which their technological capabilities align with the requirements of using OGD, the extent to which their organizational structure facilitates or hinders the integration of OGD into the decision-making process, and their response to the growing trend of making OGD more accessible.

References

[1] D. o. E. a. S. A. United Nations, *United nations e-government survey 2022: The future of digital government*. New York: United Nations, 2022.

[2] A. A. C. de Souza, M. J. d'Angelo, and R. N. Lima Filho, "Effects of predictors of citizens' attitudes and intention to use open government data and government 2.0," *Government Information Quarterly*, vol. 39, no. 2, p. 101663, 2022. https://doi.org/10.1016/j.giq.2021.101663

[3] T.-M. Yang and Y.-J. Wu, "Examining the socio-technical determinants influencing government agencies' open data publication: A study in Taiwan," *Government Information Quarterly*, vol. 33, no. 3, pp. 378-392, 2016. https://doi.org/10.1016/j.giq.2016.05.003

[4] N. Rizun, C. Alexopoulos, S. Saxena, F. Kleiman, and R. Matheus, "Do personality traits influence the user's behavioral intention to adopt and use open government data (OGD)? An empirical investigation," *Telematics and Informatics*, vol. 87, p. 102073, 2024. https://doi.org/10.1016/j.tele.2023.102073

[5] E.-G. S. United Nations, "Digital government in the decade of action for sustainable developmenta," United Nations, E-Government Survey, 2020.

[6] K.-T. Tai, "Open government research over a decade: A systematic review," *Government Information Quarterly*, vol. 38, no. 2, p. 101566, 2021. https://doi.org/10.1016/j.giq.2021.101566

[7] C. Alexopoulos, S. Saxena, N. Rizun, R. Matheus, and M. Janssen, "Are creative users more apt in reusing and adopting open government data(OGD)? Gender differences," *Thinking Skills and Creativity*, vol. 52, p. 101478, 2024. https://doi.org/10.1016/j.tsc.2024.101478

[8] M. T. Islam, M. S. Talukder, A. Khayer, and A. N. Islam, "Exploring continuance usage intention toward open government data technologies: An integrated approach," *VINE Journal of Information and Knowledge Management Systems*, vol. 53, no. 4, pp. 785-807, 2023. https://doi.org/10.1108/VJIKMS-10-2020-0195

[9] M. S. Talukder, L. Shen, M. F. H. Talukder, and Y. Bao, "Determinants of user acceptance and use of open government data (OGD): An empirical investigation in Bangladesh," *Technology in Society*, vol. 56, pp. 147-156, 2019. https://doi.org/10.1016/j.techsoc.2018.09.013

[10] M. M. Khurshid, N. H. Zakaria, M. I. Arfeen, A. Rashid, S. U. Nasir, and H. M. F. Shehzad, "Factors influencing citizens' intention to use open government data—a case study of Pakistan," *Big Data and Cognitive Computing*, vol. 6, no. 1, p. 31, 2022. https://doi.org/10.3390/bdcc6010031

[11] J. Zhong and T. Chen, "Antecedents of mobile payment loyalty: An extended perspective of perceived value and information system success model," *Journal of Retailing and Consumer Services*, vol. 72, p. 103267, 2023. https://doi.org/10.1016/j.jretconser.2023.103267

[12] M. Chen, Y. Cao, and Y. Liang, "Determinants of open government data usage: Integrating trust theory and social cognitive theory," *Government Information Quarterly*, vol. 40, no. 4, p. 101857, 2023. https://doi.org/10.1016/j.giq.2023.101857

[13] Y. K. Dwivedi, N. P. Rana, M. Janssen, B. Lal, M. D. Williams, and M. Clement, "An empirical validation of a unified model of electronic government adoption (UMEGA)," *Government Information Quarterly*, vol. 34, no. 2, pp. 211-230, 2017. https://doi.org/10.1016/j.giq.2017.03.001

[14] Y. Zhao and B. Fan, "Understanding the key factors and configurational paths of the open government data performance: Based on fuzzy-set qualitative comparative analysis," *Government Information Quarterly*, vol. 38, no. 3, p. 101580, 2021. https://doi.org/10.1016/j.giq.2021.101580

[15] F. Wang, Z. Zhang, X. Ma, Y. Zhang, X. Li, and X. Zhang, "Paths to open government data reuse: A three-dimensional framework of information need, data and government preparation," *Information & Management*, vol. 60, no. 8, p. 103879, 2023. https://doi.org/10.1016/j.im.2023.103879

[16] Y. Zhao and B. Fan, "Effect of an agency's resources on the implementation of open government data," *Information & Management*, vol. 58, no. 4, p. 103465, 2021. https://doi.org/10.1016/j.im.2021.103465

[17] Y. Kim, J. Seok, and T. Roh, "The linkage between quality of information systems and the impact of trust-based privacy on behavioral outcomes in unmanned convenience store: Moderating effect of gender and experience," *Technological Forecasting and Social Change*, vol. 196, p. 122852, 2023. https://doi.org/10.1016/j.techfore.2023.122852

[18] T.-Q. Dang, G. W.-H. Tan, E. C.-X. Aw, K.-B. Ooi, B. Metri, and Y. K. Dwivedi, "How to generate loyalty in mobile payment services? An integrative dual SEM-ANN analysis," *International Journal of Bank Marketing*, vol. 41, no. 6, pp. 1177-1206, 2023. https://doi.org/10.1108/IJBM-05-2022-0202

[19] T. Zhou, "An empirical examination of initial trust in mobile banking," *Internet Research*, vol. 21, no. 5, pp. 527-540, 2011. https://doi.org/10.1108/10662241111176353

[20] A. H. D. Nguyen, T. T. Le, T.-Q. Dang, and L.-T. Nguyen, "Understanding metaverse adoption in education: The extended UTAUMT model," *Heliyon*, vol. 10, no. 19, p. e38741, 2024. https://doi.org/10.1016/j.heliyon.2024.e38741

[21] L.-T. Nguyen, D. T. V. Duc, T.-Q. Dang, and D. P. Nguyen, "Metaverse banking service: Are we ready to adopt? A deep learning-based dual-stage sem-ann analysis," *Human Behavior and Emerging Technologies*, vol. 2023, no. 1, p. 6617371, 2023. https://doi.org/10.1155/2023/6617371

[22] R. S. Basloom, M. H. S. Mohamad, and S. M. Auzair, "Applicability of public sector reform initiatives of the Yemeni government from the integrated TOE-DOI framework," *International Journal of Innovation Studies*, vol. 6, no. 4, pp. 286-302, 2022. https://doi.org/10.1016/j.ijis.2022.08.005

[23] S. Tweneboah-Koduah, B. Endicott-Popovsky, and A. Tsetse, "Barriers to government cloud adoption," *International Journal of Managing Information Technology*, vol. 6, no. 3, pp. 1-16, 2014. https://doi.org/10.5121/ijmit.2014.6301

[24] J. Baker, "The technology–organization–environment framework," *Information Systems Theory: Explaining and Predicting Our Digital Society*, vol. 1, pp. 231-245, 2011. https://doi.org/10.1007/978-1-4419-6108-2_12

[25] A. Wael AL-Khatib, "Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework," *Technology in Society*, vol. 75, p. 102403, 2023. https://doi.org/10.1016/j.techsoc.2023.102403

[26] K. Zhu, K. L. Kraemer, and J. Dedrick, "Information technology payoff in e-business environments: An international perspective on value creation of e-business in the financial services industry," *Journal of Management Information Systems*, vol. 21, no. 1, pp. 17-54, 2004. https://doi.org/10.1080/07421222.2004.11045797

[27] L.-Y. Leong, J.-J. Hew, V.-H. Lee, G. W.-H. Tan, K.-B. Ooi, and N. P. Rana, "An SEM-ANN analysis of the impacts of blockchain on competitive advantage," *Industrial Management & Data Systems*, vol. 123, no. 3, pp. 967-1004, 2023. https://doi.org/10.1108/IMDS-11-2021-0671

[28] P. M. Ng, K. K. Lit, and C. T. Cheung, "Remote work as a new normal? The technology-organization-environment (TOE) context," *Technology in Society*, vol. 70, p. 102022, 2022. https://doi.org/10.1016/j.techsoc.2022.102022

[29] O. E. Williamson, "Calculativeness, trust, and economic organization," *The Journal of Law and Economics*, vol. 36, no. 1, pp. 453-486, 1993. https://doi.org/10.1086/467284

[30] Y. Bart, V. Shankar, F. Sultan, and G. L. Urban, "Are the drivers and role of online trust the same for all web sites and consumers? A large-scale exploratory empirical study," *Journal of Marketing*, vol. 69, no. 4, pp. 133-152, 2005. https://doi.org/10.1509/jmkg.2005.69.4.133

[31] A. Beldad, M. De Jong, and M. Steehouder, "How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust," *Computers in Human Behavior*, vol. 26, no. 5, pp. 857-869, 2010. https://doi.org/10.1016/j.chb.2010.03.013

[32] R. Filieri, S. Alguezaui, and F. McLeay, "Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth," *Tourism Management*, vol. 51, pp. 174-185, 2015. https://doi.org/10.1016/j.tourman.2015.05.007

[33] N. Tamimi and R. Sebastianelli, "The relative importance of e-tailer website attributes on the likelihood of online purchase," *Internet Research,* vol. 25, no. 2, pp. 169-183, 2015.

[34] V. Venkatesh, J. Y. Thong, F. K. Chan, P. J. H. Hu, and S. A. Brown, "Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context," *Information Systems Journal,* vol. 21, no. 6, pp. 527-555, 2011. https://doi.org/10.1111/j.1365-2575.2011.00373.x

[35] P. Upadhyay and M. Chattopadhyay, "Examining mobile based payment services adoption issues: A new approach using hierarchical clustering and self-organizing maps," *Journal of Enterprise Information Management,* vol. 28, no. 4, pp. 490-507, 2015. https://doi.org/10.1108/JEIM-04-2014-0046

[36] M. K. Lee and E. Turban, "A trust model for consumer internet shopping," *International Journal of Electronic Commerce,* vol. 6, no. 1, pp. 75-91, 2001. https://doi.org/10.1080/10864415.2001.11044227

[37] O. Marjanovic and D. Cecez-Kecmanovic, "Open government data platforms–A complex adaptive sociomaterial systems perspective," *Information and Organization,* vol. 30, no. 4, p. 100323, 2020. https://doi.org/10.1016/j.infoandorg.2020.100323

[38] A. S. Al-Adwan, "The government metaverse: charting the coordinates of citizen acceptance," *Telematics and Informatics,* vol. 88, p. 102109, 2024. https://doi.org/10.1016/j.tele.2024.102109

[39] A. S. Al-Adwan, S. Al Masaeed, H. Yaseen, H. Balhareth, L. a. Al-Mu'ani, and M. Pavlíková, "Navigating the roadmap to meta-governance adoption," *Global Knowledge, Memory and Communication,* 2024. https://doi.org/10.1108/GKMC-02-2024-0105

[40] S. Shamim, Y. Yang, N. U. Zia, Z. Khan, and S. M. Shariq, "Mechanisms of cognitive trust development in artificial intelligence among front line employees: An empirical examination from a developing economy," *Journal of Business Research,* vol. 167, p. 114168, 2023. https://doi.org/10.1016/j.jbusres.2023.114168

[41] D. Li, G. J. Browne, and P. Y. Chau, "An empirical investigation of web site use using a commitment-based model," *Decision Sciences,* vol. 37, no. 3, pp. 427-444, 2006. https://doi.org/10.1111/j.1540-5414.2006.00133.x

[42] V. A. Zeithaml, "Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence," *Journal of Marketing,* vol. 52, no. 3, pp. 2-22, 1988. https://doi.org/10.1177/002224298805200302

[43] L.-T. Nguyen, Y. K. Dwivedi, G. W.-H. Tan, E. C.-X. Aw, P.-S. Lo, and K.-B. Ooi, "Unlocking pathways to mobile payment satisfaction and commitment," *Journal of Computer Information Systems,* vol. 63, no. 4, pp. 998-1015, 2023. https://doi.org/10.1080/08874417.2022.2119444

[44] B. H. T. Nguyen, T. H. Le, T. Q. Dang, and L. T. Nguyen, "What role does AI chatbot perform in the F&B industry? Perspective from loyalty and value Co-creation: Integrated PLS-SEM and ANN techniques," *Journal of Law and Sustainable Development,* vol. 11, no. 4, p. e794, 2023. https://doi.org/10.55908/sdgs.v11i4.794.

[45] G. Casimir, K. Lee, and M. Loon, "Knowledge sharing: Influences of trust, commitment and cost," *Journal of Knowledge Management,* vol. 16, no. 5, pp. 740-753, 2012.

[46] T. Dang Quan, G. Wei-Han Tan, E. C.-X. Aw, T.-H. Cham, S. Basu, and K.-B. Ooi, "Can you resist the virtual temptations? Unveiling impulsive buying in metaverse retail," *Asia Pacific Journal of Marketing and Logistics,* vol. 36, no. 10, pp. 2259-2280, 2024. https://doi.org/10.1108/APJML-09-2023-0911

[47] K. H. Rose, *Project quality management: Why, what and how*. Boca Raton Florida: J. Ross Publishing, 2005.

[48] A. Nikiforova and K. McBride, "Open government data portal usability: A user-centred usability analysis of 41 open government data portals," *Telematics and Informatics,* vol. 58, p. 101539, 2021.

[49] H.-J. Wang and J. Lo, "Factors influencing the adoption of open government data at the firm level," *IEEE Transactions on Engineering Management,* vol. 67, no. 3, pp. 670-682, 2019. https://doi.org/10.1109/TEM.2019.2898107

[50] J. Nielsen, *Usability engineering san francisco*. California: Morgan Kaufmann Publishers, 1994.

[51] S. F. Verkijika and B. N. Neneh, "Standing up for or against: A text-mining study on the recommendation of mobile payment apps," *Journal of Retailing and Consumer Services,* vol. 63, p. 102743, 2021. https://doi.org/10.1016/j.jretconser.2021.102743

[52] L. Gualtieri, F. Fraboni, M. De Marchi, and E. Rauch, "Development and evaluation of design guidelines for cognitive ergonomics in human-robot collaborative assembly systems," *Applied Ergonomics,* vol. 104, p. 103807, 2022. https://doi.org/10.1016/j.apergo.2022.103807

[53] S. Kaabachi, S. Ben Mrad, and B. O'Leary, "Consumer's initial trust formation in IOB's acceptance: The role of social influence and perceived compatibility," *International Journal of Bank Marketing,* vol. 37, no. 2, pp. 507-530, 2019. https://doi.org/10.1108/IJBM-12-2017-0270

[54] S. Kimiagari and N. S. A. Malafe, "The role of cognitive and affective responses in the relationship between internal and external stimuli on online impulse buying behavior," *Journal of Retailing and Consumer Services,* vol. 61, p. 102567, 2021. https://doi.org/10.1016/j.jretconser.2021.102567

[55] S. Alimamy and J. Gnoth, "I want it my way! The effect of perceptions of personalization through augmented reality and online shopping on customer intentions to co-create value," *Computers in Human Behavior,* vol. 128, p. 107105, 2022. https://doi.org/10.1016/j.chb.2021.107105

[56] K. Marett, A. W. Pearson, R. A. Pearson, and E. Bergiel, "Using mobile devices in a high risk context: The role of risk and trust in an exploratory study in Afghanistan," *Technology in Society,* vol. 41, pp. 54-64, 2015. https://doi.org/10.1016/j.techsoc.2014.11.002

[57] G. De Kerviler, N. T. Demoulin, and P. Zidda, "Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers?," *Journal of Retailing and Consumer Services,* vol. 31, pp. 334-344, 2016. http://dx.doi.org/10.1016/j.jretconser.2016.04.011

[58] L. Chen, J. Jia, and C. Wu, "Factors influencing the behavioral intention to use contactless financial services in the banking industry: An application and extension of UTAUT model," *Frontiers in Psychology,* vol. 14, p. 1096709, 2023. https://doi.org/10.3389/fpsyg.2023.1096709

[59] P. Shamala, R. Ahmad, A. Zolait, and M. Sedek, "Integrating information quality dimensions into information security risk management (ISRM)," *Journal of Information Security and Applications,* vol. 36, pp. 1-10, 2017. https://doi.org/10.1016/j.jisa.2017.07.004

[60] Z. Lei, Y. Chen, and M. K. Lim, "Modelling and analysis of big data platform group adoption behaviour based on social network analysis," *Technology in Society,* vol. 65, p. 101570, 2021. https://doi.org/10.1016/j.techsoc.2021.101570

[61] M. L. Meuter, M. J. Bitner, A. L. Ostrom, and S. W. Brown, "Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies," *Journal of Marketing*, vol. 69, no. 2, pp. 61-83, 2005. https://doi.org/10.1509/jmkg.69.2.61.60759

[62] C.-H. Wong, G. W.-H. Tan, S.-P. Loke, and K.-B. Ooi, "Adoption of mobile social networking sites for learning?," *Online Information Review*, vol. 39, no. 6, pp. 762-778, 2015. https://doi.org/10.1108/OIR-05-2015-0152

[63] H. Tanriverdi, "Performance effects of information technology synergies in multibusiness firms," *MIS Quarterly*, pp. 57-77, 2006. https://doi.org/10.2307/25148717

[64] A.-C. Teo, G. W.-H. Tan, K.-B. Ooi, and B. Lin, "Why consumers adopt mobile payment? A partial least squares structural equation modelling (PLS-SEM) approach," *International Journal of Mobile Communications*, vol. 13, no. 5, pp. 478-497, 2015.

[65] A. Katebi, P. Homami, and M. Najmeddin, "Acceptance model of precast concrete components in building construction based on Technology Acceptance Model (TAM) and Technology, Organization, and Environment (TOE) framework," *Journal of Building Engineering*, vol. 45, p. 103518, 2022.

[66] R. Yan, C. Xing, X. Chen, and Y. Zhao, "Is it real or illusory? An empirical examination of the impact of open government data on innovation capability in the case of China," *Technology in Society*, vol. 75, p. 102396, 2023.

[67] J.-H. Wu and S.-C. Wang, "What drives mobile commerce?: An empirical evaluation of the revised technology acceptance model," *Information & management*, vol. 42, no. 5, pp. 719-729, 2005.

[68] A. Pal, C. K. Tiwari, and N. Haldar, "Blockchain for business management: Applications, challenges and potentials," *The Journal of High Technology Management Research*, vol. 32, no. 2, p. 100414, 2021.

[69] T. L. Nguyen and T. V. D. DANG, "Critical factors affecting the adoption of artificial intelligence: An empirical study in Vietnam," *The Journal of Asian Finance, Economics and Business*, vol. 9, no. 5, pp. 225-237, 2022.

[70] P. Maroufkhani, M.-L. Tseng, M. Iranmanesh, W. K. W. Ismail, and H. Khalid, "Big data analytics adoption: Determinants and performances among small to medium-sized enterprises," *International Journal of Information Management*, vol. 54, p. 102190, 2020.

[71] M. Haffar *et al.*, "Organizational culture and affective commitment to e-learning'changes during COVID-19 pandemic: The underlying effects of readiness for change," *Journal of Business Research*, vol. 155, p. 113396, 2023.

[72] P. Punyatoya, "Effects of cognitive and affective trust on online customer behavior," *Marketing Intelligence & Planning*, vol. 37, no. 1, pp. 80-96, 2019.

[73] D. Shin and Y. Hwang, "The effects of security and traceability of blockchain on digital affordance," *Online Information Review*, vol. 44, no. 4, pp. 913-932, 2020.

[74] F. Bhuiyan, K. Baird, and R. Munir, "The association between organisational culture, CSR practices and organisational performance in an emerging economy," *Meditari Accountancy Research*, vol. 28, no. 6, pp. 977-1011, 2020.

[75] T.-Q. Dang, P.-T. Tran, and L.-T. Nguyen, *Are you ready for tapping into the metaverse in higher education? Integrated by dual PLS-SEM and ANN approach*. Cham: Springer, 2023.

[76] L.-T. Nguyen, D.-T. Nguyen, K. N.-N. Ngoc, and D. T. V. Duc, "Blockchain adoption in logistics companies in Ho Chi Minh city, Vietnam," *Cogent Business & Management*, vol. 10, no. 2, p. 2216436, 2023. https://doi.org/10.1080/23311975.2023.2216436

[77] N. T. H. Binh, T.-Q. Dang, and L.-T. Nguyen, "Metaverse: The future for immersive logistics and international business education," *Journal of Teaching in International Business*, vol. 35, no. 3-4, pp. 75-107, 2024.

[78] D. T. V. Duc, L. T. V. Mai, T.-Q. Dang, T.-T. Le, and L.-T. Nguyen, "Unlocking impulsive buying behavior in the metaverse commerce: A combined analysis using PLS-SEM and ANN," *Global Knowledge, Memory and Communication*, 2024. https://doi.org/10.1108/GKMC-05-2024-0266

[79] T.-Q. Dang, T.-M. Nguyen, P.-T. Tran, T.-T. C. Phan, T.-B. Huynh, and L.-T. Nguyen, "From reality to virtuality: Unveiling Gen Z's purchasing behavior through virtual influencers in the metaverse," *Digital Business*, p. 100141, 2025. https://doi.org/10.1016/j.digbus.2025.100141

[80] L.-T. Nguyen, T.-T. C. Phan, and T.-Q. Dang, "The power of interactive mobile advertising: How self-brand congruity shapes brand engagement in self-concept," *Journal of Creative Communications*, p. 09732586251359718, 2025. https://doi.org/10.1177/09732586251359718

[81] T.-Q. Dang, L.-T. Nguyen, and D. D. V. Thi, "Comprehensive analysis of mobile payment's customer loyalty: The sem-ann approach," *Quality-Access to Success*, vol. 26, no. 208, 2025.

[82] L.-T. Nguyen, T.-T. C. Phan, D.-V. T. Dang, and T.-T. T. Tran, *Mobile payment adoption in Vietnam: A two-staged SEM-ANN approach*. Cham: Springer, 2023.

[83] N.-T. T. Nguyen, P.-T. Tran, T.-Q. Dang, and L.-T. Nguyen, "The future of non-contact commerce: The role of voice payments," *Journal of Financial Services Marketing*, vol. 29, no. 4, pp. 1260-1278, 2024. https://doi.org/10.1057/s41264-024-00292-6

[84] L.-Y. Leong, T.-S. Hew, K.-B. Ooi, and J. Wei, "Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach," *International Journal of Information Management*, vol. 51, p. 102047, 2020.

[85] T. T. C. Phan, L. T. Nguyen, and T. Q. Dang, "Does impulsive buying lead to compulsive buying in metaverse? a dual-stage predictive-analytics SEM-ANN analysis the empirical study from Vietnam," *Thailand and The World Economy*, vol. 43, no. 2, pp. 44-66, 2025.

[86] L.-T. Nguyen, N.-T. T. Tran, T.-Q. Dang, and D. T. V. Duc, "Beyond transactions: Building customer loyalty and brand value cocreation in vietnamese financial apps," *Human Behavior and Emerging Technologies*, vol. 2025, no. 1, p. 5599209, 2025.

[87] L.-G. N. Phan, D. Q. Tri, S.-H. Dang, and L.-T. Nguyen, "Hooked on livestreaming: What drives customer repurchase intention in e-commerce?," *Journal of Creative Communications*, p. 09732586241311001, 2025. https://doi.org/10.1177/09732586241311001

[88] T.-Q. Dang, L.-T. Nguyen, and D. T. V. Duc, "Impulsive buying and compulsive buying in social commerce: An integrated analysis using the cognitive-affective-behavior model and theory of consumption values with PLS-SEM," *SAGE Open*, vol. 15, no. 2, p. 21582440251334215, 2025.

[89] T.-Q. Dang, D. T. V. Duc, L.-H. P. Tran, and L.-T. Nguyen, "Examining the impact of trust on customer intention to use metaverse payments: A next-gen transactions strategic outlook," *Corporate and Business Strategy Review,* vol. 6, no. 1, pp. 166-177, 2025.

[90] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks, California: SAGE, 2014.

[91] G. W.-H. Tan and K.-B. Ooi, "Gender and age: Do they really moderate mobile tourism shopping behavior?," *Telematics and Informatics,* vol. 35, no. 6, pp. 1617-1642, 2018.

[92] L.-W. Wong, G. W.-H. Tan, K.-B. Ooi, and Y. Dwivedi, "The role of institutional and self in the formation of trust in artificial intelligence technologies," *Internet Research,* vol. 34, no. 2, pp. 343-370, 2024.

[93] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research,* vol. 18, no. 1, pp. 39-50, 1981. https://doi.org/10.2307/3151312

[94] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review,* vol. 31, no. 1, pp. 2-24, 2019.

[95] K.-B. Ooi, V.-H. Lee, J.-J. Hew, L.-Y. Leong, G. W.-H. Tan, and A.-F. Lim, "Social media influencers: An effective marketing approach?," *Journal of Business Research,* vol. 160, p. 113773, 2023.

[96] N. Urbach and F. Ahlemann, "Structural equation modeling in information systems research using partial least squares," *Journal of Information Technology Theory and Application,* vol. 11, no. 2, p. 2, 2010.

[97] J. Hensler *et al.*, "Common beliefs and reality about PLS," *Organizational Research Methods,* vol. 2, pp. 182-209, 2014. https://doi.org/10.1177/1094428114526928

[98] Y.-M. Wang and T. M. Elhag, "A comparison of neural network, evidential reasoning and multiple regression analysis in modelling bridge risks," *Expert Systems with Applications,* vol. 32, no. 2, pp. 336-348, 2007. https://doi.org/10.1016/j.eswa.2005.11.029

[99] O. M. Horani, A. S. Al-Adwan, H. Yaseen, H. Hmoud, W. M. Al-Rahmi, and A. Alkhalifah, "The critical determinants impacting artificial intelligence adoption at the organizational level," *Information Development,* vol. 41, no. 3, pp. 1055-1079, 2025. https://doi.org/10.1177/02666669231166889

[100] D. A. Whetten, "What constitutes a theoretical contribution?," *Academy of Management Review,* vol. 14, no. 4, pp. 490-495, 1989. https://doi.org/10.2307/258554