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IoT Readiness Model for Urban Vocational School: Case Study in Indonesia

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ABSTRACT: The Internet of Things (IoT) holds significant potential to enhance vocational education, yet its implementation in this sector remains limited and has a low success rate. Ensuring organizational readiness is essential for successful IoT adoption. This study aims to develop a readiness model to assess the preparedness of urban vocational high schools (VHS) in Indonesia for IoT adoption. The research objectives are to identify key factors influencing VHS readiness, analyze their interrelationships, and determine priority areas for improvement to facilitate IoT adoption in urban VHSs. A quantitative online survey, covering ten factors and 54 indicators, was conducted with top management representatives from 159 urban VHSs in West Java, Indonesia. Data were analyzed through reflective measurement assessments, structural model assessments, and Importance-Performance Map Analysis (IPMA). The study identified four dimensions impacting VHS readiness for IoT adoption: environment, organization, technology, and people. The environmental dimension encompasses market forces, supporting industries, and government regulation, which in turn affect the organizational dimension, including governance and management support and financial readiness. The organizational dimension influences the technological dimension, represented by IoT infrastructure and data readiness and IoT operational readiness. The people dimension comprises technological pedagogical content knowledge and readiness to use technology, all of which directly or indirectly influence the primary factor, readiness to use IoT. Reflective assessments confirmed the validity and reliability of the indicators and factors, and structural model tests supported 12 of the 13 proposed hypotheses. IPMA results identified readiness to use technology and IoT infrastructure and data readiness as top priorities for improvement. This study offers valuable insights for VHS management in preparing for IoT adoption, contributing to the advancement of vocational education by synthesizing multiple foundational readiness frameworks. Additionally, it provides a reference for developing new models to assess and improve IoT readiness in educational settings or in other settings.

Keywords: adoption model, Internet of Things, readiness model, vocational education.

I. INTRODUCTION

The Internet of Things (IoT) represents a key technology in the Fourth Industrial Revolution (IR4.0), an era marked by the integration of advanced technologies that blur the boundaries between physical, digital, and biological realms [1]. IoT's capability to integrate virtual and physical systems at both local and global scales, along with its synergy with software-based technologies (e.g., artificial intelligence, big data, cloud computing) and hardware-based devices (e.g., sensors, edge computing nodes), has revolutionized industrial operations and innovation processes [2-4].

Vocational and Technical Education and Training (VTET) plays a critical role in equipping workers with the skills necessary to meet the demands of various industries and job levels [5, 6]. However, the rapid technological advancements under IR4.0 present challenges for VTET, particularly in developing countries. These advancements have impacted infrastructure, curriculum design, teaching methodologies, and industry-school partnerships, necessitating alignment with evolving industry standards [7, 8]. As technology continues to advance at an unprecedented pace, VTET institutions face increasing challenges in keeping pace with emerging skill requirements and frequent disruptions [6, 9-11]. This dynamic environment calls for a flexible learning model that maximizes resources, maintains relevance, and fosters interactive, adaptive, and personalized learning experiences [12-14]. Integrating IT-based innovations into educational processes and infrastructure has become essential in IR4.0 era.

Despite IoT's proven impact in sectors such as manufacturing, smart cities, healthcare, and logistics, its adoption in education remains limited [15-17]. Nevertheless, IoT offers promising applications in education, especially in the post-COVID-19 era, where digital learning innovations have accelerated [18]. Existing literature highlights IoT's potential to enhance learning through various applications, such as educational tools [19, 20], development of smart classrooms, laboratories, and campuses [21-25], support for inclusive education [26-28], and lifelong learning for diverse age groups [29-33]. Despite these benefits, IoT implementation across sectors faces challenges. Studies reveal that fewer than 50% of IoT projects achieve success. For instance, Beecham Research and Software AG report that only 12% of IoT projects are fully successful, with around 85% failing at the pilot or early deployment stages due to factors such as unclear objectives, infrastructure limitations, and technical challenges [34-37]. Given these statistics, ensuring organizational readiness is essential to minimize risks and increase the likelihood of successful IoT implementation. As in other sectors, the adoption of IoT in vocational education faces various challenges, including external factors such as competition and support from stakeholders that influence vocational education institutions, internal management readiness, the availability of supporting technologies, and the preparedness of teachers as end-users.

Vocational High Schools (VHS), as institutions responsible for vocational education in high school level, must adapt to produce graduates with competencies that align with industry needs. In this disruptive era, industries are required to optimize various technology-driven innovations, one of which is the IoT. The adoption of these innovations impacts the demand for skilled graduates, particularly in technical sectors. In Indonesia, the implementation of IoT holds significant potential for vocational education, aiming to enhance the quality of learning and improve student competencies. Successful IoT implementation depends on assessing both individual and organizational readiness comprehensively [38-40]. To evaluate the readiness of urban VHS institutions in Indonesia, it is essential to identify the key factors influencing their preparedness. Urban VHS institutions were chosen as the focus of this study because, given their resources and capabilities, they are better positioned to implement IoT compared to their rural counterparts. Understanding the relationships among these key factors is crucial for providing a holistic picture of urban VHS readiness for IoT adoption. Once these relationships have been established and analyzed, the next step is to determine which key factors should be prioritized for improvement. A critical analysis of recent literature reveals that no existing publications or tools specifically evaluate the readiness of VHS institutions for IoT adoption. This research aims to address this gap by developing an empirical-based framework to assess IoT adoption readiness in urban VHS.

- To address these challenges, the objectives of this study are as follows:
- To identify the key factors influencing the readiness of VHSs in Indonesia to adopt IoT.
- To develop a conceptual model of IoT adoption readiness for VHSs, incorporating the relationships between key factors from an organizational perspective.
- To determine the priority factors that urban VHSs should focus on to enhance their readiness for IoT adoption.

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II. RELATED WORK

The literature review aims to establish the contextual, theoretical, and conceptual models or frameworks pertinent to this study and identify research gaps that underscore the importance of this work compared to existing publications. To gather relevant literature, queries were carefully formulated to locate studies on IoT readiness models within the education sector. The search was conducted across major indexing databases: Google Scholar, Scopus, and Web of Science (WoS). The findings from the literature review identify conceptual models pertinent to IoT readiness in education and reveal specific research gaps that this study seeks to address.

To identify the existing research landscape, a literature search focused on readiness/adoption models/frameworks for implementing/adopting IoT in educational settings. Several key studies that align with this context were identified. Shaikh et al. investigated the factors influencing technology adoption in Higher Education Institutions (HEIs) in Pakistan [41]. The study proposed a conceptual framework based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), incorporating security and privacy risk factors. However, the study remained conceptual and did not conduct empirical validation of the proposed framework. Salah Hashim and Amin Al-Sulami explored IoT adoption in the educational context of Iraq [42]. Using a quantitative approach, they surveyed 221 students and faculty members at Basra University through stratified sampling. The study extended the UTAUT model by incorporating security as an exogenous factor and found that social influence was the most significant determinant of behavioral intention. Study by Rico-Bautista et al. examined IoT integration in HEIs through a comprehensive literature review to identify external and individual factors affecting IoT adoption [43]. The study developed a framework based on the TAM to assess critical components of IoT adoption. However, similar to Shaikh et al. [41], this study did not include empirical testing of the proposed framework.

Sabri et al. investigated the cultural factors affecting university readiness to adopt IoT in Saudi Arabian universities [44]. The study utilized Hofstede's cultural dimensions to construct its IoT acceptance model. A quantitative survey approach was employed, collecting responses from 390 faculty members and staff across six universities. Chweya proposed an IoT readiness model based on the SaaS Tripod Readiness Model and the TRI to analyze factors influencing IoT readiness in HEIs in Kenya [45]. The study surveyed 181 employees from three leading ICT institutions and applied SEM-PLS for empirical analysis. Additionally, the study employed IPMA to identify key areas for improvement in IoT adoption readiness. Madni et al. conducted a comprehensive literature review on IoT adoption in e-learning within developing countries [46]. The study identified four major contexts influencing IoT adoption: individual factors and the Technology-Organization-Environment (TOE) framework. However, no empirical validation was conducted.

Negm evaluated the readiness of Generation Z students to adopt IoT for online learning using the TRI model [47]. This quantitative deductive study surveyed 400 Egyptian university students and found that optimism, discomfort, and insecurity significantly influenced students' intention to adopt IoT. Uspabayeva investigated high school students' perceptions of IoT adoption in education [48]. The study utilized semi-structured interviews to collect qualitative data from 83 students in Kazakhstan. Unlike previous research, this study did not reference a specific IoT readiness model. Instead, the findings highlighted the need for integrating IoT awareness into educational curricula. Ali et al. examined IoT adoption in HEIs in Saudi Arabia using an inferential methodology [49]. A total of 384 participants from Saudi HEIs were surveyed. The study proposed a model based on four TOE dimensions and individual factors. The results confirmed that both TOE and individual factors significantly influenced IoT adoption.

A critical analysis of the reviewed literature reveals several key research gaps. Firstly, most studies focus on higher education institutions, while research on vocational education remains scarce. Vocational schools have distinct learning models emphasizing practical skills, requiring extensive interaction with laboratory and training equipment. IoT integration in vocational education can enhance the quality of training by ensuring the availability, industry relevance, and curriculum alignment of laboratory tools. A readiness model for IoT adoption in vocational education must address these unique aspects. Secondly, in Indonesia, high schools—particularly VHS—are significantly influenced by government policies regarding curriculum design and funding allocations for technological innovations. None of the reviewed models explicitly consider government roles as a determining factor in IoT readiness for educational institutions. Third, studies such as Chweya and Ali et al. incorporate technology dimensions within their IoT readiness frameworks but fail to capture the unique characteristics of IoT technology. Although Chweya explicitly references IoT in the data collection instrument, it does not sufficiently differentiate IoT from other digital technologies like SaaS. Other studies by Arsenijević et al. [38], Benotmane et al. [39] and Halper [50] provide a more detailed examination of technology dimensions specific to IoT, which should be integrated into this proposed model. Fourth, while several studies examine individual factors affecting IoT adoption, none specifically investigate teachers as the primary end-users in the learning process. There is a need to develop a model that assesses teachers' pedagogical competencies and their readiness to adopt IoT-based learning innovations. Lastly, studies evaluating organizational readiness for IoT adoption, such as as Chweya and Ali et al., do not explicitly indicate whether their respondents include decision-makers in educational institutions. In the context of urban vocational schools in Indonesia, school management—typically teachers with additional structural responsibilities plays a dual role as institutional decision-makers and end-users of IoT in classrooms. Future research should ensure that managerial respondents are adequately represented to provide a comprehensive perspective on organizational IoT readiness.

While prior research has made significant contributions to understanding IoT adoption in educational settings, gaps remain in addressing vocational education, government influence in vocational settings, IoT-specific technological characteristics, teacher and institutional decision-making readiness. This study focuses on evaluating IoT readiness among urban VHS in Indonesia, where there are approximately 14,000 VHS institutions and 5 million students [51]. Given this scale, the proposed IoT readiness model is expected to have a significant impact on improving the quality of vocational education. To address the gap, the first objective of this study is to identify and select key factors that comprehensively assess both organizational and user perspectives. Additionally, this research aims to identify critical areas that require improvement, providing practical contributions to VHS institutions in their IoT adoption efforts. VHS are high school institutions in Indonesia designed for students aged 16–18. VHS had the highest number of students and schools among secondary education levels between 2020 and 2022. The large number of VHS and student population presents significant potential for technological innovation to substantially impact vocational education.

However, vocational education in Indonesia faces several challenges, including inadequate and insufficient infrastructure, the quality and availability of teachers, learning effectiveness, industry engagement and collaboration, financial constraints [11], as well as policy-related issues and curriculum relevance [52]. These challenges have directly affected the quality of vocational education, as reflected in the open unemployment rate among VHS graduates. Over the past decade (2015–2024), VHS graduates have consistently recorded the highest unemployment rates compared to graduates of general high schools, diploma programs, and universities [53]. Although information technology has proven to enhance education quality, its adoption in VHS alone does not automatically resolve all existing issues. As an evolving and highly integrative technology, the IoT offers significant potential for use as a learning medium and a supporting infrastructure in VHS education [54-55]. IoT implementation can contribute to improving learning quality by serving as an automated and integrated teaching aid or simulator [56-60] and by optimizing operational processes in educational activities [61-63]. Given its potential for driving educational innovation, VHS institutions must prepare for IoT adoption. One of the key objectives of this study is to evaluate VHS readiness for IoT adoption through the proposed readiness model.

III. RESEARCH METHOD

Considering the context, analyzed data, research timing, and data collection and processing methods, this study utilizes a positivist paradigm, quantitative, cross-sectional research method, employing an online survey to develop and validate the proposed IoT readiness model [64]. To achieve the research objectives, the design of this study encompasses five key stages: first, determining the primary factors as the model's foundation; second, constructing the hypotheses and IoT readiness model; third, developing appropriate indicators or instruments to gather the necessary data; and finally, analyzing and interpreting the collected data to test the validity of the proposed model.

1. IDENTIFY THE KEY FACTORS

The proposed model evaluates organizational readiness from organizational and user/people perspectives to ensure successful IoT adoption in VHS. The organizational perspective assesses readiness through environmental, organizational, and technological dimension adapted from the TOE framework. In contrast, the user perspective examines teachers' capacity and readiness to use technology, represented by the people dimension. Factors for each dimension are developed by adopting and adapting validated frameworks/models specifically designed to evaluate corresponding dimensions in diverse contexts, ensuring robustness and contextual relevance.

1.1 Organizational Perspective

The TOE framework is a model proposed by Tornatzky et al. to assess an organization's readiness to adopt technological innovations [65]. It is a validated, empirically proven, and reliable framework for evaluating an organizations or enterprise's preparedness for adopting information system (IS)-based innovations [66-67]. The TOE framework consists of three primary contexts: technological, organizational, and environmental. *Technological Context*: evaluates the availability of technology, including existing technologies owned by the organization, new technologies that may enhance competitiveness, and the characteristics of these technologies. *Organizational Context*: refers to internal organizational characteristics that influence technology adoption, including top management support, organizational structure, financial and human resources, and innovation culture. *Environmental Context*: examines external factors beyond the organization's control, such as government policies and regulations, market trends and competition, and pressures from business partners or customers.

Apart from the TOE framework, another model used to measure organizational readiness for adopting e-commerce and digital technologies is the Perceived E-Readiness Model (PERM), proposed by Molla and Licker [68]. PERM evaluates two key dimensions: *Perceived Organizational E-Readiness* (POER): Consists of awareness, human resources, business resources, technology resources, commitment, and governance. *Perceived External E-Readiness* (PEER): Includes government, market forces, and support industries.

The TOE and PERM models serve as references for constructing an IoT readiness model for VHS. The IoT readiness model adopts the TOE framework, which comprehensively evaluates the three primary aspects influencing an organization's capacity to adopt innovation. After defining the dimensions for evaluating VHS readiness, the next step is identifying the underlying factors.

A. Environmental dimension

In Indonesian vocational education, the government plays a critical role as a policymaker and regulator, providing infrastructure, funding, and oversight [69]. Thus, government regulation (GVR) is a fundamental factor in the environmental dimension, aligning with TOE and PERM. Additionally, industry support significantly influences VHS institutions by shaping policies and fostering technology-driven learning innovations [70]. Industry collaboration is essential for IoT adoption, as it supplies the necessary infrastructure and drives policies to align VHS curricula with industry standards [71]. In TOE, technology support infrastructure is a key component, while PERM includes support industries. Considering that industrial support extends beyond infrastructure to include internships and curriculum development, the supporting industries (SPI) factor is proposed as the second environmental dimension factor. Furthermore, competition among VHS institutions fosters early adoption of technological advancements [72]. The demand for high-quality VHS graduates from industries and students/parents expecting quality education further motivates IoT adoption [73-75]. Consequently, market forces (MKF) are identified as the third factor in the environmental dimension, representing the competitive pressures from competitors, customers, and partners.

B. Organizational Dimension

The readiness of VHS top management in establishing governance and implementing strategies is crucial for achieving institutional objectives [76]. Top management support is essential for ICT-based innovations aligned with Industry 4.0 [77, 78]. Therefore, governance and management support (GMS) is the first organizational factor. The second factor is financial readiness (FRD), which refers to the availability of financial resources, directly impacting technology procurement and management [50, 77]. Unlike the TOE framework's organizational structure and PERM's organizational e-readiness, this IoT readiness model selects GMS and FRD, as these factors best represent the characteristics of VHS institutions in Indonesia. VHS institutions generally have large-scale but non-complex organizational structures, making the adoption of other TOE organizational components unnecessary. Additionally, awareness, human resources, and business resources from PERM are excluded as VHS institutions do not meet the criteria for these components. However, commitment and governance from POER are adapted.

C. Technological Dimension

In PERM, there is no specific dimension addressing technology, whereas TOE's technological context primarily considers technology availability (including existing technology, market supply, technical support, and expertise) and technology characteristics (such as relative advantage, compatibility, complexity, and observability). However, these factors do not fully represent IoT characteristics. Therefore, this study adapts models specifically addressing IoT adoption readiness. Two relevant models are: (1) TDWI IoT Readiness Model: Consists of six dimensions for assessing technological readiness: organizational readiness, data readiness, infrastructure readiness, analytics readiness, and IT, development, and operations readiness [50]. (2) IoT-Assessment Maturity Model (IoT-AMM): Defines five maturity stages for IoT adoption: organizational and business readiness, data and application, technology and infrastructure, governance and compliance, and requirement and change management [39]. From these models, two key technological readiness factors are identified: IoT infrastructure and data readiness (IDR): Covers infrastructure availability and system integration [50, 79]. IoT operational readiness (IOR): Concerns system configuration and technical support [39, 80, 81]. The IDR factor is developed by adapting data readiness and infrastructure readiness from TDWI IoT readiness model and Stages 2 and 3 of IoT-AMM. The IOR factor is derived from analytics readiness, IT, development, and operations readiness from TDWI IoT readiness model and governance and compliance (Stage 4) from IoT-AMM.

1.2 People Perspective

Incorporating the end-user perspective into a model that assesses organizational readiness enhances the model's performance [49, 82, 83]. This study adopts frameworks that specifically measure the readiness of end-users—VHS teachers—from a pedagogical perspective to integrate IoT in learning process. The Technology-Pedagogical-Content Knowledge (TPACK) framework is widely used to help teachers assess their knowledge to integrate technology into the learning process [84]. TPACK consists of three core knowledge components: technological knowledge (understanding how to use technology effectively), pedagogical knowledge (knowledge of effective teaching methods), and content knowledge (expertise in the subject being taught). This framework is applied to evaluate teachers' knowledge to combine technology, instructional strategies, subject content, and to develop IoT-based learning strategies. Research has shown that teachers' proficiency in technology integration, as measured by TPACK, positively influences their readiness to adopt IoT [85, 86]. Research shows that teachers' proficiency in technology application, as measured by TPACK, positively influences their readiness to adopt IoT [85, 86]. Several studies published by Öztürk et al. [87] and Torggler et al. [88] have evaluated TPACK among VHS teachers, including the development and application of data collection instruments. Another framework used in this study is the Technology Readiness Index (TRI), a widely recognized model for assessing an individual's readiness to adopt technology-based innovations. The TRI categorizes factors that either promote or hinder technology adoption. Parasuraman's revised TRI v2 reduced the original 36-item scale to 16 items, making it more applicable in both theoretical and practical contexts contexts [89]. This study adapts the TRI framework to evaluate the readiness of vocational educators to adopt IoT.

Within the proposed model, TPACK readiness is treated as an exogenous factor, influencing overall technology readiness within the people dimension. The people dimension represents the human perspective and consists of two primary factors: TPACK readiness (TPCK) and readiness to use technology (RUT). Additionally, alongside factors from organizational and people perspectives, the model incorporates a key endogenous factor: readiness to use IoT (RTI).

2. PROPOSED HYPOTHESES AND MODEL IOT READINESS

The proposed model utilizes 10 factors to assess VHS readiness for IoT adoption from organizational and individual perspectives, with RTI as the main endogenous factor. The structural relationships among these factors form a comprehensive model of VHS readiness to adopt IoT in educational processes, with significant practical implications for management and teachers in VHS institutions, as illustrated in Figure 1. The hypotheses in this study are formulated based on the relationships between factors that have been previously explained. The proposed hypotheses are as follows:

H1: MKF exert a significant and positive influence on GMS. MKF represent external pressures—such as competition, customer demand, and business partner expectations—that drive organizations toward adopting new technologies [68, 90, 91]. MKF serves as a significant motivator for VHS institutions, influencing them to align with industry demands by equipping graduates with specific information technology skills. MKF shapes strategic initiatives aimed at achieving the vision and mission of VHS institutions, which are realized through the support and management of relevant programs.

H2. SPI have significant and positive impact on GMS. In developing countries, technology adoption is shaped by three primary factors: the affordability and accessibility of IT services, the development of the financial sector, and the penetration and reliability of transportation systems [46, 92, 93]. SPI encompass the development, service levels, and cost structure of essential sectors such as telecommunications, finance, and IT. These industries facilitate IoT initiatives within the learning environment by providing critical infrastructure and services. Specifically, in the context of IoT implementation, industries supplying IoT components and services significantly contribute to VHS management's readiness to adopt IoT to enhance educational practices [68].

H3a. GVR significantly and positively affect the GMS; and H3b. GVR significantly and positively influence FRD. Government involvement is crucial in promoting, supporting, facilitating, and regulating organizations within its jurisdiction [94-96]. In managing vocational education in Indonesia, the government plays an influential role by developing curricula and learning guidelines, providing necessary infrastructure, and offering financial support, particularly to public VHS institutions. GVR set strategic directions, shape management practices, and inform financial policies within VHS institutions, thereby impacting the adoption of IoT-based educational innovations.

H4a. GMS significantly and positively contribute to FRD; H4b. GMS significantly positively affect IDR; and H4c. GMS significantly and positively contribute to IOR. Governance form the foundation for management to allocate resources and make informed decisions [97-98]. Management support reflects management's intention to adopt technology and foster a supportive environment [68, 78, 99]. In VHS, management plays a vital role in formulating, executing, and evaluating strategies related to the learning process. Management's readiness and support for utilizing available resources to implement learning innovations directly impact the financial readiness of VHS [100], and their ability to provide IoT infrastructure, operate IoT systems and ensure IoT operational readiness [46, 101, 102].

H5a. FRD significantly and positively affect IDR; and H5b. FRD significantly and positively impact IOR. FRD refers to an organization's preparedness to allocate financial resources for the implementation and ongoing operation of technology [77, 78, 99, 103]. Implementing technology entails costs for acquiring or upgrading systems as well as operational and technological enhancements. The financial readiness of each VHS is crucial, as it directly affects their ability to provide IoT infrastructure, maintain IoT systems [104, 105], implement cybersecurity measures, and achieve full IoT adoption [46, 101, 102].

H6. IDR contribute significantly and positively to RTI. IDR indicates an organization's preparedness to establish the necessary architecture and storage systems to manage IoT data effectively. The availability and readiness of infrastructure and data are essential to the successful deployment of IoT within an organization [79]. Common challenges include hardware integration, connectivity, scalability, and data storage [35]. Data and system security are top priorities for organizations implementing IoT [36, 106-109]. Ensuring the systems are regularly updated, tested, and compliant with security policies is critical for safeguarding data.

H7. IOR contribute positively and significantly to RTI. IOR measures a VHS's capacity to configure, monitor, and update IoT components to ensure optimal functionality [50, 79]. Collecting and analyzing IoT data is vital for successful implementation [35]. IoT operations must adhere to established Information

Quality standards, and providing technical support is essential to maintain smooth operations [110]. VHS's operational security and readiness to update and test IoT systems substantially influence their preparedness for IoT-based learning [80, 81, 111]. With technical expertise and a dedicated team, teachers can focus more on the pedagogical process, significantly enhancing IoT adoption within the institution.

H8. TPCK contribute positively and significantly to RUT. TPCK readiness relates to teachers' preparedness to integrate technology into pedagogical practices to support student learning and knowledge construction. Studies show that TPACK readiness positively influences IoT adoption in educational contexts [85, 86, 112]. Elements like optimism and innovation, part of technological knowledge, closely align with teachers' pedagogical content knowledge and significantly affect IoT adoption.

H9. RUT contribute positively and significantly to RTI. RUT describes individuals' readiness to embrace and utilize new technologies to achieve personal and professional goals [89, 113, 114]. It reflects users' perceived advantages and disadvantages of using technology. Higher user readiness corresponds to increased organizational readiness for IoT-based learning adoption.

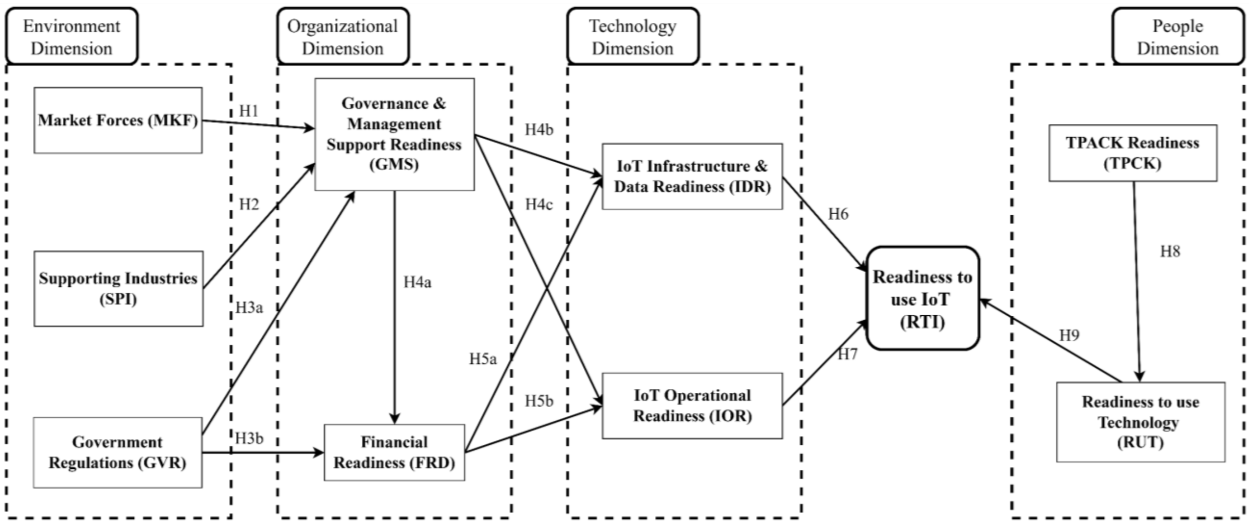

FIGURE 1. Proposed IoT readiness model.

IV. DEVELOPING QUESTIONNAIRE INSTRUMENTS

Developing valid and relevant questionnaire instruments is a critical step in measuring the readiness of VHS to adopt IoT in the learning process. The questionnaire is carefully designed by adopting and adapting various instruments previously developed and utilized in reputable publications. The instrument is then validated by experts in vocational education, IoT, and IT adoption/readiness using the Content Validity Index (CVI) framework proposed by Lynn [115]. Following the CVI evaluation, the instrument is tested through a pilot study involving 40 respondents to ensure its reliability and effectiveness.

1. DEVELOPING AND VALIDATING THE QUESTIONNAIRE INSTRUMENT

The questionnaire instruments were developed by referencing items from relevant sources aligned with the factors of the proposed model. The questionnaire was designed by adapting reference instruments to suit the context of vocational education. This adaptation involved modifying questions to align with VHS institutional processes and outcomes. Instruments for the MKF and SPI factors were adapted from the PERM model by Molla and Licker [116] and Hung et al. [90]. The TOE model for e-business by Zhu et al. [117], and the integrated TAM-TOE model by Gangwar et al. [67]. The GVR factor instrument was adapted from studies by Molla and Licker [116 and Zhu et al. [117]. Instruments for the GMS factor was adjusted from studies using the PERM model for e-commerce [68, 116], the TOE model for e-business [117], TAM-TOE model applications in cloud computing adoption [118], IoT adoption [119], B2B e-commerce [120], and cloud computing adoption in higher education institutions [105]. Instruments for FRD were adapted from models developed by Molla and Licker. Instruments for IDR and IOR were customized based on questionnaire items by Halper [50] and Alrae et al. [118]. In the people dimension, instruments for RUT and TPCK factors were primarily adapted from TRI2 by Parasuraman and Colby [89] and TPACK frameworks adapted from Madni et al. [46], Pamuk et al. [112] and Schmid et al. [121]. The main factor, RTI, was synthesized from various contributing models, including TOE, PERM, the TDWI IoT Readiness Model, IoT-AMM, TRI, and TPACK. The instrument of questionnaire consisted of 59 items measured on a 5-point Likert scale.

The CVI was used to validate the adaptation and translation, focusing on three main areas: IoT-based innovations, technology readiness, and vocational education Experts were selected based on their relevant expertise, academic background, and years of experience, following the optimal panel size of 5 to 10 experts [122]. This study involved seven experts comprising: three managers from VHS institutions offering engineering and computing programs, two IT adoption experts, and two IoT experts. The VHS managers represented expertise in relevant fields, serving as teachers with structural roles and having over five years of managerial experience. Each of these managers holds a master's degree in engineering or computing. Their insights were crucial in assessing the relationships between government, industry, and schools, as well as understanding school management and learning processes. The IT adoption and IoT experts were selected based on their academic achievements and practical experience. One IT adoption expert holds the title of Professor and has over ten years of practical experience in the education technology field. The IoT experts include a Professor and an Associate Professor, both with extensive IoT research backgrounds and more than ten years of industry involvement. The IT adoption and IoT experts played a key role in evaluating the relevance of the instrument in measuring VHS readiness for IoT-based innovations, leading to significant refinements in the questionnaire. The calculated CVI score using S-CVI/UA was 0.85, above the 0.83 threshold for panels of six to eight experts, indicating strong validity for the instrument [122, 123].

2. *PILOT STUDY*

The validated questionnaire was then pilot-tested with 40 teachers from engineering programs at urban VHS schools. Based on Hertzog's recommendation, a sample size of 30-40 is appropriate for pilot studies [124]. Pilot study results are presented in Table 1, Table 2, and Table 3, including loadings, reliability, validity, and collinearity analysis. Loadings between indicators and factors were analyzed, with a threshold of 0.708 [125-127]. Internal consistency was assessed using Cronbach's alpha, rho_a, and rho_c, with a 0.7 threshold for reliability. Convergent validity was assessed via Average Variance Extracted (AVE) values, which were acceptable above 0.5 [126]. Collinearity was analyzed with the Variance Inflation Factor (VIF), with acceptable values from 1 to 5 [127].

Table 1. Pilot study's outer loadings result.

Indicator Code	Loadings	Indicator Code	Loadings	Indicator Code	Loadings
FRD1	0.929	IDR6	0.126*	RUT05	0.096*
FRD2	0.910	IOR1	0.909	RUT06	0.698*
FRD3	0.875	IOR2	0.715	RUT07	0.697*
FRD4	0.760	IOR3	0.742	RUT08	0.387*
GMS1	0.747	IOR4	0.934	RUT09	0.563*
GMS2	0.861	IOR5	0.955	RUT10	0.297*
GMS3	0.851	IOR6	0.219*	RUT11	0.147*
GMS4	0.826	IOR7	0.125*	RUT12	-0.221*
GMS5	0.809	MKF1	0.738	RUT13	0.4*
GMS6	0.792	MKF2	0.674*	RUT14	0.217*
GVR1	0.521*	MKF3	0.802	RUT15	0.367*
GVR2	0.715	MKF4	0.697	SPI1	0.848
GVR3	0.854	RTI1	0.745	SPI2	0.699*

Indicator Code	Loadings	Indicator Code	Loadings	Indicator Code	Loadings
GVR4	0.856	RTI2	0.856	SPI3	0.637*
GVR5	0.917	RTI3	0.881	SPI4	0.802
IDR1	0.581*	RTI4	0.723	TPCK1	0.346*
IDR2	0.888	RUT01	0.557*	TPCK2	0.749
IDR3	0.804	RUT02	0.379*	TPCK3	0.803
IDR4	0.867	RUT03	0.262*	TPCK4	0.898
IDR5	0.012*	RUT04	0.253*		

* Values below the threshold

Table 1 presents the loadings results, while Table 2 provides the reliability and validity outcomes. Based on the loading's calculations, 26 indicators showed values below 0.7, with 16 indicators falling below 0.5, suggesting potential areas for refinement. The results for internal consistency (Cronbach's alpha, ρ_a and ρ_c) and convergent validity (AVE) indicate that the RUT factor values fall below recommended thresholds. However, collinearity values, shown in Table 3, remained within acceptable ranges.

Table 2. Pilot study's outer loadings result.

Factors	Cronbach's Alpha	ρ_a	ρ_c	AVE
FRD	0.892	0.909	0.926	0.759
GMS	0.899	0.903	0.922	0.665
GVR	0.836	0.881	0.886	0.617
IDR	0.654*	0.882	0.756	0.423*
IOR	0.809	0.947	0.866	0.534
MKF	0.711	0.716	0.819	0.532
RTI	0.822	0.887	0.879	0.646
RUT	0.741	0.627*	0.676*	0.169*
SPI	0.747	0.805	0.836	0.564
TPCK	0.724	0.841	0.807	0.533

* Values below the threshold

Refinements were made based on pilot findings to fit the study context better (revising the questions), as initial indicators did not fully capture the nuances of the RUT factor. Given the sample size, low outer loadings, and teacher (not managerial) participants, no indicators were removed during the pilot phase. Indicator removal will be revisited in the main analysis with the final dataset.

Table 3. Pilot study's collinearity analysis.

Path	VIF	Path	VIF
FRD -> IDR	2.167	IDR -> RTI	2.551
FRD -> IOR	2.167	IOR -> RTI	1.922
GMS -> FRD	1.491	MKF -> GMS	1.898
GMS -> IDR	2.167	RUT -> RTI	1.503
GMS -> IOR	2.167	SPI -> GMS	2.120
GVR -> FRD	1.491	TPCK -> RUT	1.000
GVR -> GMS	1.603		

To ensure clarity for respondents, the questionnaire was translated into Indonesian. Since most respondents primarily use Indonesian, translation was critical to minimize misinterpretation. A backward-forward translation approach was employed, as recommended by Degroot et al. [128]. First, the instrument was translated from English to Indonesian by bilingual experts from a language institute. It was then back-translated into English, with discrepancies reconciled by VHS management representatives to ensure accuracy and context relevance.

3. DATA COLLECTION

Research by Suharno et al. indicates that rural VHSs in Indonesia often lack the necessary infrastructure [11]. In contrast, urban VHSs tend to have better resources. By 2024, 56% of VHSs ar located in Java, particularly in West Java, which has the highest concentration of these schools [129]. West Java Province consists of 18 regencies and 9 municipalities, with population densities in municipalities generally 30 times higher than in regencies. Urban areas in Indonesia are defined as regions with a population density of over 5,000 people per square kilometer and less than 25% agricultural land [130], ensuring the presence of necessary infrastructure, including transportation, electricity, and telecommunications networks. This focused sampling ensures that selected VHS institutions possess both the capability and potential for successful IoT implementation in their educational processes. Based on these criteria, all districts within municipalities are classified as urban, while 24 districts within regencies are also considered urban. In total, 933 VHSs are located in urban areas.

The next criterion for selecting respondents involved choosing VHSs with an 'A' accreditation and those offering technical and/or computing programs. The 'A' accreditation was used to ensure that these VHSs have adequate facilities, infrastructure, and learning resources, making them more capable of implementing IoT. VHSs offering technical or computing programs were considered more likely to adopt IoT technologies, as these programs align more closely with the industries that employ their graduates, compared to non-technical or non-computing programs. Based on these selection criteria, 180 schools met the requirements. The Yamane formula was applied to determine representative sample size, resulting in a sample size of 125 schools [131]. The Yamane formula is expressed as:

$$n = N/(1 + N(e^2) \qquad (1)$$

where n is the sample size, N is the population size (N = 180), and e is the margin of error (e=0.05). In the distributed form questionnaire, the first page included an ethical concern statement outlining informed consent. This statement provided details on the survey process, potential risks, data confidentiality, and contact information The study questionnaire was distributed online to school principals or management representatives via email and messaging platforms. This process was supported by an official letter of permission and endorsement from the West Java Provincial Department of Education. Data collection took place from February to June 2024, ensuring a thorough approach to gathering insights from VHSs in the region.

V. DATA ANALYSIS AND RESULTS

The model proposed in this study aims to identify the key factors that influence the readiness of VHSs to implement IoT technology. The research begins with an assessment of the measurement model, which can be characterized as either reflective or formative, given that this study employs a reflective model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was selected as the analytical approach [132]. PLS-SEM is recommended for predictive models with complex structures, small sample sizes, and when extending existing structural frameworks, making it suitable for this research [133-135]. The assessment of the measurement model involves evaluating indicator loadings, internal consistency reliability, convergent validity, and discriminant validity. Subsequently, the study examines the relationships between factors within the structural model, focusing on VIF, explanatory power, out-of-sample predictive power, and path coefficients. In addition, an Importance-Performance Map Analysis (IPMA) is conducted to highlight key factors and indicators that should be prioritized for organizational action. The questionnaire for this study consisted of 59 indicators presented in a multiple-choice format using a 5-point Likert scale. A total of 160 responses were collected, with one response deemed invalid, resulting in 159 valid data for analysis. This sample size far exceeds the minimum threshold calculated using Yamane’s formula, ensuring the reliability of the dataset.

1. MEASUREMENT ASSESSMENT/OUTER MODEL RESULT

The initial step in assessing the measurement model involves evaluating the indicators that define each factor. Outer loadings are commonly analyzed to determine the contribution of each indicator to its corresponding factor. Table 4 presents the results of the outer loading analysis based on initial data directly obtained from respondents. Out of 59 indicators across 10 factors, 14 indicators fall below the recommended threshold of 0.708 [136].

Table 4. Outer loadings calculation results of initial instrument data.

Indicator Code	Loadings	Indicator Code	Loadings	Indicator Code	Loadings
FRD1	0.869	IDR6	0.327**	RUT05	0.176**
FRD2	0.863	IOR1	0.769	RUT06	0.428**
FRD3	0.858	IOR2	0.848	RUT07	0.26**
FRD4	0.760	IOR3	0.857	RUT08	0.790
GMS1	0.712	IOR4	0.825	RUT09	0.823
GMS2	0.762	IOR5	0.820	RUT10	0.822
GMS3	0.825	IOR6	0.614*	RUT11	0.780
GMS4	0.749	IOR7	0.523*	RUT12	0.817
GMS5	0.769	MKF1	0.746	RUT13	0.788
GMS6	0.752	MKF2	0.780	RUT14	0.762
GVR1	0.595*	MKF3	0.806	RUT15	0.645*
GVR2	0.700	MKF4	0.696*	SPI1	0.754
GVR3	0.804	RTI1	0.838	SPI2	0.841
GVR4	0.771	RTI2	0.901	SPI3	0.591*
GVR5	0.820	RTI3	0.852	SPI4	0.761
IDR1	0.779	RTI4	0.830	TPCK1	0.831
IDR2	0.756	RUT01	0.639*	TPCK2	0.824
IDR3	0.827	RUT02	0.724	TPCK3	0.756
IDR4	0.850	RUT03	0.585*	TPCK4	0.644*
IDR5	0.716	RUT04	0.509*		

* Retained indicators with outer loading values between 0.5 and 0.7.

** Indicators removed due to outer loading values below 0.5, indicating insufficient contribution to the factor.

Following the guidelines provided by Hair et al. [135], indicators with outer loadings between 0.4 and 0.7 may be removed if their exclusion enhances internal consistency reliability or convergent validity. On other Hair's publications the outer loading values above 0.5 are acceptable, although values above 0.7 are preferable [127]. Retaining indicators within the 0.5 to 0.7 range helps maintain the conceptual integrity of each factor, as these indicators were adapted from established, validated models. Indicators with loadings between 0.5 and 0.7, however, were retained in this study, as their removal did not significantly affect internal consistency reliability, convergent validity, discriminant validity, VIF, explanatory power, or path coefficients. Based on these criteria, four indicators—IDR6, RUT5, RUT6, and RUT7—were removed. After recalculating outer loadings post-removal, one additional indicator, RUT4, showed a loading value below 0.5 and was therefore removed as well, resulting in a final set of 54 indicators as detailed in Table 5.

Table 5. Outer loadings calculation results of refinement instrument data.

Indicator Code	Loadings	Indicator Code	Loadings	Indicator Code	Loadings
FRD1	0.869	IDR4	0.861	RUT02	0.684
FRD2	0.863	IDR5	0.697	RUT03	0.537
FRD3	0.858	IOR1	0.769	RUT08	0.825
FRD4	0.760	IOR2	0.848	RUT09	0.858
GMS1	0.713	IOR3	0.857	RUT10	0.882

GMS2	0.762	IOR4	0.825	RUT11	0.823
GMS3	0.826	IOR5	0.820	RUT12	0.847
GMS4	0.748	IOR6	0.613	RUT13	0.821
GMS5	0.768	IOR7	0.522	RUT14	0.801
GMS6	0.752	MKF1	0.746	RUT15	0.682
GVR1	0.595	MKF2	0.780	SPI1	0.754
GVR2	0.700	MKF3	0.806	SPI2	0.841
GVR3	0.804	MKF4	0.696	SPI3	0.591
GVR4	0.771	RTI1	0.841	SPI4	0.761
GVR5	0.820	RTI2	0.903	TPCK1	0.853
IDR1	0.798	RTI3	0.848	TPCK2	0.834
IDR2	0.754	RTI4	0.827	TPCK3	0.735
IDR3	0.826	RUT01	0.617	TPCK4	0.577

Table 6 presents the changes in internal reliability and convergent validity between the initial instrument data and the refined instrument data. In the initial instrument data, all parameters for consistency reliability exceeded the established thresholds. According to Hair et al., the threshold values for Cronbach's Alpha, ρ_a, and ρ_c, which indicates the consistency and reliability of a factor, should be above 0.7 [127]. However, the validity test using AVE showed that the RTI factor had a value of 0.446, which is below the acceptable threshold of 0.5. After the refinement process, all values for consistency reliability and convergent validity exceeded the prescribed thresholds, demonstrating significant improvements in the instrument's reliability and validity.

Table 6. Internal consistency reliability and convergent validity result of initial and refinement instrument data.

Factors	Initial Instrument Data				Refinement Instrument Data			
	Cronbach's Alpha	ρ_a	ρ_c	AVE	Cronbach's Alpha	ρ_a	ρ_c	AVE
FRD	0.858	0,859	0,904	0,703	0,858	0.859	0.904	0.703
GMS	0.855	0,859	0,893	0,581	0,855	0.859	0.893	0.581
GVR	0.795	0,817	0,858	0,551	0,795	0.817	0.858	0.551
IDR	0.814	0,859	0,866	0,534	0,848	0.858	0.891	0.623
IOR	0.874	0,894	0,903	0,578	0,874	0.894	0.903	0.578
MKF	0.753	0,759	0,843	0,575	0,753	0.759	0.843	0.575
RTI	0.896	0,910	0,916	0,446*	0,928	0.937	0.940	0.592
RUT	0.878	0,883	0,916	0,732	0,878	0.885	0.916	0.732
SPI	0.725	0,751	0,829	0,551	0,725	0.751	0.829	0.551
TPCK	0.777	0,803	0,850	0,589	0,777	0.782	0.841	0.574

* Values below the threshold

After calculating outer loadings, internal consistency reliability, and convergent validity for the pilot and main study data, significant improvements were observed. Initially, 26 indicators in the pilot study exhibited outer loading values below 0.7, with 16 indicators around 0.5. Following adjustments to questionnaire items to better fit the context, increased relevance in respondent selection, and appropriate sample size, the number of indicators with outer loadings below 0.7 decreased to 14 in the main study, of which 5 were below 0.5 (including one indicator post-recalculation). Furthermore, improvements in internal consistency reliability and convergent validity were observed from the pilot to the main study. In the pilot study phase, the IDR factor showed Cronbach's alpha and AVE values below the set thresholds, while the RUT factor had values under the recommended thresholds for ρ_a, ρ_c, and AVE, as indicated in Table 1. In the main study, however, all factor (including RUT factor) values met or exceeded the thresholds as presented in Table 5, confirming improved model robustness.

Discriminant validity was assessed to confirm that each factor is empirically distinct from others in the structural model. This was evaluated using the heterotrait-monotrait (HTMT) ratio, a robust method even when indicator loadings range between 0.65 and 0.85 [137]. Table 7 shows that all factor relationships satisfy the HTMT criterion of remaining below 0.85, with two exceptions: the relationship between IDR and IOR, and between SPI and MKF, which exhibit HTMT values of 0.860 and 0.967, respectively. These elevated values suggest potential issues with discriminant validity between these factor pairs, possibly indicating overlapping perceptions of IOR with IDR, and SPI with MKF, within the model.

Table 7. Htmt ratios among factors.

Relation	HTMT	Relation	HTMT	Relation	HTMT
GMS ↔ FRD	0.733	RUT ↔ FRD	0.448	SPI ↔ GVR	0.659
GVR ↔ FRD	0.487	RUT ↔ GMS	0.400	SPI ↔ IDR	0.747
GVR ↔ GMS	0.565	RUT ↔ GVR	0.317	SPI ↔ IOR	0.595
IDR ↔ FRD	0.686	RUT ↔ IDR	0.384	SPI ↔ MKF	0.962*
IDR ↔ GMS	0.758	RUT ↔ IOR	0.429	SPI ↔ RUT	0.500
IDR ↔ GVR	0.561	RUT ↔ MKF	0.511	SPI ↔ RTI	0.494
IOR ↔ FRD	0.570	RTI ↔ FRD	0.523	TPCK ↔ FRD	0.635
IOR ↔ GMS	0.691	RTI ↔ GMS	0.475	TPCK ↔ GMS	0.614
IOR ↔ GVR	0.473	RTI ↔ GVR	0.223	TPCK ↔ GVR	0.473
IOR ↔ IDR	0.860*	RTI ↔ IDR	0.588	TPCK ↔ IDR	0.618
MKF ↔ FRD	0.511	RTI ↔ IOR	0.532	TPCK ↔ IOR	0.681
MKF ↔ GMS	0.604	RTI ↔ MKF	0.497	TPCK ↔ MKF	0.406
MKF ↔ GVR	0.609	RTI ↔ RUT	0.654	TPCK ↔ RUT	0.419
MKF ↔ IDR	0.715	SPI ↔ FRD	0.512	TPCK ↔ RTI	0.426
MKF ↔ IOR	0.645	SPI ↔ GMS	0.637	TPCK ↔ SPI	0.479

* HTMT values exceeding the established threshold

The IOR and IDR collectively constitute the technological dimension of this study. Although in research method section outlines a clear distinction between IOR and IDR, ambiguity may still be present within the questionnaire. This potential ambiguity is primarily due to the overlapping terminology used—specifically terms like 'data,' 'information,' 'infrastructure/devices,' and 'security'—which may introduce confusion for respondents."

The MKF and SPI factors are part of the environmental dimension, examining how external organizations influence VHS. According to Hung et al. [90] and Molla and Licker [96], the key difference between MKF and SPI lies in their focus and type of influence. MKF pertains to competitive conditions where external entities—competitors, service users, suppliers, or other business partners—adopt new innovations to enhance their competitive advantage. This adoption creates competitive pressures, driving shifts in user preferences, and altering supply and demand dynamics. As a result, urban VHS are compelled to adapt to remain competitive, provide reliable and relevant services, and align their offerings with external market conditions by incorporating innovations. In contrast, SPI centers on the availability and capability of external industries to provide the essential services and infrastructure required for urban VHS to implement and operate innovations effectively. This factor emphasizes the role of supporting industries in facilitating innovation adoption by supplying the necessary resources and infrastructure, thus enabling smoother and more efficient operation.

While MKF and SPI may overlap in meaning from the respondents' perspectives, potentially leading to ambiguity, they influence urban VHS behavior in distinct ways. MKF drives urban VHS to continuously adapt and innovate to maintain market competitiveness and meet evolving industry demands. On the other hand, SPI motivates urban VHS to enhance performance and operational efficiency by ensuring that innovations are implemented effectively and supported by adequate infrastructure and resources. In instances where the HTMT value between two factors exceeds 0.85, 138. Sarstedt et al. offer practical guidance on the flexibility of applying this threshold, especially for conceptually similar factors, such as those sharing cognitive or affective elements [138]. Applying overly strict limits may lead to unnecessary modifications or even the elimination of meaningful and significant factors, ultimately affecting model integrity.

2. STRUCTURAL MODEL ASSESSMENT/INNER MODEL RESULT

The first step in assessing the structural model is to check for collinearity issues, which can introduce bias into regression results. This assessment evaluates the VIF values in the inner model. A VIF below or close to 3 typically indicates no collinearity concerns [127, 139], although some references suggest a less conservative threshold of 5 or lower [139]. As shown in Tabel 8, the VIF values for the inner model are all below 3, indicating no collinearity issues among the factors.

Table 8. Collinearity analysis result using VIF.

Path	VIF	Path	VIF
FRD -> IDR	1.668	IDR -> RTI	2.234
FRD -> IOR	1.668	IOR -> RTI	2.248
GMS -> FRD	1.285	MKF -> GMS	2.169
GMS -> IDR	1.668	RUT -> RTI	1.174
GMS -> IOR	1.668	SPI -> GMS	2.238
GVR -> FRD	1.285	TPCK -> RUT	1.000
GVR -> GMS	1.368		

Following the collinearity assessment, the coefficient of determination (R^2) for the endogenous factors was calculated to assess the model's in-sample predictive power. R^2 values range from 0 to 1, with thresholds indicating substantial predictive power at 0.75, moderate at 0.5, and weak at 0.25 [102, 140]. As shown in Table 9, the RUT factor has the lowest R^2 value, suggesting that the exogenous factors offer limited explanatory power for this factor. In contrast, the highest R^2 values were found in the IDR and RTI factors, highlighting the model's robustness in explaining key factors, particularly the main factor: RTI.

Table 9. Result of R^2 and adjusted R^2 calculation.

Factor	R^2	Adjusted R^2
FRD	0.418	0.410
GMS	0.344	0.331
IDR	0.476	0.470
IOR	0.381	0.373
RUT	0.155	0.149
RTI	0.474	0.464

To evaluate the strength and direction of relationships between factors and validate the proposed hypotheses, this study conducted a bootstrapping analysis using SmartPLS4. The analysis used 5,000 sub samples, a two-tailed test at a 0.05 significance level, and a fixed seed to ensure the reliability and reproducibility of results. Path coefficients reflect the strength and direction of relationships, where positive values indicate a positive relationship and negative values indicate an inverse relationship. Hypotheses are accepted if p-values are below the 0.05 significance threshold [141].

Table 10. Results of path coefficients, sample Mean, standard Deviation, T-statistic, P-values, and hypothesis Testing.

H	R	PC	T	P	R
H1	MKF → GMS	0.199	2.020	0.043	Accepted
H2	SPI → GMS	0.240	2.733	0.006	Accepted

H	R	PC	T	P	R
H3a	GVR → GMS	0.260	3.167	0.002	Accepted
H3b	GVR → FRD	0.148	2.265	0.024	Accepted
H4a	GMS → FRD	0.563	9.069	0.000	Accepted
H4b	GMS → IDR	0.457	5.611	0.000	Accepted
H4c	GMS → IOR	0.448	4.719	0.000	Accepted
H5a	FRD → IDR	0.303	3.528	0.000	Accepted
H5b	FRD → IOR	0.227	2.155	0.031	Accepted
H6	IDR → RTI	0.293	2.734	0.006	Accepted
H7	IOR → RTI	0.077	0.665	0.506	Rejected
H8	TPCK → RUT	0.393	5.666	0.000	Accepted
H9	RUT → RTI	0.473	3.979	0.000	Accepted

H = Hypotheses; **R** = Relations; **PC** = Path Coefficient; **T** = T-Statistic; **P** = P-Values; **R** = Result.

The bootstrapping analysis results indicate that one of the 13 hypotheses (H7) was rejected. Hypothesis H7 posited that the IOR factor positively affects RTI; however, it did not meet the significance threshold. The complete results, including path coefficients, t-statistics, p-values, and hypothesis testing outcomes, are summarized in Table 10. Three hypotheses (H6, H7, and H9) assessed relationships between exogenous and main endogenous factors, with findings grouped into technology and people dimensions. These relationships are illustrated in Figure 2, which visualizes the path coefficients and p-values.

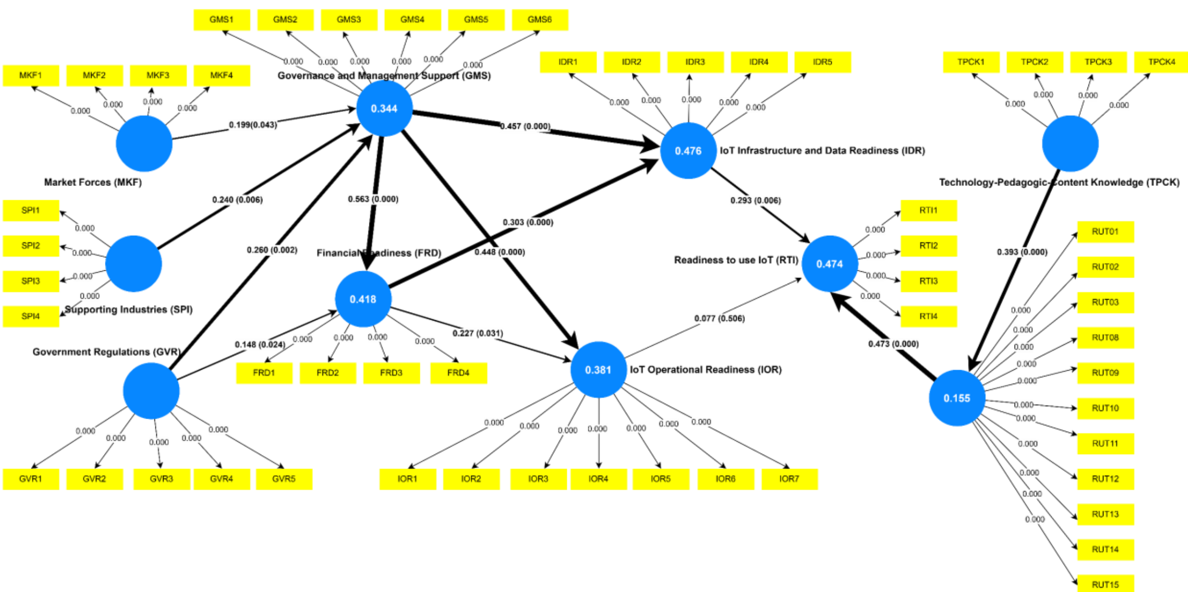

FIGURE 2. Results of the path coefficient calculations and p-values from the proposed IoT readiness model.

The data analysis results, as shown in Table 10, indicate that competition, customer demand, and business partner expectations, which represent market forces, have a significant and positive impact on governance and management support. Similarly, supporting industries and government regulations positively and significantly influence governance and management support in VHS. The financial readiness of VHS is significantly and positively influenced by government regulations as well as governance and management support. Furthermore, governance and management support play a crucial role in enhancing financial readiness, IoT infrastructure and data availability, and operational readiness for IoT adoption. Like governance and management support, financial readiness also has a positive and significant impact on IoT

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infrastructure and data availability, as well as operational readiness for IoT adoption. While IoT infrastructure and data availability significantly and positively support urban VHS readiness for IoT adoption, operational readiness for IoT does not have a significant effect on IoT adoption readiness in urban VHS. From the people dimension, a high TPACK score positively and significantly influences user readiness to adopt technology, which in turn has a significant impact on VHS to adopt IoT.

3. PRIORITY AREAS FOR FACTOR DEVELOPMENT

To further assess the model, this study employed IPMA, focusing on RTI as the main dependent variable [142, 143]. The importance dimension is represented by the total effects of each factor on RTI, indicating both direct and indirect influences. Factors with higher total effects are deemed more important. The performance dimension is measured by the mean scores of indicators, reflecting how well each factor performs within the model. Figure 3 provides a plot of these values on the x-axis (total effect) and y-axis (performance), illustrating the quadrant placement of each factor. The quadrant boundaries are defined by the mean values for each axis, allowing for a clear assessment of factor positioning relative to importance and performance metrics.

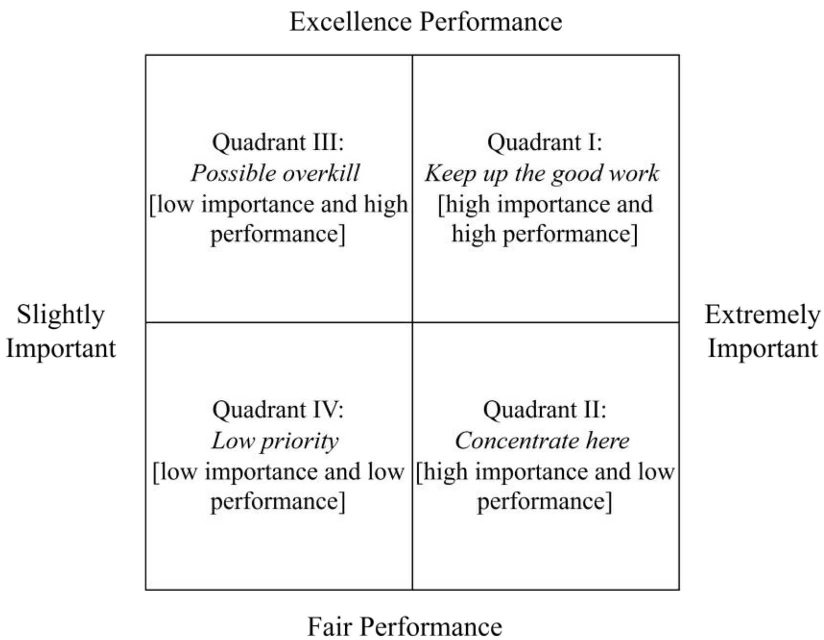

FIGURE 3. Results of the IPMA calculations for factors and their positions within the quadrant [143].

This study adopts the IPMA quadrant model proposed by Martilla and James to identify priority areas for VHS preparing to adopt IoT [143]. The IPMA results are categorized into four quadrants based on importance and performance.

- Quadrant I (Keep Up the Good Work): High importance, high performance – areas to maintain.
- Quadrant II (Concentrate Here): High importance, low performance – areas needing immediate attention.
- Quadrant III (Possible Overkill): Low importance, high performance – areas where resources may be reallocated.
- Quadrant IV (Low Priority): Low importance, low performance – areas of lesser concern.

IPMA calculation results for the model factors are presented in Table 11, which details the total effect and performance values for each factor. Figure 4 provides a plot of these values on the x-axis (total effect) and y-axis (performance), illustrating the quadrant placement of each factor. The quadrant boundaries are defined by the mean values for each axis, allowing for a clear assessment of factor positioning relative to importance and performance metrics.

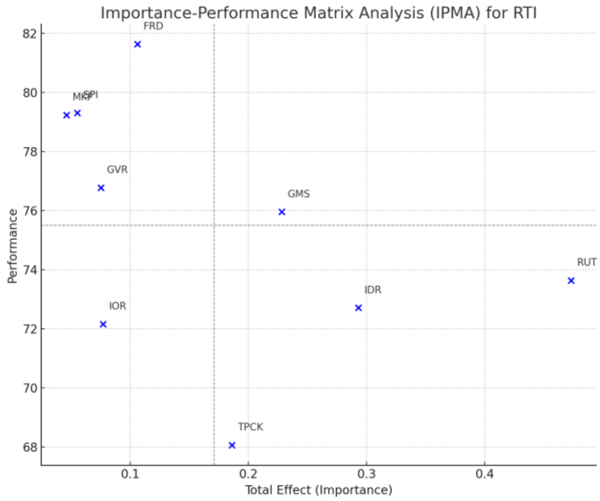

FIGURE 4. Results of the IPMA calculations for factors and their positions within the quadrant.

Table 11 and Figure 4 show the IPMA analysis results for RTI, with the RUT factor exhibiting the highest total effect (0.473), emphasizing its significant impact on RTI and its priority for improvement. The IDR and GMS factors follow with total effects of 0.293 and 0.228, respectively. The MKF factor has the lowest total effect (0.046). Performance-wise, FRD, SPI, and MKF rank highest, with mean scores of 81.629, 79.305, and 79.236. Conversely, RUT, IDR, IOR, and TPCK have the lowest performance scores, with mean scores of 73.634, 72.707, 72.160, and 68.058 indicating potential areas for improvement.

Table 11. Factor total effect and performance for RTI.

Factor	Total Effect	Performance
FRD	0.106	81.629
GMS	0.228	75.955
GVR	0.075	76.769
IDR	0.293	72.707
IOR	0.077	72.160
MKF	0.046	79.236
RUT	0.473	73.634
SPI	0.055	79.305
TPCK	0.186	68.058
Mean	0.171	75.495

Figure 4 categorizes factors accordingly: RUT, IDR, and TPCK are in Quadrant II, GMS is in Quadrant I, and FRD, SPI, MKF, and GVR are in Quadrant III, and IOR in Quadrant IV. This categorization highlights RUT, IDR, and TPCK as priority areas for improvement to enhance VHS readiness for IoT adoption.

Based on the IPMA results for factors, the priority areas for improvement in urban VHS in Indonesia are the RUT, IDR, and TPCK factors, which are situated in Quadrant II. Addressing these factors is essential for enhancing VHS readiness for IoT adoption. Following these improvements, the GMS factor, located in Quadrant I, could also be prioritized to further optimize performance. Environmental factors, which are positioned in Quadrant III, have limited controllability by the schools and thus are less important for direct management. The FRD factor demonstrates the highest performance and is positioned in Quadrant III. In public VHS institutions, financial management is primarily shaped by government policies, which restrict the schools' direct control over financial resources. Conversely, private VHS institutions, supported by their governing foundations, have slightly more financial autonomy, resulting in a relatively low importance value for the FRD factor in these settings. The high-performance value of the FRD factor suggests that financial support for learning innovation development is substantial, providing a positive outlook for IoT implementation to enhance the educational process.

VI. DISCUSSION

1. DISCUSSION OF KEY FINDINGS

For the first research objective, this study integrates multiple established readiness models to address the complex IoT adoption readiness issue in Indonesia's urban VHS. Employing a cross-sectional quantitative approach, this study developed a new model that identifies and analyzes the key dimensions affecting IoT readiness in vocational education. Key dimensions, derived from a thorough literature review, include technology, organization, environment, and individual factors—the latter of which has been shown to influence innovation readiness significantly [45, 46, 83, 144, 145]. Factors within each dimension were developed by adapting elements from the TOE framework, PERM model, TDWI IoT Readiness model, IoT-AMM, TPCK, and TRI models. These factors were validated by seven experts from three distinct fields to ensure relevance and accuracy using CVI. Following the CVI process, a pilot study involving 40 respondents was conducted. The results indicated a need for refinement, as certain questionnaire items had outer loadings, internal reliability, and convergent validity below the acceptable thresholds. These refinements were made, and the revised instrument underwent forward-backward translation to ensure linguistic and contextual accuracy. The final instrument was distributed online, supported by collaboration with the Provincial Education Office of West Java, which issued an official introduction letter to facilitate data collection. The study carefully structured each stage, from model development to expert validation, pilot testing, and final distribution, ensuring alignment with its objectives.

The reflective measurement assessment produced acceptable results across outer loadings, internal consistency reliability, convergent validity, and discriminant validity, with only minor adjustments needed. Five indicators were removed from the RUT factor due to outer loading values below 0.5, thereby enhancing the factor's reliability. The HTMT assessment for discriminant validity revealed a high correlation between the SPI and MKF factors (HTMT > 0.9), likely due to overlapping perceptions. However, since SPI and MKF belong to the same dimension and serve as exogenous factors for the same endogenous factor (GMS) and measure distinct aspects as defined in the subsection "Measurement Assessment (Outer Model) Result," the high HTMT value was considered acceptable. In line with Hair et al.'s methodology, the structural model assessment involved bootstrapping and the calculation of the coefficient of determination R^2 and adjusted R^2values [116]. The R^2 values for most factors fell within a moderate range, except for RUT, which had a weak R^2 value of 0.155. The small difference between R^2 and adjusted R^2 values indicate model stability and minimizes the risk of overfitting, despite lower predictive strength.

The analysis of this study's second research objective, focusing on the strength and direction of relationships between model factors and hypothesis testing via path coefficients and p-values, highlights significant positive associations across several dimensions. Specifically, positive relationships were found between the environmental and organizational dimensions, the organizational and technological dimensions, and from the technological dimension to the primary endogenous factor, RTI. Significant positive relationships were also observed between TPCK and the RUT factor and subsequently between RUT and the main factor, RTI. In the context of IoT implementation at urban VHS in Indonesia, path coefficient analysis indicates that environmental factors significantly and positively influence organizational factors. The exogenous factors MKF, SPI, and GVR positively and significantly impact the endogenous factors GMS and FRD. This finding aligns with previous studies, emphasizing that MKF and SPI serve as catalysts for VHS to adopt learning innovations, including IoT, to align with industry needs and remain competitive in a disruptive environment. The GVR factor notably influences organizational factors, impacting curriculum policies, infrastructure support, human resources, and financial policies shaped heavily by government regulations [11, 69]. Path coefficient tests confirm that GVR significantly affects the GMS and FRD factors. The GMS factor has a strong positive impact on FRD within the organizational dimension, and both GMS and FRD significantly influence the endogenous factors IDR and IOR within the technological dimension. GMS, encompassing policy, strategy, and support for financial and infrastructural readiness, is essential for IoT adoption in VHS. Financial readiness further enhances technological factors, as VHS's ability to establish infrastructure, manage data, and operate IoT solutions is financially dependent.

Within the technological dimension, the exogenous IDR factor significantly influences RTI, while the exogenous IOR factor has a positive but weaker or non-significant effect. VHS management often views IOR activities, such as technical support and system management, as non-critical when there is robust governance, managerial backing, and financial support. VHS management generally favors outsourcing operational activities to third parties to prioritize core competencies and strategic goals [146]. Outsourcing enhances cost efficiency, allows focus on primary educational activities, leverages external expertise, and improves scalability and flexibility. This strategy can reduce costs associated with hiring, training, or maintaining in-house staff [147]. By outsourcing, VHS can optimize core competencies, focusing on effective learning activities and strategic initiatives [148]. Outsourcing also enables VHS to adjust operational scale based on demand or internal resources. In the people dimension, the exogenous TPCK factor significantly impacts the RUT factor, which subsequently affects RTI. The path coefficient and p-value analysis support all hypotheses except one, indicating the proposed model—integrating environmental, organizational, technological, and people dimensions—is well-suited to the study's context.

The third objective of this study is to identify key factors and indicators that urban VHS management should improve upon, as highlighted by the IPMA. The IPMA analysis reveals that RUT and IDR are top priorities for intervention, as they exhibit high importance but low performance. Improving these areas is essential for developing VHS's capacity for IoT implementation. Suggested strategies for enhancing teacher readiness include promoting self-efficacy with technology [149-150], cultivating an innovation-supportive culture [151], addressing data security concerns and providing clear operational guidelines and support [152], and encouraging collaborative learning [153]. Strategies to reduce insecurity and discomfort include improving data security and privacy [149], and offering personalized technology experiences [153]. Policymakers and VHS administrators can support readiness by providing training programs centered on IoT management and incremental innovation, initially focusing on simpler technologies [154, 155]. Continuous technical support and creating communities of practice are also recommended to build teachers' confidence with technology.

The second priority area identified by the IPMA analysis is the IDR factor, which also demonstrates high importance but low performance. In the technological dimension, preparing for the IDR factor involves ensuring fundamental infrastructure, such as stable electricity, reliable internet connectivity, secure data storage, and comprehensive documentation. These preparations align with studies that report high failure rates in IoT implementation due to infrastructure gaps [34, 37, 156]. To ensure the readiness of VHS for IoT adoption, several strategies are recommended:

- management should develop short-term and long-term plans based on infrastructure needs assessments [157];
- key infrastructure for IoT implementation, including security infrastructure and data management, should be prepared [158];
- professional development programs for teachers and IT staff should be implemented, building on the strategies proposed for enhancing RUT [154];
- collaboration with industry [159]; and
- evaluation and continuous improvement of IoT innovations should be integrated into the process [157].

A critical strategy to improve readiness from both the RUT and IDR perspectives in collaboration with industry [157]. In vocational education, industry partnerships play a vital role in enhancing the quality of education. Within the context of this study, the industry can contribute by improving the knowledge and skills of teachers, IT staff, and students in alignment with market demands [160, 161]. Moreover, industry collaboration can support the provision of essential infrastructure and resources, including financial support, to enhance the learning process [162]. The government also plays a crucial role in supporting VHS readiness for IoT adoption. Government bodies can introduce policies and regulations that encourage innovation in education, such as revitalization programs for VHS and the establishment of Centers of Excellence (CoE) [163]. For public VHS, financial support from the government is critical, provided through scholarships, grants for teachers, or infrastructure assistance [164]. The interaction between industry, government, and academia, known as the Triple Helix Model, is particularly important. This model allows academia to benefit from applied research and innovative teaching practices, which improve the quality of education and provide advanced training for students [155].

The proposed IoT readiness model in this study can be utilized by VHS management and government authorities to assess the readiness of VHS for IoT adoption. VHS management can apply this model to evaluate their schools' preparedness, with respondents comprising school administrators and teachers. The management team of an VHS typically consists of more than ten individuals, depending on the organizational structure of the institution. This number is sufficient to complete all the instruments within the IoT readiness model, as referenced by Hair et al. [165]. The respondents of the IoT readiness model include not only school administrators but also teachers, as the model incorporates a people dimension that assesses the readiness of end-users. Additionally, the technology and organizational dimensions are directly related to teachers in the learning process. The technology dimension is particularly relevant, as teachers rely on technological infrastructure to facilitate teaching and learning activities. The organizational dimension, represented by GVR and FDR factors, directly influences the effectiveness of the learning process.

Furthermore, government authorities can leverage the IoT readiness model to evaluate the preparedness of VHSs within their jurisdiction by involving school management teams. The empirical findings from the model can serve as a basis for assessing and addressing factors that require improvement. The model's outcomes may vary depending on the specific characteristics and capabilities of VHSs in different regions, allowing policymakers to tailor interventions accordingly.

2. THEORITICAL AND PRACTICAL CONTRIBUTIONS

This research offers a theoretical contribution by introducing a novel IoT readiness model specifically designed for urban VHS. The model has been empirically validated through a case study in Indonesia and enriches the body of knowledge in readiness models, IoT adoption, and education. It integrates and refines previously validated frameworks to create a more comprehensive approach. The proposed model is structured around the TOE framework, a widely recognized model for evaluating organizational preparedness for adopting technological innovations and people dimension.

- Environmental Dimension: This study expands on existing models (TOE and PERM) by introducing the GVR factor, which examines the role of government policies in VHS IoT readiness—an aspect not previously considered by previous models.
- Technological Dimension: The study utilizes specific instruments adapted from TDWI IoT Readiness model and IoT-AMM to measure an institution's ability to establish the necessary infrastructure and manage IoT operations.
- People Dimension: The inclusion of the TPACK factor is a distinguishing feature, as it directly assesses user readiness (adopt TRI) in an educational setting.

This research facilitates the evaluation of VHS preparedness for IoT adoption by providing a practical assessment tool. Given its transformative potential, IoT can catalyze innovation in education, enhancing teaching quality and aligning vocational training with industry requirements.

This study makes a practical contribution by providing recommendations on potential opportunities for implementing IoT in education, particularly in vocational education. The IoT readiness model developed in this research identifies the relationships between factors influencing the preparedness of VHS to integrate IoT. Empirical analysis using SEM-PLS confirms that the environmental dimension is critical in determining VHS readiness for IoT adoption. Although environmental factors are beyond the direct control of VHS institutions, administrators who understand external conditions can develop strategies to maximize opportunities and mitigate risks associated with environmental challenges. The organizational and technological dimensions also significantly impact VHS readiness for IoT adoption. Since both dimensions are within the control of VHS management, identifying key factors in these areas enables institutions to develop more flexible and proactive strategies. From the human dimension perspective, this study provides insights that can encourage and motivate teachers—who serve as the primary facilitators of learning—to enhance their use of technology in the teaching process. Additionally, VHS institutions can implement training and professional development programs for educators based on the findings of the IoT readiness model. This study also introduces an instrument for evaluating VHS performance, helping institutions identify priority areas for development. By applying the IPMA, VHS institutions can assess the significance and effectiveness of various readiness factors, allowing them to formulate more targeted improvement strategies. Furthermore, the results obtained using the proposed IoT readiness model can serve as a valuable reference for policymakers and industry stakeholders in supporting and facilitating the implementation of IoT in vocational education.

3. LIMITATIONS AND FUTURE DIRECTIONS

This study has several limitations. First, the sample was limited to top management at VHS in urban areas of West Java. Including respondents from urban areas in other provinces with diverse industrial characteristics—such as maritime or mining regions—could have enriched the findings. Moreover, this study did not consider moderating variables such as age, experience, gender, or educational background. This decision was based on the assumption that school management personnel in Indonesia generally consist of teachers with educational and managerial experience. Additionally, the study relied exclusively on quantitative survey data without incorporating qualitative insights from respondents' opinions or feedback, which could have provided a deeper understanding of the findings. Another limitation of this study is its focus on assessing IoT readiness rather than the development or implementation of IoT-based innovations. The study does not provide specific examples of IoT applications or systems in education. Future research should investigate a broader range of IoT applications to support learning processes at various educational levels, from early childhood to higher education, including inclusive education. Furthermore, IoT should not only serve as infrastructure but should also be integrated as a learning tool to enhance teaching and learning quality.

Future studies could explore the integration of IoT with advanced technologies such as AI, which offers promising potential to provide personalized, adaptive, and automated educational experiences. Combining IoT with AI could improve accessibility, offer accurate real-time feedback, and enable innovative learning processes. This convergence of technologies may significantly impact modern education by creating more adaptive and inclusive learning environments [166-168]. Security remains one of the primary concerns, as IoT adoption in educational settings involves managing sensitive data, protecting network integrity, and ensuring compliance with regulations [20, 46, 49]. According to Caso et al., there are six key principles for securing IoT environments: data privacy and access (confidentiality), reliability and compliance (integrity), and uptime and resilience (availability) [169]. This study does not specifically address IoT security issues; however, security-related aspects are incorporated within the IOR and IDR factors. These factors were selected because they encompass confidentiality, integrity, and availability—considerations that are appropriate for VHS institutions, which can be classified as small or simple organizations. In the future, for contexts involving larger and more complex organizations and business processes, IoT security could be treated as an independent factor.

This research focused exclusively on urban VHS in Indonesia, which generally exhibit higher readiness in terms of infrastructure and operational capabilities. This narrow scope offers future research opportunities to apply or adapt the proposed IoT readiness model in different contexts, including rural areas or other countries. Rural areas in Indonesia often face challenges such as limited infrastructure, fewer supporting or collaborating industries, and lower teacher competence in implementing digital technologies. Despite these constraints, rural VHS could still adopt simpler, low-cost IoT innovations without continuous internet connectivity or significant electrical power [170]. Testing the IoT readiness model in rural settings may help refine or strengthen the identified factors, making the model more applicable across diverse educational environments. Implementing the IoT readiness model for vocational education across different countries (e.g., in developed or developing nations) could lead to the emergence of segmented IoT readiness models—such as those specifically for vocational schools in developed or developing countries. Implementing or adapting IoT readiness models in developed countries (e.g., most Western nations) presents a unique opportunity due to their distinct characteristics, such as government support through funding programs, regulatory frameworks, and grants for jurisdictions and agencies to procure and deploy IoT solutions would provide a more comprehensive perspective, making the IoT readiness model more universally applicable [171]. Additionally, this model offers opportunities to measure the IoT readiness of various educational levels intending to adopt this technology, providing a flexible tool adaptable to varied educational settings.

The factors identified in this study could form the basis of a practical IoT readiness maturity model for vocational schools. This model would provide vocational schools with a structured pathway to navigate the complexities of IoT adoption. Furthermore, the research highlights the importance of evaluating teacher readiness for IoT adoption through frameworks such as TPCK or TRI. Alternatively, future studies could assess teacher preparedness by examining specific IoT innovations already in use. By applying these practical frameworks, educational institutions can gain a more detailed understanding of the factors influencing teacher preparedness and readiness for IoT adoption.

VII. CONCLUSION

This study provides valuable insights into the factors influencing IoT readiness in Indonesia's urban VHS. The empirical findings underscore the importance of understanding the interplay between various dimensions for successful IoT implementation. Evaluating VHS readiness for IoT requires focusing on dimensions that directly impact organizational effectiveness. To achieve this, the study employed the TOE framework, a well-established model for assessing technology adoption within organizational contexts. Given the specific requirements of IoT implementation in VHSs, modifications to the TOE framework were necessary, including introducing a new dimension, People, to capture the readiness of end-users—particularly teachers and support staff—who are essential for successful IoT adoption in education. The study's methodology involved systematically selecting and adapting indicators and factors to ensure their relevance and accuracy. A questionnaire was administered to the top management of eligible urban VHSs in Indonesia, yielding 159 valid responses. The reflective measurement assessment, which included tests for outer loadings, internal consistency reliability, and discriminant validity, confirmed that the indicators and factors in the empirical model met established standards. Additionally, the structural model, outlining relationships between factors, was developed with careful consideration of the unique context of VHS IoT implementation. Assessments of the model, including collinearity, path coefficients, and p-values, demonstrated its effectiveness in measuring VHS readiness for IoT adoption. The IPMA identified two critical areas for improvement: (1) enhancing teacher readiness for technology use and (2) ensuring adequate IoT infrastructure and data management capabilities within VHSs. These insights provide actionable guidance for VHS top management in strategizing IoT adoption. Specifically, the findings suggest that school administrators should focus on upskilling staff, planning and expanding IT infrastructure, and fostering collaborations with industry and government to support IoT-based learning innovations and strategic initiatives. The practical implications of this study extend beyond VHSs in Indonesia. For theoretical contribution, the methodology and framework applied here can serve as a reference for other educational institutions aiming to assess their readiness for technology adoption.

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Author Contribution

Conceptualization, Suwastika and Masrom; methodology Suwastika; development instrument, Suwastika and Masrom; validation, Qonita and Suwastika; data collection, Qonita and Suwastika; data analysis, Suwastika; writing—review and editing, Suwastika and Qonita; supervision, Masrom and Anwar; funding acquisition, Masrom, Anwar, and Suwastika. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available from the authors upon request by emailing to: anggis@telkomuniversity.ac.id

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