IEEE *Access*
Multidisciplinary : Rapid Review : Open Access Journal

Factors That Influence the Adoption of Enterprise Architecture by Public Sector Organizations: An Empirical Study

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ABSTRACT The adoption of enterprise architecture (EA) is deemed to be low despite EA's substantial benefits to organizations, especially in the public sector, as evidenced by the scarce literature on the EA adoption stage, which focuses on the decision or intention to adopt EA. This research attempts to identify the significant factors that influence EA adoption in the public sector by using the technology–organization–environment framework and organizational theory. The conceptual model was validated using partial least squares structural equation modeling with data collected from 255 key informants from public sector organizations. Empirical results show that clear communication, coercive pressure, expected benefit, good governance, mimetic pressure, normative pressure, and organizational size have a significant influence on the adoption of EA by public sector organizations. Surprisingly, top management support, ICT infrastructure, EA complexity, organizational readiness, and external support have a nonsignificant influence on EA adoption by public sector organizations. The implications of the findings are also discussed in theoretical, contextual, and practical aspects of EA adoption in the context of public sector organizations. This model facilitates decision-makers in focusing only on the significant factors in the organizational and environmental context that influence EA adoption in Malaysian public sector organizations. Subsequently, the findings may contribute to better insights for EA initiators in their EA implementation plan and strategic planning to support EA implementation among Malaysian public sector organizations.

INDEX TERMS Adoption, enterprise architecture, institutional theory, public sector, TOE.

I. INTRODUCTION

Enterprise architecture (EA) is a strategic tool for defining the overall structure and operation of an organization. EA comprises multiple viewpoints, including business, application, information, and technology, which enable organizations to understand their current state and promote a desirable future information technology (IT) model [1]. Gartner [2] predicts that by 2021, enterprise architects will be helping organizations plan and design technology innovation toward digital services and new customer experiences. Consequently, EA benefits decision-makers and IT practitioners by achieving desired technology solutions [3], eliminating the duplication of applications and processes [4], allowing interoperability, and improving coordination between business

and IT [5]. Despite its substantial benefits, however, EA is not widely embraced [6].

Electronic government (e-government) is one of the substantial services of the digital government to ensure that good, seamless, and connected public sector service is provided, as clearly stated in the report of the 2010 UN e-Government Survey [7], [8]. As a result of the e-government report, the adoption of EA has become a primary strategy to improve public service delivery and contribute to national development [8]. Many developed countries such as the United States, Denmark, and Finland have proactively encouraged the implementation of EA [9]–[11]. An EA survey by.McKinsey [1] conducted among CIOs, heads of EA, and business leaders working in EA fields found that EA plays a vital role in running digital transformation [12], [13]. In their report, 62% of organizations recognize EA as an enabler of digital transformation [1].

The associate editor coordinating the review of this manuscript and approving it for publication was Shouguang Wang[ID].

EA was realized in the Malaysian public sector's (MPS) information communication technology (ICT) transformation model in 2013 as a transformational program and an enabler of digital transformation. Therefore, the MPS has allocated a large investment in the development of the Malaysia Government Enterprise Architecture (MyGovEA) [14]. MyGovEA, formerly known as 1GovEA, is a government EA framework that enables initiatives in the digital government agenda for the public sector to be achieved effectively. MyGovEA is clearly incorporated in the Public Sector ICT Framework of the Public Sector ICT Strategic Plan (ISP) 2016–2020 and followed by a series of workshops, awareness, and training for MPS organizations [15]. Initially, the government targeted 25 public sector agencies to have implemented EA by the end of 2016, but only five agencies adopted EA, including two federal agencies, which were included in the EA pilot project [16]. A report published by the Malaysian Administrative Modernization and Management Planning Unit (MAMPU) reveals that the EA capability maturity assessment of MPS indicated that the EA adoption of the MPS is moving toward level 2, or the formalized stage [17]. This finding proves that the EA projects of government agencies are still at a low degree and its significance has yet to be proven [14]. Thus, a mechanism or method to help the MPS adopt EA is clearly needed.

The decision-making process to institutionalize EA in the public sector organization is slow, which indicates a low success rate [18]–[20]. This condition might be related to the absence of suitable EA adoption guidelines to follow, the lack of success stories from organizations that have successfully adopted EA, or the lack of awareness of the existence of EA in the public sector [21].

Suitable EA adoption models that consist of significant factors of EA adoption is absent in the literature, as a great deal of previous EA research has focused on the post-adoption and implementation phases [22]–[25]. The current literature also lacks focus on the EA adoption phase, which is the intention to adopt EA at the organizational level [26]. A review of EA adoption literature shows that the current adoption models are applicable for the post-adoption phase, such as the assessment model by Bakar *et al.* [27] and the critical success factor of EA adoption by Lange *et al.* [22], instead of adoption issues, particularly in developing countries. Furthermore, EA adoption studies, especially in developing countries, remain scarce [20]. No scientific research on EA adoption in the MPS organization context was found at the beginning of the research project [21], [26].

To address the gaps in the existing literature and the problem with EA adoption by MPS organizations, this research investigates the factors that influence organizational adoption of EA by MPS. To achieve this objective, the following main research questions are raised: What are the factors that influence EA adoption by MPS organization? What model can be used to explain factors that influence EA adoption in MPS organizations?

This research employs a quantitative approach, using survey questionnaires to answer these questions. This research followed the partial least squares structural equation modeling (PLS-SEM) research design [28]. The survey was distributed randomly to the decision-makers of MPS organizations. This research integrates the technology–organization–environment (TOE) framework and institutional theory as underpinning theories in developing the conceptual model. This research identifies the organizational and environmental factors that influence EA adoption by MPS organizations. Our findings may assist the top management of public sector organizations in strategizing EA adoption by recognizing the important factors of EA adoption in their organization.

This paper is composed of nine themed sections. Section 1 introduces the research. Section 2 conducts a literature review regarding EA and the theoretical background. Section 3 describes the model development and hypotheses of this research. Section 4 explains the methodology on the basis of the research design that this research employed. Section 5 demonstrates the results of the analysis. Section 6 discusses the findings of the research in detail. In Section 7 elaborates on the research implications, followed by the research limitations and future work. Finally, the paper ends with the conclusion.

II. LITERATURE REVIEW
A. ENTERPRISE ARCHITECTURE

Various definitions of EA are found in this field. First, from the perspective of enterprises, architecture could be defined as a set of descriptive representations (i.e., models) that are relevant for describing an enterprise such that it can be produced according to management's requirements (quality) and maintained over the period of its useful life (change). Zachman (1996) defined EA as the *architecture that is a set of design artefacts, or descriptive representations, that are relevant for describing an object such that it can be produced to requirements (quality) as well as maintained over the period of its useful life (change)*. References [29], [30] described EA as *a coherent whole of principles, methods, and models that are used in the design and realization of an enterprise's organizational structure, business processes, information systems, and IT infrastructure*. This definition is consistent with that of Gilliland *et al.* [31], who said that EA provides a long-term view of the organization. In addition, EA is defined as the process of translating and converting strategic requirements into processes, data, and technology, providing the organization's big picture in detail and handling change management [32]. Although various definitions of EA exist, some consensus appears to have been reached with regard to the idea that EA refers to the ISO/IEC/IEEE FDIS 42010:2011 standard definition [33] and is also stated in one of the prevalent books on EA [34]. In the present research, EA is defined as a holistic view that effectively integrates different domains in business, data, application, and information in organizations.

The non-harmonized view of EA could cause confusion among novice EA stakeholders, such as the MPS. As such, one of the main motivations of this research is to assist EA adoption in the MPS, because EA acts as a middleman between business and IT, as well as plays an essential role in facilitating the evolution of high-level capabilities at the organization level [13], [35] and managing the change from the current state to the future state [31], [36].

B. TECHNOLOGY ADOPTION MODELS
Notable theories and models that focus on the individual level of adoption include but are not restricted to the theory of reasoned action [37], the theory of planned behavior (TPB) [37], the technology acceptance model (TAM) [38] and the extended TAM [39], the unified theory of acceptance and use of technology [40], and the model combining TAM and TPB [41]. At the organization level of adoption, TOE [42], diffusion of innovation (DOI) theory [43], institutional theory [44], resource-based theory [45], and the DeLone and McLean information system success model are prevalent theories in IS research. Rogers Everett [43] proposed DOI for innovation acceptance and adoption among individuals and organizations. However, DOI focuses only on technology characteristics and does not emphasize the environmental aspect. The TOE framework posits that the decision of adoption decision is strongly influenced by three contexts, namely, technological, organizational, and environmental. The TOE framework provides generic contexts, thus allowing easy inclusion of new predictors [46].

Institutions or organizations are a critical component in the environment and exert three types of pressure, namely, coercive, normative, and mimetic [47], [48]. These pressures are present in institutional theory. Institutional theory focuses on the extensive and more robust characteristics of the social framework [49], unlike the DeLone and McLean model, which focuses on six significant dimensions, namely, information, system, and service quality, (intention to) use, user satisfaction, and net benefits [50], and is thus more suitable to IS products that are already implemented in the organization or marketplace. The integration of TOE and institutional theory is deemed suitable as both theories incorporate the multidimensional factors involved in the organizational adoption of IS or technology such as EA. Apart from one of the most popular IS models, the TOE framework has three technological, organizational and environmental contexts, while the three factors of the institutional theory are present in the organizational and environmental contexts [51]. This allows for easy integration into the TOE framework [46]. Moreover, it can be seen from the relevant literature that these two theories have not been used to examine the adoption of EA. On this premise, this research adopts the TOE framework and institutional theory on the basis of their relevance in explaining the factors of EA adoption by MPS organizations

C. TOE FRAMEWORK
The TOE framework is an organizational-level theory that consists of technological, organizational, and environmental contexts [42]. It has been described as a generic theory because it allows easy inclusion of additional constructs or factors [46]. The TOE framework is consistent with DOI theory, as DOI adoption is comparable to the elements in the TOE framework's organizational and technological contexts [51]. The TOE framework has proven useful for a wide range of innovations and contexts, and it has been broadly supported by empirical and well-established works [52]. The adoption of innovations is affected by technological, organizational, and environmental contexts within a firm [51], [53]. Therefore, many IS studies have adopted the TOE framework in various settings such as halal warehouse service [54], electronic customer relations management (CRM) [55], e-procurement [56], RFID [57], e-government [58], open government data (OGD) [59], open platform [60], cloud computing [61], software as a service (SaaS) [62], electronic record management system (ERMS) [63], and the Internet of Things (IoT) [64]. This feature strengthens the rationale for adopting the TOE framework for this research because it provides clear and important empirical support for research. On the basis of the literature review, the three contexts of the TOE framework underpin this research to identify factors that influence the organizational adoption of EA by MPS.

D. INSTITUTIONAL THEORY
Institutional theory focuses on pressures, namely, coercive, normative, and mimetic pressures [44]. Institutional theory is used to analyze diverse sectors and organization fields. Pressures suit the organizational and environmental context, because the theory probes how pressure is created, diffused, adopted, and adapted over space and time by rules and regulations, cultural expectation, and imitation from other organizations [65]. Pressures appear as the influential factor for organizational reform [66]–[68] and have been examined as motivational pressures in green IT and suggested as a motivational factor for EA adoption [9]. As stated earlier, the elements of institutional theory are comparable to those of the TOE environmental context, such as regulatory and internal pressures. Other studies analyzed pressure in different contexts, such as those on green IT by Kuo and Dick [69], ecological sustainability by Chen *et al.* [65], and public sectors by Hjort-Madsen [68].

From the theoretical lens, EA requires a wide-ranging theory to explain its adoption challenges in organizations. However, few studies have analyzed the determinants from the perspective of pressure in EA adoption studies [67]. Prior research on the adoption of EA revealed a dearth of environmental and organizational pressure factors. Therefore, this research deems that institutional theory is relevant in investigating EA adoption in the context of influence factors within the scope of this research.

E. RELATED WORKS

The literature review revealed that the EA adoption model has different names, such as 3D model [9], improved EA adoption method (EAAM) [19], framework for analyzing the change and influence of EA programs and their institution-alization [67], model of resistance during the EA adoption process [70], and knowledge relationship model of EA and top management roles [71]. Previous studies on EA adoption are summarized in Appendix A. Evidently, previous studies investigated and analyzed the topic from fragmented contexts, such as the context of pressure. For example, Gamiet [72] proposed a model to avoid the application duplication problem and to recognize the diversity of different EA adoption projects [9], [73] proposed an integrated EA model that focuses on social and technical impact only. EAAM was proposed to reduce resistance to the EA adoption process [19]. The EAAM model addressed the issue of lack of understanding of EA concepts [19]. However, these models are formulated based on different perspectives and issues. The literature also indicated a lack of EA adoption studies despite increasing attention on IT/IS adoption studies from developing countries.

The first study on EA in the Malaysian context investigated EA practices in Malaysian enterprises, including public and private sectors [74]. Business and IT alignment were found to be the most important business issue in EA, followed by business change and application renewal [75]. The study by [78] revealed that the issues and challenges faced by MPS organizations include the lack of EA awareness and readiness, limited EA knowledge and skill among team members, improper governance, absence of a mandate from the stakeholders or the government, and the absence of an EA tool to maintain EA artefacts. Therefore, their study identified the factors that are relevant to EA adoption in the context of MPS. Other EA studies have been performed in the context of the MPS on the EA implementation model [76] and the EA readiness assessment model [77]. However, these studies have a narrow focus, concentrating only on talent management, readiness, and the implementation phase.

Although the TOE framework has been adopted in various IS research, it has not been extensively applied to the domain of EA, particularly in the area of EA adoption. EA has been the topic of a variety of empirical research with specific purposes and findings. Such research also investigated various factors that influence the adoption of EA. To date, the adoption and implementation of the EA in developing nations have been minimal [20]. Countries face difficulties in adopting the EA; the challenges are similar and do not rely on the nature of the country. Studies on the public sector's adoption of EA are fewer than those on other sectors, such as small and medium-size enterprises and the private sector. Nevertheless, the experience, culture, and purpose of the sectors in implementing EA are different. The perceptions gained in the various sectors are not exchangeable in terms of the design, model, and viewpoints of organizations.
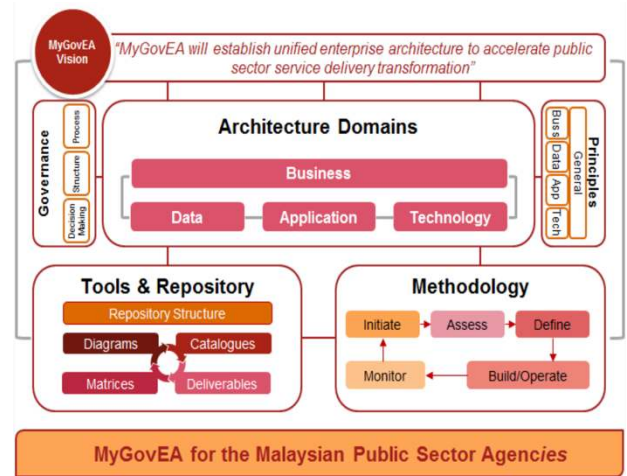

FIGURE 1. MyGovEA framework.

F. EA IMPLEMENTATION IN THE MALAYSIAN PUBLIC SECTOR

In 2014, MAMPU introduced MyGovEA as the national EA framework. The development of EA was based on The Open Group Architecture Framework. MyGovEA provides ecosystem services for the public sector. MPS also realized that the benefit of EA toward digital transformation in government services could be accomplished by adopting EA [78]. Further acceleration of the use of MyGovEA is specifically stated in the MPS Strategic Plan 2016–2020 [15]. The government targeted 25 government agencies to implement EA in designing desirable IT solutions. MAMPU reported that sustaining EA practices in public sector agencies is challenging [79]. Hence, EA in MPS is still in its infancy. The survey conducted by MAMPU in 2014 on EA capability maturity assessment reveals that the MPS is moving toward level 2 (formalized stage) with regard to the adoption of EA practices. The survey also examined the EA framework used by MPS organizations.

MyGovEA is guided by the developed architectural framework to define the core elements of the architecture in developing and implementing EA practices. As shown in Figure 1, the MyGovEA framework acts as a guide to describe the main components of MyGovEA. The components of MyGovEA are vision, governance, architecture domains, principles, tools and repository, and methodology. MPS organizations have to develop these components because they are fundamental to the implementation of the EA practice.

III. MODEL DEVELOPMENT AND HYPOTHESES

A review of IS/IT technology adoption and implementation suggests that many technological, organizational, and environmental factors are likely to affect the adoption of EA. Adoption is frequently observed as a dependent variable in the related literature [80]. Independent variables are categorized in the three contexts of TOE: 1) technological, 2) organizational, and 3) environmental. This research adopts two technology adoption models, namely, the TOE framework and institutional theory, which have been widely adopted for
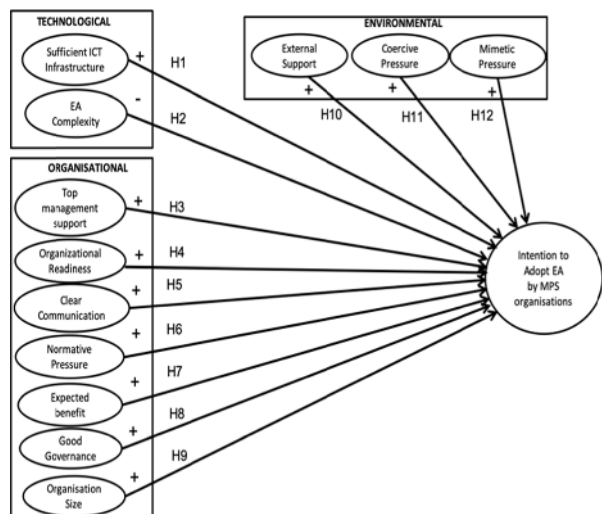
FIGURE 2. Conceptual model.

IS studies in the organizational context. The factors were also found from prior research on EA and TOE conducted across different industries in different countries, as shown in Appendix A. This research proposes 12 TOE factors that could influence EA adoption by public sectors, as illustrated in Figure 2: sufficient ICT infrastructure, EA complexity, top management support, organizational readiness, clear communication, normative pressure, expected benefit, good governance, organization size, external support, mimetic pressure, and coercive pressure. These factors are the most utilized factors for the three principle contexts of the TOE framework and institutional theory. This research also proposed clear communication as a specific factor of EA adoption phases within the organizational context of the organization. The selection of these twelve factors was based on the mapping analysis of the systematic literature review of the adoption models in the EA studies [21], [26] and the prior TOE-based technology adoption studies (see Appendix A). Factors that have appeared from both these domains and thus are believed to be essential for understanding and explaining the adoption of EAs have been proposed in the research model. Therefore, the researcher measured these factors to explain the intention or decision of an MPS organization to adopt EA. The researcher formulated the following hypotheses to assess the proposed model of EA adoption by MPS organizations.

A. TECHNOLOGICAL FACTORS

The technological context includes internal and external technologies that are relevant to the organization. The technologies may include types of equipment and processes that can foster EA adoption, as found by Depietro *et al.* [42]. Many studies argued that technology plays an important role and found a positive effect on innovation adoption at the organization level [54], [55], [59], [60], [62], [81]. The accessible technology variables are perceived advantage, perceived easiness, compatibility, observability, trialability, compatibility, complexity, and perceived barrier. However, this research employs the technology variables of

sufficient ICT infrastructure and EA complexity, as suggested by [9], [13], [19], [82]–[85]. The rationale of measuring technology readiness, which is the degree to which the organization has the necessary technology infrastructure and IT human resources to implement the EA, is crucial to the pace of adoption because organizations that have the necessary technology will be able to adopt EA faster than organizations that do not have the technology. This variable is also found to be significant by the study of Interorganizational Business Process Standards [86].

EA complexity has been recognized as a technological factor because it affects time, cost, and management control [87], [88]. Technological complexity is the degree to which the use of technology is free of effort [89]. Analyses of the relationship between technological factors and technology adoption can be extended to EA adoption. Therefore, this research proposes the following hypotheses:

H1: Sufficient ICT infrastructure positively influences the intention to adopt EA.

H2: EA complexity significant positively influences the intention to adopt EA.

B. ORGANIZATIONAL FACTOR

The organizational context refers to the characteristics, internal pressure, and resources of the organization, including top management support, organizational readiness, clear communication, normative pressure, expected benefit, good governance, and organization size, which are among the most accepted predictors of innovation adoption [53], [90]. These characteristics also refer to the descriptive measure. However, the extent to which these organizational variables influence the phases of adoption has not been examined [53]. Top management support has been considered one of the most influential organizational factors for IT adoption in organizations [91], [92]. Other scholars argued that top management support is accountable for the norms, cultures, values, visions, and missions, e.g., Balaid *et al.* [93], which eventually encompass the entire community in the form of regulations, policies, routines, and procedures, and serve as powerful templates. Wang *et al.* [94] revealed that top management support provides the necessary involvement, resources, and authority in guiding and assisting innovation. For example, financial resource has long been posited as a barrier to innovation adoption [95].

In contrast to the other studies that focus on the post-adoption stages, including those that focus on the actual use of innovation as in e-business, such as the study by Zhu and Kraemer [80], this research focuses on the adoption stage (or intention to adopt). EA involves costly investment in hardware, software, system integration, and change management [31]. Therefore, sufficient financial resources help the organization obtain these necessary resources and develop EA skillsets and competency. The researcher argued that in the attempt to make innovation more cost-effective for the organization, a large amount of money needs to be allocated for innovation, as it will increase the motivation to innovate

more seriously and actively within the organization [96]. This finding is consistent with that of other scholars who studied EA [13], [19], [82], [83]. The choice of this variable also emerged during an interview session with the EA practitioner team. Another variable, which is top management support, is also deemed important in the adoption of innovation and has been found to positively affect RFID, SaaS, e-government adoption, and cloud computing [58], [62], [97]. Specific studies on EA [9], [68], [82]–[84], [98]–[100] found that top management support is a critical determinant of adoption. In this regard, the researcher hypothesizes the following:

H3: Top management support positively influences the intention to adopt EA.

Organizational readiness is another crucial variable in innovation adoption [94], [101]. Organizational readiness includes support from different organizational levels, adequate technical support, experienced people, and EA knowledge and skill within the organization, and it can provide a significant business advantage [102]. In general, EA knowledge and skill represent the totality of organizational EA knowledge and skilled personnel within an organization. This factor is urgently required among organizational employees for adoption intention [10], [19], [84], [103]. In the context of EA adoption, EA knowledge and skill are practical ways in which organizations can promote EA adoption. In return, the organization would benefit from the return on investment [104]. Hence, organizational readiness is considered a driver of adoption in similar IS studies, such as those on halal warehouse service by Ngah *et al.* [54], IoT by Hsu and Yeh [64], and OGD by Wang and Lo [59]. The present research hypothesizes the following:

H4: Organizational readiness positively influences the intention to adopt EA.

An additional factor is recognized under organizational context, namely, clear communication. Clear communication constitutes another important variable in the EA literature [83], [84]. and prevalent studies discovered that one of the problems hindering EA adoption is communication failure between the EA team and the business and IT personnel [9], [84], [105]. To understand the value of EA, communication among different stakeholders is required. Communication can give positive perceptions and identify the potential values of EA [106]. This variable is strongly recommended by.Hjort-Madsen [98], who said that IT planning must address the language gap between business and IT personnel to gain a mutual understanding of the organization's strategies and objectives. In this case, team members in the organization feel that they can state their opinions, thoughts, and feelings without fear. This variable appears vital in the TOE framework and DOI [42], [43], as both are complementary. Therefore, the next hypothesis is proposed as follows:

H5: Clear communication positively influences the intention to adopt EA.

Normative pressure is "*driven by pressures brought about by professions. One mode is the legitimization inherent in*

the licensing and crediting of educational achievement. The other is the inter-organizational networks that span organizations. Norms developed during education are entered into organizations" [48]. According to DiMaggio and Powell, the norms will develop through education within the organization. As a result, people from the same educational backgrounds will approach problems in much the same way. In this case, organizational culture holds the uniqueness in every organization. The study by [110] reveals that the role of organizational culture is significant so that the amount of needed investment can be known given limited resources for EA management in different organizational cultures [107]. The organization has a different perspective and reaction toward the intention to use or adopt EA and hence leads the organization to change, which is one of the most difficult things to achieve [9], [107]. Organizational culture is portrayed in terms of how committed employees are to the common objectives and decisions in EA adoption. Therefore, normative pressures result from the demands of professional associates, organizational culture, and the extent to which the government promotes the use of information technology and especially EA [108], [109]. This variable has been shown in a study by Weiss [110] to significantly influence EA and is suggested for EA adoption [9], [10], [19], [98]. Hence, the present research hypothesizes the following:

H6: Normative pressure positively influences the intention to adopt EA.

Including the expected benefit of adopting EA for the organization as one of the factors that influence EA adoption is also reasonable. Return on investment is a consideration in weighing the expected benefit before the decision to adopt EA is made [111]. Expected benefit can be seen as the relative advantage, "*who saw it as the degree to which an innovation is perceived as providing greater organizational benefits than the idea it supersedes or the status quo.*" Rogers Everett [43] perceived expected benefit as a part of the organizational context. For example, an IoT adoption study found that expected benefit is an influential factor in Taiwan's logistics industry [64] and the mobile supply chain management system in manufacturing firms in Malaysia [111]. EA benefit is an important factor that influences an organization to adopt EA [9], [13], [18], [19], [30], [105]. Therefore, the next hypothesis is proposed as follows:

H7: Expected benefit positively influences the intention to adopt EA.

Good governance includes the strategy and the operating model in terms of defining the roles, responsibilities, and procedures used by an organization for internal activities and EA adoption [112]. Although governance has a significant adverse effect on the study of e-participation and e-government maturity from a global perspective (Krishnan *et al.* [113]), it is highly suggested by other scholars [9], [13], [18], [19], [82]–[85] for EA adoption. To institutionalize EA in the organization, a new governance regime must be introduced [114]. For example, good governance is significantly found as an indicator between ICT and

socioeconomic development in developing countries because the concept of governance is gaining increasing focus as a national-level construct [115]. According to [115], "*Governance is thus responsible for creating an environment that enables the participants in all aspects of the economy to easily evolve, learn and adapt while being publicly and openly accountable*." Other scholars mentioned that governance is not the same as government, describing it instead as "*the action of the state and, besides, encompasses actors such as communities, businesses, and NGOs*." [116]. EA allows interconnection of governments through online services [8], [117], thus providing supervision or a control communication network from within the industry, especially in the public sector for governance. Previous scholars claimed that through such a network, all the diverse interest groups from within the public sector can interact and reach consensus on important issues that are beyond the unitary control of one particular stakeholder [115], [118], [119]. The role of governance is an antecedent in shaping the economic and social development of a country. However, the issue of governance has rarely been raised in mainstream IS research, especially when considering macro-level indicators [115], such as an MPS organization. For example, EA documents evolve as business processes change. Thus, the government should keep up with this agility [106]. Therefore, the variable is considered to be measured in this research, and the following is posited:

H8: Good governance positively influences the intention to adopt EA.

Organization size refers to the organization's number of employees [120]. Previous studies by Seppänen [9], Korhonen and Halen [13], Syynimaa [19], Shaanika and Iyamu [84] reveal that organization size critically influences the adoption of EA. Other specific studies confirm that size is the critical factor for technology, e-procurement, and RFID adoption, although it is not critical in techno-relationship innovation [56], [57], [108]. The inclusion of this variable in this research is important and has a possible effect on EA adoption, as indicated by literature reviews and the TOE framework [42]. Other prominent scholars [42], [80], [101] found that a large organization makes an EA adoption decision more quickly than smaller organizations do because they have a greater need to stay at the leading edge of technology. These scholars also mentioned that larger organizations have benefited because they have more resources for investing in and adopting innovation. Therefore, this research proposes the following hypothesis on the basis of the evidence:

H9: Organization size positively influences the intention to adopt EA.

C. ENVIRONMENTAL FACTOR

The environmental context refers to the sector within which the organization operates, the external pressures, and the opportunities that may influence the EA adoption [46]. Concerns are given to three critical environmental factors that are factored into this conceptual research model; they are external support, coercive pressure, and mimetic pressure,

as presented in Figure 2. External support refers to the existence of vendors, agencies, and businesses in the external environment of the organization to support the adoption of EA activities [121], that is, a third-party dependency in which the group relies on IT suppliers for problem determination and resolution, customization, interfaces, and functional enhancement to new IT [122]. EA is a long-term view of the organization, according to Gilliland *et al.* [31], and may therefore be a lifelong commitment for many organizations. External support was identified and recognized in the technology adoption phase especially in enterprise resource planning (ERP) [123]. According to Baker [46], support from the availability of skilled labor, consultants, or third-party suppliers of a technology is important to foster the new idea being adopted in the organization. Consequently, external support is a vital factor in procuring, installing, maintaining, and training regardless of the type of technology that the organization has. Therefore, this research proposes the following hypothesis on the basis of the evidence:

H10: External support positively influences the intention to adopt EA.

Pressure focuses on external pressures, which are coercive and mimetic [48]. These pressures are presented in institutional theory, which has been widely used in IS research to understand the mechanisms of adoption and implementation of innovation in organizations. This theory postulates that organizations are influenced by external pressures when forming organizational structures [48]. Such pressures have been shown to significantly affect adoption in IS studies [53], [124], [125]. Furthermore, previous studies revealed that institutional theory is relevant when examining OGD, as Wang and Lo [59]; assimilation processes; and technology adoption [108]. Thus, this research forecasts that such pressures remain a significant influence on EA adoption in the organization, as described in institutional theory.

Coercive pressure refers to "*the formal pressure and external pressure exerted upon them by other organizations upon which they are dependent, and the cultural expectations in the society within which the organization's function*" [48]. From previous EA adoptions, such pressure suggests that regulation could affect project results in negative and positive ways [10]. Furthermore, this pressure has a great influence during the adoption phase by force of mandate [11]. This variable is selected because its potential effect on EA was identified in previous studies [9], [10], [66], [99], [126]. This finding is consistent with the study of Pudjianto *et al.* [58], who found that lack of a supportive regulatory environment for e-government will result in a negative effect on assimilation. Therefore, the following is posited:

H11: Coercive pressure positively influences the intention to adopt EA.

Previous studies maintain that mimetic pressure is more noticeable at the early stage of innovation diffusion, where the uncertainty of outcome is high [60], [127]. They stated that few organizations adopt innovation at the early stage in belief of its efficiency. This action then influences other

organizations that have not adopted the innovation to surrender to pressure because they are worried about appearing different. Such capitulation then generates added bandwagon pressure [128]. According to Shim *et al.* [60], this pressure induces other organizations to follow the decision to adopt an innovation. Many reviews of this notion have been conducted [44], [129], [130]. Hence, this research expects mimetic pressure to have a salient influence at an early stage. Therefore, the present research hypothesizes the following:

H12: Mimetic pressure positively influences the intention to adopt EA.

IV. METHODOLOGY

The operational research design outlines the sequence of the phase of the research process involved in this research. The process of this research follows the Urbach [28] model, which is typically applied in SEM-based research. The operational research design of this research comprises four steps: conceptual model development, instrument development, data collection, and model validation. First, the conceptual model was developed based on comprehensive literature reviews of EA adoption and IT/IS adoption studies. Twelve factors from three perspectives influence EA adoption by MPS organizations. The technological factors consist of sufficient ICT infrastructures and EA complexity, while organizational factors include top management support, organizational readiness, clear communication, normative pressure, expected benefits, good governance, and organization size. The environmental perspective consists of three factors: external support, coercive pressure, and mimetic pressure.

Second, a questionnaire was developed as a data collection instrument. In the survey, the measurement items were adapted from past studies and were revised in terms of content validity based on expert reviews. Experts from the academic and industry sectors were identified based on their expertise in various fields, such as IS, EA, research methods, statistics, academic, and public sectors. The experts' reviews found that two items were rejected and only 50 items remained. Subsequently, a pilot test was conducted to assure the reliability and the quality of the questionnaire. Third, the survey was distributed randomly to actual respondents in MPS organizations. The unit of analysis of this research is the organization. Therefore, the survey was sent to the chief information officer (CIO) or head of the organization, such as mayor, director general, or manager. These respondents were chosen because they are involved in the decision-making process of the organization. A total of 255 valid responses were collected from the survey. Finally, these responses were analyzed to validate the model by using PLS-SEM, which involves two types of analysis: measurement model and structural model analyses.

A. INSTRUMENT DEVELOPMENT

The instrument development takes into account the design of the questionnaires. This research adapted the instrument development procedures in [131]. The validity of the questionnaire was determined by conducting a pre-test and pilot test to ensure the appropriateness and sensitivity of the questions. The second milestone was the completion of data collection, which was achieved by determining the sampling procedures and administering the survey. Then, on the basis of the collected data, the causal relationship outlined in the conceptual model was analyzed in the next phase.

The instrument that was used in this research is a questionnaire. Therefore, the measurement items were collected using a combination of deductive and inductive approaches. The researcher reviewed literature published in high-impact journals such as *MIS Quarterly*, showed empirical information such as Cronbach's alpha, and is widely cited and used in relevant research [132]. Multiple items were gathered in the item pool to measure the different dimensions of the construct. Then, the items to be measured were adapted from previous relevant research. The instruments that were widely cited and frequently used by other researchers are good criteria for choosing a good instrument [132]. Therefore, the content validity was fulfilled [133]. The reliability and accuracy of scores from instruments were obtained through internal consistency across the items [132]. The Cronbach's alpha is used to test the internal consistency [134]. The measurement items then underwent pilot testing. All measurement items used in this research are shown in Appendix B.

Various opinions have been expressed about the number of points on a Likert scale, such as whether the scale should be even-numbered (2, 4, 6, 8, or 10) or odd-numbered (3, 5, 7, or 9) scale [135]. A seven-point Likert scale is suggested in this research to represent the responses of the respondents [136]. The seven-point Likert scale has been proven to have the highest magnitude of factor loadings and composite reliability of the latent variables. This condition indicates a stronger association between measurement items and latent variables and demonstrates adequate discriminant validity of the latent variables [137]. Miller [138] stated that human perceptions cannot discern more than seven different categories. In addition, the odd-numbered Likert-type scale was used in this research to overcome the problem of too many neutral responses, which are common among Asian people, especially in the Malaysian context, when given the option to choose [139].

Two techniques are used to control common method biases in the research, namely, 1) procedural remedies and/or 2) statistical remedies [140]. These two techniques are adopted for this research. The procedural remedies include improving scale items through the development of items. The development of items was carefully designed to reduce the ambiguity of items in the comprehension stage of the response process. The researcher kept the questions simple, concise, and specific, and avoided double-barreled questions. Pre-test and pilot test were conducted to ensure that the questionnaire items are simple and can be clearly understood by the respondents. The researcher also included instructions for completing the questionnaire, and the terms used in the questionnaire were clearly defined at the beginning. The instructions also

TABLE 1. Cronbach's alpha values for the pilot test.

Variable	Items	Alpha	Interpretation
Sufficient ICT infrastructure (ICT)	3	0.931	Excellent
EA complexity (CPX)	4	0.938	Excellent
Top management support (TMS)	4	0.932	Excellent
Organizational readiness (OR)	4	0.785	Good
Clear communication (COMM)	6	0.962	Excellent
Normative pressure (NP)	3	0.913	Excellent
Expected benefits (EB)	5	0.991	Excellent
Good governance (GVR)	6	0.958	Excellent
External IS support (EXT)	5	0.899	Very Good
Coercive pressure (CP)	3	0.936	Excellent
Mimetic pressure (MP)	3	0.961	Excellent
Intention to adopt (INT)	3	0.987	Excellent

stated that the respondent's answers are anonymous and that there are no right and wrong answers. The respondents were advised to answer the questions as honestly as possible. This procedural remedy can protect respondents' anonymity and reduce evaluation hesitation.

1) PILOT TEST

The pilot test evaluates and determines the survey instrument empirically with a small sample rather than the actual sample size. The respondents of the pilot test have similar characteristics as the actual population [141], [142]. Twenty-three respondents from different MPS organization types answered the bilingual survey for this research. Statistical analysis was used to validate and verify the pilot test responses by using SPSS version 20. This research adopted the rule of thumb of Field [143] and George and Mallery [144] that a Cronbach's alpha of more than 0.7 is acceptable and reliable, which is also consistent with the idea of Kline [145] and Sekaran and Bougie [141], [146] that a value of more than 0.7 and near 1.0 is considered excellent, realistic, and reliable. With the inconsistency in determining the minimum value of Cronbach's alpha, the cut-off point for this research is 0.7, as suggested by Hair *et al.* [147]. Thus, no item was dropped for this research. Table 1 shows the Cronbach's alpha value of each construct. The Cronbach's alpha value for the questionnaire is 0.976.

B. SAMPLE AND DATA COLLECTION

Questionnaires were used as the data collection instrument and were sent to the heads of organizations or key respondents such as the CIO of the selected public sector organizations under study. The personnel were chosen because they have high positions and are normally involved in decision-making, aside from knowing the overall aspects and performance of the organization. The unit of analysis of this research is the organization. Therefore, the key respondents from five MPS organization types were asked to participate in the survey. The population of MPS organizations was represented by multiple strata. Thus, this research employed probabilistic stratified

random sampling approach due to its efficiency in avoiding misrepresentation of population members [132], [141]. Determination of sample size was calculated using G*Power tool, a power analysis method. The prior power analysis of this research used the error probability of $\alpha = 0.05$, the power $(1 - \beta) = 0.8$, effect size = 0.15. Therefore, this research found a minimum total sample of 178 to be drawn from a population of 741.

Questionnaires were administered through online and postal approaches, and they were also distributed by hand in public sector organizations located in Putrajaya. Although better and fast response rates could be attained by hand distribution, time and cost limitations were major constraints. The public sector organizations in the sample were located all over Malaysia, and the researcher could not distribute the questionnaires by hand given the limited time and budget. The total number of organizations involved in the survey is 600. Initially, the online survey was sent to the key respondents of organizations such as the CIO, mayor, or head of the agency by email. However, the response rate was low (20%). Following Creswell [132], [141] suggestions, the researcher conducted follow-ups via email reminder, telephone call, and paper-based approach. As a result, the number of responses increased to 285. The response rate of collected data for this research is 47.5%. The benchmark of response rate for organizational research studies is within the range of 35% to 40% [148]. Therefore, the response rate of 47.5% can be reasonably accepted in organizational research studies and adequate to generalize the population of the research context.

V. RESULT

A. DATA PREPARATION

The essential step in PLS-SEM before conducting data analysis is data preparation. Four activities are involved in this step: response rate analysis, data cleaning, nonresponse bias test, common method bias test, and normality test. This research collected empirical data by using questionnaires. Therefore, data collection issues, such as missing data, suspicious response pattern, and outliers, have to be addressed and examined accordingly. Data preparation was conducted to check and solve the issues. These issues were addressed by performing four activities: response rate analysis, data cleaning, common method bias test, and normality test. The missing data on a questionnaire regarding the blank responses of the demographic profile of the respondents and the Likert rating scale questions for the items to be measured, however, did not exceed 15% and are less than 5% values per indicator [147].

The researcher also examined for suspicious response patterns. Similar or repetitive answers for numerous questions affect the data analysis. This type of response pattern is often described as straight lining. The data can be detected by the value of standard deviation = 0 among the given questions. Nine responses were affected and were therefore dropped from the dataset, as suggested by [141], [147]. An outlier

can be identified by using multivariate graphs and statistics, for example, box plots. Outliers occur when combinations of variable values are particularly rare. In this research, the outlier or extreme case is identified as 1.5 times or 3 times the interquartile range below the lower quartile or above the upper quartile [147]. Twenty responses were identified as outliers and were therefore dropped from the dataset to prevent them from causing problems with coefficient correlation [149]. Therefore, 255 out of the total collected responses remained as valid responses and are considered to be accepted and adequate sample size.

The researcher checked for nonresponse bias issue using an independent T-test sample. Nonresponse bias can be analyzed by validating that both early and late respondents are not significantly different[28]. From 255 valid responses, 144 were considered as early responses and the remaining 111 were late responses. The research conducted the independent sample T-test using SPSS for early responses versus late responses on the Likert scale answers of the survey questions. The non-response bias results indicate that there is no significant difference (p>0.05, two-tailed test) between early and late responses on any of the survey items. It can, therefore, be concluded that this research is free from non-response bias, which is a potential issue in survey-based studies.

Common method bias, also known as common method variance (CMV), identifies the error variance that is attributable to the measurement method and causes a potential problem in behavioral research. Potential CMVs were found in this research because the research method was conducted with independent and dependent variables from the same respondents [140]. According to Podsakoff [140], method biases are a problem because they cause one of the measurement errors that threaten the validity of conclusions regarding the relationships between variables. This argument is consistent with Bagozzi *et al.* [150], who noted that one source of measurement error is method variance, which may arise from a variety of sources, such as the content of specific items, scale type, response format, and the general context.

Finding a procedural remedy that meets all needs is difficult. Therefore, statistical remedies are available to control common method biases. Common statistical remedies are Harman's single-factor test, Lindell and Whitney's (2001) marker variable, collinearity, and partial correlation method [140]. The present research chose Harman's single-factor test and correlation matrix to examine the common method bias. These two tests are highly recommended for the PLS-SEM research context [28], [151]. The result of Harman's single-factor test from SPSS showed that the maximum covariance explained by one factor is 43.1%, which is less than the majority or 50% of the variances in the variable. Therefore, common method bias did not occur in this research [152]. The total variance of this research is explained by Harman's single-factor test. The result of the correlation matrix obtained by using SPSS showed that all construct values were significant ($p < 0.01$ and $p < 0.05$) which are lower than the cut-off value of $r < 0.90$ [150], [153]. The result of

the correlation matrix shows that no correlations went beyond 0.9 to indicate a high correlation. The two statistical tests indicate that common method bias is not a problem for this research.

A skewness and kurtosis value of 0 show a perfectly normal data distribution. As suggested by Hair *et al.* [154] and Ramayah *et al.* [155], this study used an online statistical power analysis tool called Webpower (https://webpower.psychstat.org/models/kurtosis) to test the normality of multivariate data. Mardia's multivariate skewness value $\beta = 32.32$ and $p < 0.01$, and Mardia's multivariate kurtosis value $\beta = 260.51$ and $p < 0.01$, thereby showing that the distribution of data is not normal [156]. Therefore, the PLS-SEM analysis can be performed on both normal and not normal data.

B. DESCRIPTIVE ANALYSIS

Descriptive statistics was performed to analyze the demographic profile of the respondents. Afterwards, inferential statistics, which involved a two-stage approach that consists of measurement model analysis and structural model analysis, was performed. Table 2 presents the details of the demographic profile of the respondents. The respondents were classified according to distinct demographic categories, namely, organization type (OT), age, education level (EDU), position grade (GR), years of work experience (YOW), number of employees (NOE), and number of IT employees (NoIT).

The survey results demonstrate that the majority of the respondents work at the federal level (36.5%). Most of the respondents are within the range of 36 to 40 years of age (29.4%), and only 2.4% of respondents are below 26 years of age. This result indicates that respondents are generally from the young generation. Thus, technology should not be an unfamiliar topic for them. Over half of the respondents reported that their educational qualifications are a degree (56.9%), master's degree (26.7%), and doctor of philosophy (2.7%). These results indicate that the majority of the respondents come from a strong socioeconomic background and are educated. Consequently, they are capable and eligible to contribute to the decision-making for their organization. In response to position grade, 46.3% of respondents are between the grade of 41–44 and only 20% of the respondents hold a grade lower than 41. This table evidently shows that more than two-thirds of the respondents hold a position grade from 41 and above and indicates that the respondents are officers, middle management, and top management. Therefore, the majority of respondents are part of the decision-making team. The respondents that hold a position grade below 41 belong to the support group.

Notably, more than two-thirds (68.6%) of the respondents have work experience of more than 10 years in the public sector. Only 6.3% of the respondents have less than two years of work experience in the public sector. The result indicates that the respondents have adequate experience and knowledge in public sector initiatives. They can also be considered experts in undertaking specific tasks for the organization. The result

TABLE 2. Demographic analysis.

Demographic	Category	Frequency	Valid (%)
Organization type (OT)	Federal Level	93	36.5
	Federal statutory body	30	11.8
	State level	61	23.9
	State statutory body	31	12.2
	Local authority	40	15.7
Age	Less than 26 years	6	2.4
	26–30 years	16	6.3
	31–35 years	43	16.9
	36–40 years	75	29.4
	41–45 years	60	23.5
	46–50 years	23	9.0
	Above 50 years	32	12.5
Education level (EDU)	Diploma	35	13.7
	Degree	145	56.9
	Master	68	26.7
	Doctor of philosophy	7	2.7
Position grade (GR)	< 41	51	20.0
	41–44	118	46.3
	48	51	20.0
	52	24	9.4
	54	7	2.7
	JUSA/TURUS	4	1.6
Years of work experience (YOW)	Less than 2 years	16	6.3
	2–4 years	10	3.9
	5–7 years	15	5.9
	8–10 years	39	15.3
	More than 10 years	175	68.6
Number of employees (NOE)	< 100	56	22.0
	100–399	81	31.8
	400–699	38	14.9
	700–999	14	5.5
	>=1000	66	25.9
Number of IT employees (NoIT)	Less than 3	67	26.3
	4–10	65	25.5
	11–20	35	13.7
	21–30	26	10.2
	31–40	13	5.1
	41–50	12	4.7
	More than 50	37	14.5

also showed that from the 255 questionnaires, the data on the number of employees (a measurement of organization size) demonstrated that the majority of the organizations were categorized as 100–399 (31.85%), followed by more than 1000 (25.9%), lower than 100 (22%), and 400–699 (14.9%). Only a small number was classified in the 700–999 range (10.3%).

With regard to the number of employees in the IT department to which the respondents were attached, organizations with fewer than 3 IT employees were the largest group (26.3%), followed closely by organizations with 4–10 IT employees (25.5%), more than 50 IT employees (14.5%), 11–20 IT employees (10.69%), 21–30 IT employees (10.2%), 31–40 IT employees (5.1%), and 41–50 IT employees (4.7%). This finding shows that most of the organization have IT strengths, although they did not have many IT employees. The most surprising aspect of the data is in the response to the organization type. The respondents' numbers exceed the stratified sampling rule of 30 for every stratum [157]: federal level (63%), federal statutory body

(11.8%), state level (23.9%), state statutory body (12.2%), and local authority (15.7%).

C. MEASUREMENT MODEL ANALYSIS
This research assessed the reliability and validity of the reflective measurement model. The metrics used for the reflective measurement model were internal consistency reliability, indicator reliability, convergent validity, and discriminant validity.

1) INTERNAL CONSISTENCY RELIABILITY
As suggested by Hair *et al.* [156], the first metric to be evaluated is typically internal consistency reliability. Cronbach's alpha is a traditional criterion to estimate the reliability of intercorrelations of the indicator or item of constructs. The idea of Cronbach's alpha is that all indicators are equally reliable on the constructs, hence reflecting a relatively low reliability value. Given this limitation of Cronbach's alpha, an alternative measure called composite reliability (CR) was applied in this research. CR is a criterion to estimate different outer loadings of indicators of the constructs. The CR varies from 0 to 1, with higher values indicating higher reliability. According to Hair *et al.* [147], the measure of analyzing and assessing the internal consistency reliability lies between the Cronbach's alpha and CR. Therefore, this research considers and reports both reliability measures. Specifically, CR and Cronbach's alpha values of more than 0.70 are acceptable, while a value below 0.60 indicates a lack of internal consistency reliability [156]. For this research, the values of CR and Cronbach's alpha for each construct were more than 0.70. Therefore, all indicators are reliable for measuring the constructs.

2) INDICATOR RELIABILITY
Indicator reliability refers to the consistency of indicators with what it anticipates to measure. The size of the outer loading is also called indicator reliability, which reflects the proportion of the indicator variance described by the latent variable [28]. The acceptable value of outer loadings of more than 0.70 shows that the associated indicators of constructs have much in common or are consistent. Outer loading values below 0.5 should be considered for removal [156]. The path weighting scheme was selected for the inner weights' calculation. This weighting scheme provides the highest R2 value for endogenous latent variables and is commonly appropriate for all types of PLS path model specifications and estimations [158]. As shown in Table 4, the construct OR4 showed a value of 0.465, indicating weakness and that it should be considered for removal from the scale [159]. Other constructs are retained because the values of outer loadings were more than 0.70. Therefore, the indicator reliability (outer loadings) for this research was achieved.

3) CONVERGENT VALIDITY
Another metric of the reflective measurement model is convergent validity. Convergent validity is usually determined by

TABLE 3. HTMT result.

Construct	COMM	CP	CPX	EB	EXT	GVR	ICT	INT	MP	NP	OR	SIZE	TMS
COMM													
CP	0.345												
CPX	0.093	0.059											
EB	0.509	0.550	0.218										
EXT	0.450	0.594	0.248	0.513									
GVR	0.594	0.610	0.221	0.875	0.531								
ICT	0.485	0.466	0.313	0.566	0.471	0.658							
INT	0.328	0.733	0.152	0.699	0.474	0.718	0.514						
MP	0.436	0.686	0.223	0.578	0.649	0.616	0.559	0.634					
NP	0.523	0.673	0.201	0.859	0.560	0.796	0.609	0.736	0.643				
OR	0.502	0.687	0.305	0.708	0.683	0.718	0.689	0.654	0.704	0.798			
SIZE	0.032	0.039	0.026	0.041	0.030	0.039	0.062	0.035	0.079	0.035	0.067		
TMS	0.438	0.533	0.218	0.566	0.353	0.570	0.519	0.523	0.490	0.673	0.805	0.136	

assessing the average variance extracted (AVE) and means that the construct contains more than 50% of the indicator variance. AVE is the degree to which a construct explains the inconsistency of its indicators. The result of outer loadings contributes to the AVE value. The convergent validity of the construct can be adequately achieved if the value of AVE for each construct is equal to or greater than 0.50 [150], [160]. The AVE values for every construct in this research were more than 0.50 (ranging between 0.594 and 0.943). Specifically, after one item was deleted, which is organizational readiness, the value of AVE and CR increased to 0.594 and 0.746, respectively. The results from both indicator reliability (outer loadings) and AVE values in this research demonstrated that the measurement model conforms to the convergent validity assessment.

4) DISCRIMINANT VALIDITY

After convergent validity is confirmed to not be a problem for this research, the next step was to verify the discriminant validity. Discriminant validity refers to the construct under investigation being distinct or different from one another. This metric examines the bivariate correlation of overlapping. Following Hair *et al.* [156]'s guidelines in analyzing and reporting discriminant validity by using the PLS-SEM approach, three methods are available for assessing reflective indicators, namely, Fornell and Lacker criterion, cross-loadings, and heterotrait–monotrait ratio of correlations (HTMT). Each criterion is explained below.

5) FORNELL AND LACKER CRITERION

The bivariate correlation matrix using Fornell and Larcker criterion was used to assess the correlation between constructs. Results indicate discriminant validity between all constructs. The square root of AVE (in yellow color) on the diagonal are higher than the off-diagonal's values on the respective column and row. Thus, the requirements set by Fornell and Larcker [160] were met in this condition.

6) CROSS-LOADINGS

The result of cross-loading shows that the majority of indicators loaded highly on their respective constructs. However, the indicator OR4 showed a value of 0.465, thereby showing that this item has an issue of high loading. Therefore, OR4 was deleted before structural model analysis was continued.

7) HTMT CRITERION

The third criterion for assessing the discriminant validity is the HTMT criterion of correlation. The HTMT criterion is meant for reflective indicators and can be applied for both multi-item and single-item constructs [161]. A recent study suggested that HTMT produces a more accurate and established assessment than typical criteria such as the Fornell and Larcker criterion [147]. As shown in Table 3, all construct values of HTMT fulfilled the HTMT criterion of $HTMT_{0.90}$ [162]. The result ascertains the discriminant validity of the constructs for this research context.

As a whole, the measurement model analysis demonstrated adequate convergent validity and discriminant validity to bring this research to the next level: structural model analysis for testing the relationship among variables in the research model. The results of the reflective measurement model for this research is summarized in Table 4.

D. STRUCTURAL MODEL ANALYSIS

After the indicators of the constructs are confirmed to be reliable and valid, the next step is to perform structural model analysis. The structural model assesses the model in terms of predictive capabilities and relationships between the constructs. The PLS-SEM approach maximizes the explained variance of the endogenous construct; for this research, it is the intention to adopt EA. Following Hair *et al.* [156], [161]'s guideline and suggestion, six measures— significance of collinearity, path coefficient (β), coefficient of determination (R^2), effect size (f^2), blindfolding and predictive relevance (Q^2), and effect size (q^2)—can be adopted to assess

TABLE 4. Summary of reflective measurement model.

Constructs	Items	Convergent Validity		Internal Consistency Reliability		Discriminant Validity		
		OL > 0.70	AVE > 0.50	CR > 0.7	α > 0.7	FL	CL	HTMT $_{0.90}$
COMM	COMM1	0.835	0.777	0.943	0.954	Yes	Yes	Yes
	COMM2	0.920					Yes	
	COMM3	0.927					Yes	
	COMM4	0.897					Yes	
	COMM5	0.866					Yes	
	COMM6	0.839					Yes	
CP	CP1	0.914	0.864	0.922	0.950	Yes	Yes	Yes
	CP2	0.943					Yes	
	CP3	0.932					Yes	
CPX	CPX1	0.871	0.804	0.923	0.942	Yes	Yes	Yes
	CPX2	0.869					Yes	
	CPX3	0.928					Yes	
	CPX4	0.916					Yes	
EB	EB1	0.960	0.926	0.980	0.984	Yes	Yes	Yes
	EB2	0.957					Yes	
	EB3	0.965					Yes	
	EB4	0.964					Yes	
	EB5	0.966					Yes	
EXT	EXT1	0.830	0.629	0.856	0.894	Yes	Yes	Yes
	EXT2	0.798					Yes	
	EXT3	0.702					Yes	
	EXT4	0.827					Yes	
	EXT5	0.802					Yes	
GVR	GVR1	0.873	0.834	0.960	0.968	Yes	Yes	Yes
	GVR2	0.879					Yes	
	GVR3	0.901					Yes	
	GVR4	0.947					Yes	
	GVR5	0.935					Yes	
	GVR6	0.941					Yes	
ICT	ICT1	0.814	0.680	0.767	0.864	Yes	Yes	Yes
	ICT2	0.866					Yes	
	ICT3	0.791					Yes	
INT	INT1	0.975	0.943	0.970	0.980	Yes	Yes	Yes
	INT2	0.977					Yes	
	INT3	0.960					Yes	
MP	MP1	0.965	0.931	0.963	0.976	Yes	Yes	Yes
	MP2	0.973					Yes	
	MP3	0.956					Yes	
NP	NP1	0.943	0.856	0.916	0.947	Yes	Yes	Yes
	NP2	0.893					Yes	
	NP3	0.939					Yes	
OR	OR1	0.836	0.594	0.746	0.848	Yes	Yes	Yes
	OR2	0.865					Yes	
	OR3	0.844					Yes	
	OR4	0.465					No	
OS	CAT1	1.000	1.000	1.000	1.000	Yes	Yes	Yes
TMS	TMS1	0.900	0.816	0.925	0.946	Yes	Yes	Yes
	TMS2	0.884					Yes	
	TMS3	0.904					Yes	
	TMS4	0.924					Yes	

OL – outer loadings; FL = Fornell and Larcker; CL = cross-loading; CR = composite reliability

the structural model by using PLS-SEM. Next, importance-performance map analysis (IPMA) was performed to identify the factors that have a relatively high influence on EA adoption by MPS organizations. IPMA is an advanced method and a useful tool but is less frequently used in research [161], [163]. An illustrative outcome of IPMA enables researchers to identify the critical constructs of attention and action. Finally, the summary of the hypotheses of this research context is presented.

1) COLLINEARITY ASSESSMENT
Collinearity assessment typically involves assessing the formative measurement model. This step is necessary in structural model assessment. According to Hair *et al.* [147], collinearity for the structural model estimates the path

coefficient based on ordinary least squares regression of each endogenous construct on its corresponding exogenous construct. A collinearity issue occurs when two exogenous constructs are causally related to each other. The criterion of collinearity is VIF, and the threshold value of VIF is below 5 (VIF < 5) [147]. Every construct involved in this research was examined using this measure. The critical level of collinearity (VIF > 5) may indicate the biasness in the path coefficient for multiple regression and does not reliably explain the endogenous construct or dependent variable in the research model. Although the VIF values of EB and GVR are near the critical levels of multicollinearity, multicollinearity is not a serious issue for a predictive model of dependent variables such as the intention to adopt EA [141], [164], [165] because multicollinearity does not affect the reliability of prediction. The value of VIF suggested by Sekaran and Bougie [141],

TABLE 5. VIF result.

Construct	INT
COMM	1.733
CP	2.414
CPX	1.178
EB	4.956
EXT	1.919
GVR	4.596
ICT	1.766
MP	2.373
NP	3.98
OR	2.308
SIZE	1.096
TMS	2.258

→ Significant relationship
→ Insignificant relationship

FIGURE 3. Hypothesis testing.

Yu [164], Ho [165] is lower than 10 (VIF < 10). Table 5 shows the result of the collinearity analysis of the model. All the inner VIF values of all constructs are lower than 10 and 5. Therefore, no multicollinearity issue exists for the research model.

2) PATH COEFFICIENT

Path coefficient (β) assesses the hypothesized relationships among the constructs in the research model. This research has a nonparametric distribution. Thus, both measures of t-value and path coefficients (β) were obtained using the bootstrapping procedure. The standardized values of the path coefficient are approximately within the range ± 1. The path coefficient relies on its standard error by running the bootstrapping procedure. Consequently, the standard error enables the confidence interval, t-value, and p-value to be computed and exhibited for all structural path coefficients. The bootstrapping procedure of 500 samples, no sign changes, basic bootstrapping, bias-corrected and accelerated, one-tailed test, and significance level of 0.05 were selected to provide consistent values by using SmartPLS 3.0. The critical value of t-value is equal to or greater than 1.65 (t $\geq$ 1.65), and the p-value is lower than 0.05 (p < 0.05) [147]. In this research, 12 direct hypotheses were developed between constructs, and the results of the path coefficients are presented in Table 6. Seven relationships have a t-value $\geq$ 1.65 and are hence significant at 0.05. The factors are clear communication (β = −0.133, p < 0.01), coercive pressure (β = 0.330, p < 0.01), expected benefit (β = 0.180, p < 0.05), good governance (β = 0. 237, p < 0.05), mimetic pressure (β = 0.130, p < 0.05), normative pressure (β = 0.165, p < 0.01), and organization size (β = 0.07, p < 0.05). Therefore, H1, H2, H4, H6, H8, H9, and H11 are supported.

Interestingly, complexity (CPX), external support (EXT), sufficient ICT infrastructure (ICT), organizational readiness (OR), and top management support (TMS) have insignificant relationships with EA adoption by MPS public sector organizations. Thus, H3 with β = −0.018, p < 0.05, H5 with β = −0.039, p < 0.05, H7 with β = 0.004, p < 0.05, H10
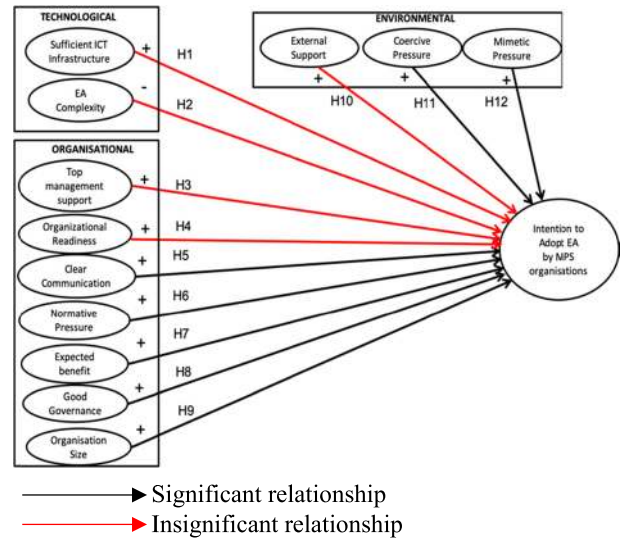
with β = −0.010, p < 0.05, and H12 with β = 0.022, p < 0.05 are not supported. Figure 3 shows the path coefficients with p-values on each relationship defined for this research model.

3) COEFFICIENT OF DETERMINATION (R2)

Another important measure for assessing the structural model is the coefficient of determination (R^2). This measure explains the model's predictive power and represents the combinations' effect of exogenous constructs on the endogenous construct [147]. The criterion of the coefficient of determination is R^2 because it represents the values of square correlations between exogenous constructs and a specific endogenous construct. Therefore, the R^2 defines a measure of in-sample predictive power and ranges between 0 and 1 [156]. Although scholars claimed that providing rules of thumb for an acceptable R^2 value is difficult, the [159], [166] guidelines were adopted. The R^2 values of 0.75, 0.50, or 0.25 are defined as high, moderate, or weak, respectively. The high value of R^2 indicates a high predictive accuracy. The R^2 value of the structural model for this research is 0.665, which is above the 0.20 and 0.26 values suggested by [167]. The result indicates a substantial model for this research. Scholars also claimed that R^2 values should be high enough to achieve a minimum level of explanatory power, and a value greater than 0.10 is reasonably adequate to explain the variance of the endogenous construct [28], [168].

4) EFFECT SIZE F2

The next measure is the effect size of exogenous constructs toward the endogenous construct by using Cohen f^2 [167]. This measure is highly recommended and encouraged by scholars and reviewers [28], [156], [158], [159], [169]. A guideline for assessing the effect size (f^2) is that values of 0.35, 0.15, and 0.02 indicate large, medium and small effects [167] of the exogenous constructs, respectively.

TABLE 6. Hypothesis testing.

H	Relationship	SB (β)	SE	t-value	p-value	LL (0.05)	UL (0.95)	Supported
H1	COMM -> INT	−0.133	0.054	2.459	0.007	−0.213	−0.033	Yes
H2	CP -> INT	0.330	0.075	4.387	0.000	0.208	0.459	Yes
H3	CPX -> INT	−0.018	0.047	0.376	0.353	−0.095	0.057	No
H4	EB -> INT	0.180	0.090	2.002	0.023	0.032	0.327	Yes
H5	EXT -> INT	−0.039	0.061	0.643	0.26	−0.139	0.054	No
H6	GVR -> INT	0.237	0.102	2.314	0.011	0.060	0.391	Yes
H7	ICT -> INT	0.004	0.049	0.089	0.465	−0.076	0.088	No
H8	MP -> INT	0.130	0.074	1.760	0.040	0.009	0.257	Yes
H9	NP -> INT	0.165	0.079	2.076	0.019	0.041	0.298	Yes
H10	OR -> INT	−0.010	0.062	0.157	0.438	−0.119	0.085	No
H11	SIZE -> INT	0.07	0.035	1.968	0.025	0.009	0.127	Yes
H12	TMS -> INT	0.022	0.058	0.376	0.353	−0.066	0.120	No

Note: H = hypothesis, SB = standard beta, SE = standard error, ** p < 0.01, * p < 0.05

TABLE 7. Result of effect size (F^2).

	INT	F^2
COMM	0.034	Small
CP	0.152	Medium
CPX	0.000	None
EB	0.022	Small
EXT	0.001	None
GVR	0.042	Small
ICT	0.000	None
MP	0.021	Small
NP	0.021	Small
OR	0.002	None
SIZE	0.000	None
TMS	0.000	None

TABLE 8. Result of predictive relevance (Q^2) and effect size (Q^2).

Construct	Q^2	$Q^2_{Included}$	$Q^2_{Excluded}$	q^2	Effect Change
COMM			0.575	0.565	0.024	Small
CP			0.575	0.527	0.114	Medium
CPX			0.575	0.576	−0.001	No effect
EB			0.575	0.570	0.013	No effect
EXT			0.575	0.571	0.010	No effect
GVR			0.575	0.562	0.031	Small
ICT			0.575	0.576	−0.001	No effect
INT	0.575 (High)	0.575			
MP			0.575	0.571	0.010	No effect
NP			0.575	0.570	0.013	No effect
OR			0.575	0.575	0.001	No effect
SIZE			0.575	0.571	0.010	No effect
TMS			0.575	0.581	−0.013	No effect

A value lower than 0.02 indicates no effect on the endogenous construct. The effect size's result for the exogenous constructs in this research is presented in Table 7. The exogenous construct CP has a medium size effect, while COMM, EB, GVR, MP, and NP have a small size effect toward the endogenous construct (INT). Exogenous constructs (CPX, EXT, ICT, OR, SIZE and TMS) have no effect size toward the endogenous construct (INT).

5) PREDICTIVE RELEVANCE (Q2)

In addition to R^2 values as a criterion of predictive accuracy power, the predictive relevance criterion should be examined for assessing the structural model [170], [171]. Unlike R^2, Q^2 is also referred to as the out-sample predictive power due to

its ability to predict data that are not used in the model. Therefore, the blindfolding procedure depending on the omission distance was applied to provide the Q^2 value of endogenous constructs that have a reflective measurement model [147]. The blindfolding algorithm is based on the cross-validated redundancy approach and was defined with omission distance = 7, path weighting scheme, 500 maximum iterations, and stop criterion = 7. The result of the predictive relevance of endogenous constructs in this research is presented in Table 8. The Q^2 value for endogenous construct (INT) is 0.575, which is greater than 0. Therefore, all the exogenous constructs have predictive relevance for the endogenous construct. Also, as a rule of thumb, Hair *et al.* [147] stated that the values of 0.35, 0.15, and 0.02 represent large, medium, and small predictive relevance of endogenous constructs, respectively.

6) EFFECT SIZE (Q2)

The relative impact of predictive relevance was assessed by using a similar approach of effect size for R^2 values. The q^2 effect size values were computed using the formula

$$q^2 = (Q^2_{Included} - Q^2_{Excluded})/(1 - Q^2_{Included}) \qquad (1)$$

A relative measure of predictive relevance values of 0.35, 0.15, and 0.02 represents large, medium, and small predictive relevance, respectively, of exogenous constructs toward the endogenous construct for this research context [147]. As Table 8 shows, a medium $q2$ effect size is found for CP, while a small $q2$ effect size is observed for COMM and GVR. Other exogenous constructs have no effect size of predictive relevance toward the endogenous construct (INT).

7) IMPORTANCE-PERFORMANCE MAP ANALYSIS

The IPMA contrasts the total effects of the structural model, which is the endogenous construct (INT) with the average scores of exogenous constructs [154], [158], [170]. The total effects represent the importance of the exogenous construct in influencing the endogenous construct, while their average scores of exogenous constructs represent their performance. The exogenous constructs that have a strong total effect perform relatively well for the endogenous construct. However, low performance is observed with low average scores of exogenous constructs.

Table 9 provides the result of IPMA under study by using IPMA procedure in SmartPLS 3.0. The construct of EB (70.227) performs well in influencing the intention to adopt EA (INT). The result also indicates that a one-unit index value for the performance of EB increase results in an increased overall performance of target construct (INT) by the value of the total effect of EB (0.187). Although the exogenous construct of CP has a high importance in explaining the target construct because its total effect data is 0.313, the performance of CP is relatively low, thereby leaving substantial room for improvement. Consequently, the construct CP is the most relevant for managerial actions. On the other hand, the construct EB is the most relevant for managerial attention. The IPMA of intention to adopt EA (INT) reveals that the construct COMM also has high performance. However, it is not an important construct in the prediction of intention to adopt EA (INT). Therefore, managers or decision-makers should not put much focus and attention on COMM because it may result in possible overkill in public sector services in the case of EA.

The researchers plotted the index values and total effects scores in a priority map, as shown in Figure 4. the more important constructs are CP, GVR, EB, NP, and MP. Therefore, managers or decision-makers should focus on these constructs to enhance adoption. The interpretation of IPMA is consistent with [154], [156]. The construct OS has little influence on EA adoption due to its low importance and performance. The results of IPMA allow the identification of factors with a relatively high importance and relatively low performance. These are key improvement areas that can

TABLE 9. Result of the IPMA.

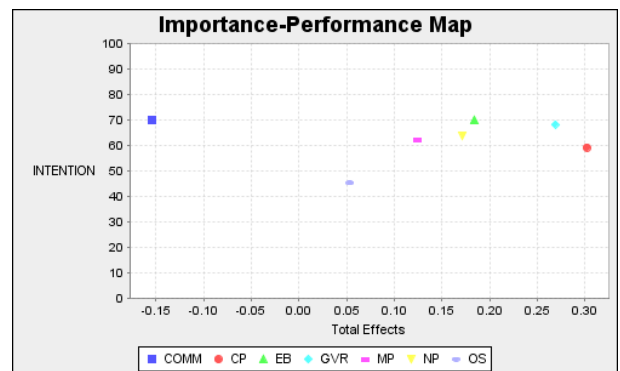| Constructs	Total Effect (Important)	Index Value (Performances)
COMM	−0.148	70.051
CP	0.313	59.242
EB	0.187	70.227
GVR	0.26	68.311
MP	0.135	62.188
NP	0.165	63.916
OS	0.054	45.392

FIGURE 4. IPMA (priority map) for EA adoption among MPS organizations.

be addressed by management activities afterwards. However, insignificant constructs CPX, EXT, ICT, OR, and TMS are excluded from further IPMA because the basic requirements of PLS-SEM assessment were not met [163].

VI. DISCUSSION

This research examined the factors that influence EA adoption by the MPS and identified these factors by designing and modeling the organizational view to achieve desirable IT solutions. EA adoption by the public sector is dependent on clear communication, coercive pressure, expected benefit, good governance, mimetic pressure, normative pressure, and organizational size. Surprisingly, top management support, ICT infrastructure, EA complexity, organizational readiness, and external support have a nonsignificant influence on the intention to adopt EA by public sector organizations. The following discussion is based on the perspectives of technology, organization, and environment.

A. TECHNOLOGICAL CONTEXT

Unexpectedly, sufficient ICT infrastructure does not associate with EA adoption by MPS, as indicated by the value of the path coefficient ($\beta = 0.004$) and probability ($p > 0.05$). This finding is inconsistent with past studies on the adoption of e-government [58], SaaS [62], IoT [64], and ERP [108], where this factor was a significant factor influencing IS/IT adoption in different contexts that use the TOE framework. This finding is not surprising because they have not adopted

EA yet, so they might not be aware of the technical requirement of EA. Furthermore, the responses were collected among five different MPS organization types, from the federal level to the local authority. For the state-level organizations, their ICT infrastructure is coordinated by the federal or central agency in the state, such as the office of the state secretary. Therefore, they cannot decide on the sufficiency of ICT infrastructure in their organization.

Complexity has an insignificantly negative influence on EA adoption by MPS organizations, as indicated by the value of path coefficient ($\beta = -0.018$) and probability (p > 0.05). However, the finding of the research is also inconsistent with previous research where many organizations are concerned about the adoption of new IT innovations, particularly EA. One possible reason complexity is not considered a barrier to EA implementation in MPS is that many agencies might not be aware and have adequate knowledge on the subject. They may think and assume that the EA approach is similar to the ISP and are not aware that EA uses a dedicated tool to manage the organization's architecture. The EA tool designs and models the complexity of the organization from the business, information, application, and technology perspectives, thereby requiring skilled architects. Designing the organization view involves a detailed process and critical thinking. Another possible reason is the availability of third-party support such as EA vendors, who fully appreciate the new trend and technology needs of the public sector. Furthermore, the initiator of EA, such as MAMPU, has been promoting EA since 2014. This condition could be another reason EA complexity negatively influences EA adoption in MPS.

B. ORGANIZATIONAL CONTEXT

Remarkably, top management support has no significant influence on EA adoption, as indicated by the value of path coefficient ($\beta = 0.022$) and probability (p > 0.05). This result is inconsistent with most previous studies, which found that top management support has a positive relationship with IT/IS adoption such as technology adoption [108], cloud computing [172], social CRM [173], and IoT [64]. However, past studies also found that top management is a barrier or has a negative influence on IS/IT adoption, such as RFID in the retail industry [174], RFID in manufacturing [57], and mobile reservation systems [175]. The reason for this insignificant result is that most of the respondents are non-adopters and are thus indistinguishable in terms of the factor of top management support. The factor of top management support that leads to the unreadiness of MPS decision-makers to adopt EA to their service operation is their level of understanding about the EA concept as a whole.

Most MPS organizations use the ISP as their guide and plan to implement desirable IT solutions. For them, EA is ISP, which they believe they already have. The real understanding of the EA concept is a problem for them. Consequent to this notion, they cannot understand the reason behind the adoption decision; they are not ready to spend or allocate resources and are already satisfied with only the ISP. Another possible

reason is that EA is still in its infancy, as reported by [17]. Furthermore, due to the lack of a common standard of EA adoption and implementation in the public sector, top management would rather adopt the wait-and-see approach by looking at other agencies that have adopted EA, developed EA, and successfully implemented and validated EA projects. MPS organization types are generally under the exclusive purview of the state and federal governments; for example, a state statutory body is under the purview of the state government. A local authority is under the purview of the state government and the Ministry of Urban Wellbeing, Housing, and Local Government. These types of purview are indistinguishable in terms of the factor of top management support. Thus, top management support would be an insignificant factor in EA adoption by MPS organizations.

The relationship between organizational readiness and EA adoption by MPS organizations is insignificant ($\beta = -0.010$, t = 0.157, p = 0.438). This empirical result is inconsistent with findings from past studies, which established the significant role of organization readiness, e.g., halal warehouse by Ngah *et al.* [54], business intelligence systems [176], and IoT [64]. Motivated MPS organizations that want to adopt a new IS/IT initiative must have the technical ability, organizational support, and experienced people and skill before new IS/IT initiative adoption is possible [177], [178]. In this case, even the predictive relevance to the intention to adopt EA by MPS organizations is high ($Q^2 = 0.575$, mean = from 7-point Likert scale). EA is a detailed process, which implies the need for skilled and experienced people in EA and organizational business to design and model the organizational viewpoints and desirable IT solutions for the organization. Organizational readiness means that the organization is expected to have the technological and managerial resources and skills to adopt EA more intensively and pervasively. The study also shows that financial situation is one of the factors that lead to the unreadiness of the adoption of a new IS/IT initiative. Skilled and experienced people are a time-sensitive and monetary investment. The majority of the respondents claimed that the top management did not provide any financial support for adopting the EA and training their employees to have a better understanding of and competency in EA. This idea is supported by the result of top management support (H3) factor in this research.

The findings of this research show that clear communication is a significantly positive influence on the intention to adopt EA in the MPS context ($\beta = 0.133$, t = 2.459, p = 0.007). As suggested by EA scholars, EA has to be established among organizational members and communicated clearly to gain a mutual understanding of the adoption of EA [179], [180]. To be successful, EA should be accepted at all other work levels, including engineering, technical, and worker levels. This success requires clear EA communication, which includes a process of informing and obtaining facilitation from stakeholders about all EA-related issues [181]. EA should not just take place in IT or offices of the CIO, but it also requires strong recognition from the

highest level of the organization [182]. Hence, EA stakeholders' participation is necessary, which means stakeholders should be involved in decision-making [183]. Ultimately, clear communication is viewed as the driver and voice of any initiative in the organization, thereby ensuring that EA will be more appreciated and accepted in the organization [184]. Therefore, clear communication is an important factor for EA adoption in the MPS context.

Remarkably, the normative pressure factor from institutional theory has a connection with EA adoption, as indicated by the value of $\beta = 0.165$, t = 2.076, p = 0.019 derived from the path coefficient analysis. The finding is similar to that of adoption studies in ERP [108], EA in Vietnam [67], IT governance [185], and social media [186]. This result may be explained by the fact that neglecting normative pressure may be operationally counterproductive in the organization. These findings imply that normative pressure is relatively more important than top management support and organization readiness in influencing the intention to adopt EA. A possible explanation for these results is that the extent to which an organization engages in cloud computing services and resources is still substantively reliant on the demands of professional associates, organizational culture, and the extent to which the government promotes the use of EA. Although MPS organizations are composed of different organization types that have varying organizational cultures and environments, they agree that normative pressure is a significant factor that influences EA adoption.

The expected benefit is revealed to have a significant positive influence on EA adoption by MPS organizations ($\beta = 0.180$, t = 2.002, p = 0.023). This result is consistent with past studies on the adoption of halal warehouse by Ngah *et al.* [54], business intelligence systems [176], hospital information system (HIS) [49], IoT [64], and cloud computing [187]. In this research, MPS organizations are interested in adopting EA if they are expected to benefit from it. A possible explanation for this situation might be the role of the organization types of the public sector. Willingness to adopt EA depends on how EA can clearly manage the complexity of the organization, eliminate the segmentation of process and application, and deliver better services to citizens. In this regard, when the expected benefits are high and convincing, EA adoption rates increase. The belief is that using EA guarantees a holistic view of organizational strategies and desirable IT solutions. Consequently, EA should increase the efficiency of service delivery and citizens' confidence in the public sector. The initiator of EA, such as MAMPU, should aggressively promote EA by explaining its benefits to the stakeholders and the decision-making team of organizations. Such promotion could be conducted by organizing a talk session and awareness program regarding the importance and benefits of adopting EA, especially during the Public Sector CIO Convex because the target participants are the CIOs of public sector organizations and the majority of them are non-adopters of EA. Government agencies should help convey the message that EA obtains more benefits if they

change from an unstructured view of the organization to the EA approach. As a result, it will help the decision-makers decide on a strategic organizational goal [188].

The relationship between good governance and EA adoption is significant, as indicated by $\beta = 0.237$, t = 2.314, and p = 0.011 derived from the path coefficient analysis. The empirical result also accords with earlier literature inferences, which showed that the role of good governance is a determinant of EA studies such as those on service-oriented EA (SOEA) [189], the deployment of EA in the Namibian government [84], EA in IS controls [190], and transformation readiness of EA [77]. Good governance in EA affects EA adoption by MPS organizations as a result of the complexity of the organizational structure of the public sector. The complexity of the organization consists of multiple viewpoints, including business, information, technology, and system. Different architects design and model these viewpoints accordingly to obtain a holistic and strategic view of the organizational goal. To accomplish this, the identification of stakeholders, roles and responsibilities, systematic procedures, and ongoing commitment across organizational members and stakeholders related to EA are necessary. Therefore, most decision-makers in public sector organizations are willing to adopt EA when clear accountability, roles, and responsibility for decision-making are available. In addition, EA implementation has to be measured for its impact on the organization. Only then can EA be realized and cultivated by establishing good governance.

The findings of this research show that organizational size is an important factor for EA adoption in the MPS context, as indicated by the value of $\beta = 0.07$, t = 1.968, and p = 0.025 derived from the path coefficient analysis. The empirical result is consistent with the recent previous studies in EA [13], HIS adoption [49], e-government assimilation [58], and mobile hotel reservation system adoption [175]. This result may be explained by the fact that large organizations benefit more because they have more manpower and support to invest in and adopt EA compared with smaller organizations. Another possible explanation for this situation is that, due to the need of the government for digital transformation in the public sector and the greater demand from citizens, a sizeable amount of manpower should accelerate the process of decision-making of EA adoption. Organization size plays an important role as a facilitator because having sufficient resources enables organizations to accommodate any consequences of steps taken by the decision-makers or stakeholders. As a result, the confidence level of the decision-makers at larger organizations is higher, making it easier to measure the implication of EA and enhance organizational innovations. Furthermore, larger organizations exhibit value creation by developing their attractiveness and motivation among the decision-makers and then influence organizational members to accept innovation regardless of the organization's size.

The IT department size represents the technical resources of the organization to adopt EA because EA needs skilled architects to design and model the viewpoints of application,

system, and information. On the basis of the demographic profile of the number of IT employees in the organization, the majority of the respondents (51.8%) have fewer than 10 IT personnel. From the percentage of the IT department size of this research, the researcher can infer that having a small number of IT employees may increase innovation resistance; hence, they refuse to accept EA. Therefore, MPS organizations seem to agree that IT department size is important in the adoption of EA because a big department size corresponds to the wide technological base of the organization for initiating and implementing IS innovations [191].

C. ENVIRONMENTAL CONTEXT

The external support factor has an insignificant impact on EA adoption by MPS organizations ($\beta = -0.039$, t = 0.643, p = 0.26). This outcome is contrary to that of MacLennan and Van Belle [82], Ahmadi, *et al.* [49], Rababah [192], and Sophonthummapharn [55], who found that external support was significant to the SOA, HIS, CRM, and techno-relationship innovation adoption, respectively. This contradictory result may be due to the effect of external support on the adoption of cloud computing, especially from vendors, which may be different for each organization. Not all organizations received support from the same vendors for the same solutions provided. To the researcher's knowledge, Malaysia has only one dominant EA vendor. Hence, the cost of skill and competency development, such as training, certification, and consultation, is high. This scenario indirectly influences the demotivation among decision-makers to adopt EA. An EA tool is a must in EA for designing and modeling the architecture. It is available in the market as both open-source and proprietary software. For example, the ArchiMate language can perform modeling, but it requires paid training and a certified EA trainer. These relationships may partly be explained by the inadequate training from The National Institute of Public Administration (INTAN) and the MAMPU. INTAN is the training arm of the Public Service Department, Malaysia, which offers a fundamental course on EA but not the technical part of EA to model the architecture. These agencies may not be able to accommodate demand, especially for certification and coaching, from MPS organizations. Another possible explanation is that the inherent characteristics of the agencies that have sufficient internal expertise makes them independent of external support for EA activities and resource implementation. The external support becomes insignificant in this research due to the lack of awareness of external support available in the industry. MPS organizations might not be aware of what EA requirements have to be in place and of the industry's overall practices. Hence, the dependency of EA adoption on the external support of the MPS organizations increases with awareness.

As shown in the previous section, the relationship between coercive pressure and EA adoption by MPS organizations is significant ($\beta = 0.330$, t = 4.387, p = 0.00). This result corroborates the findings of a great deal of previous works on IS/IT adoption studies, such as OGD by Wang and

Lo [59], HIS by Nilashi *et al.* [193], supply chain management system by Liu *et al.* [194], and e-commerce technology by Kurnia *et al.* [195]. Specifically, this factor reflects that of Duong [67], who also found that coercive pressure is an important pressure in institutionalizing EA in the Vietnam public sector. Hence, this argument supports previous research into this area, which links coercive pressure and EA adoption by MPS organizations. A possible explanation for this finding might be the pressure perceived by virtue of the competitive conditions, requirements, and incentives from the federal or local government and industry associations in MPS [49]. The requirements are raised by political, regulatory, and constituents' influences, including citizens and the federal and central governments. As an important knowledge source for its agencies, powerful organizations such as federal, state, and central agencies can pressure agencies under their exclusive purview by raising requirements. In this research, the IPMA results proved that the factor of coercive pressure is the one that most influenced EA adoption by MPS organizations. This result is likely to be related to the decision-making of MPS organizations, which considers written and formal directions from superior parties such as the central government as desirable, so that EA can be seen as important and beneficial to the public sector in general. Therefore, a possible suggestion is that coercive pressure is a key improvement area that can be addressed by management activities afterwards. Further studies that take this factor into account will need to be undertaken.

Coercive pressure is viewed as the promotion, direction, and support from MAMPU as the main agency for IT administration and policymakers in MPS. This research found that promotion, direction, and support from MAMPU influence other agencies in the MPS to explore the potential benefits of EA. This result may be explained by the asymmetry of power in the MPS structure, in which an organization's dependent agencies, such as a local authority or a state statutory body, under the exclusive purview of the state government may comply with such a requirement or policy to secure their competitive condition. In the case of EA adoption, when the federal and state governments require the agencies under their purview to adopt EA, the top management in the agencies may coercively push themselves to adopt EA as well. In this scenario, with a policy being put in place to support EA, resource support in terms of budget, training, consultation and other incentives are attainable for the future. Going against the requirements of the powerful organization may jeopardize the dependent organization's survival due to its dependence on the powerful organization. Therefore, the dependent organization tends to comply with the powerful organization under its exclusive purviews' requirements and be motivated to adopt EA.

The findings also revealed that mimetic pressure is important for EA adoption by MPS organizations, as indicated by the value of $\beta = 0.130$, t = 1.76, and p = 0.04 derived from the path coefficient analysis. This result reflects that of Duong [67], who also found that mimetic pressure

TABLE 10. Prior studies on ea adoption and the toe framework.

Factor	EA adoption studies																							Previous studies that used TOE										
	[68]	[35]	[9]	[30]	[82]	[103]	[19]	[190]	[31]	[84]	[32]	**[83]	**[77]	[189]	[66]	*[54]	[57]	[58]	[59]	[60]	[108]	[64]	[113]	*[200]	[55]	*[192]	*[49]	[59]	**[121]	*[111]	**[185]	[86]	[201]	[175]
ICT infrastructure				√				√				√	√	√			√				√	√												
EA complexity										√	√					√										√	√	√	√				√	√
Expected benefit				√		√								√			√	√		√	√					√	√	√						√
Top management support	√					√	√	√	√	√				√				√	√		√					√		√	√				√	√
Organizational readiness	√	√				√	√		√					√	√		√		√		√					√		√					√	
Clear communication								√				√	√	√	√																		√	
Normative pressure	√		√				√									√					√										√	√		
Organization size																		√										√				√	√	
Good governance					√			√		√		√	√	√							√													
External IS support					√					√													√	√	√		√							
Mimetic pressure	√															√			√	√		√	√					√						
Coercive pressure	√															√			√			√						√	√	√		√		

*Malaysian context, **MPS

influences the adoption of EA in the Vietnam public sector. In addition, this factor corroborates the findings of a great deal of previous work on supply chain management system by Liu *et al.* [194], open platform adoption by Shim *et al.* [60], EDI use by Hart and Saunders [124], HIS by Ahmadi *et al.* [49], and SOEA [189]. These types of research are instances of complex innovation of mimetic pressure to conform to other organizations caused by the extent of EA adoption or by the perceived success of EA adoption by other organizations in the same industry [49]. In this research, such perception reflects the organization's perception of the environment and its reasonable status. Several possible explanations are given for this result. The non-adopter of EA will benchmark and credit the exemplary organization's success to its strategic alternatives and imitate this successful organization by embracing the same practices. Hence, the particular organization can reduce its risks and costs. This logic can be proffered to the context of the organization's EA adoption decision. The organization may learn how other government agencies benefit from EA and perceive mimetic pressures to imitate these successful agencies [194].

Furthermore, this example of a successful agency impacts the level of certainty among MPS decision-makers in adopting EA and may reduce the cost of investigating the value of EA. In this research context of the public sector, cost is a motivation to adopt EA. MPS organizations may accept the mimetic pressure and be inclined to adopt EA. Another possible reason is that mimetic pressures play a role in this research because MPS organizations perceive EA as complex to understand and use. This argument is supported by the insignificant relationship between EA complexity and EA adoption (H2). Public sector organizations differ according to the type of organization structure and are thus likely to be unaware of the benefits of EA. Therefore, they may be prone to mimetic pressure. Such reasons may explain why this research found support for the positive effect of mimetic pressures on organizational intention to adopt EA.

VII. RESEARCH IMPLICATIONS

This research has three implications: theoretical, contextual, and practical. First, the development of a new EA adoption model contributes to a new theoretical finding in the field of EA that focuses on the technology, organization, and environment contexts based on the TOE framework as the underpinning theory and the integration of elements of institutional theory. This research is the first to examine the technological, organizational, and environmental factors that influence public sector adoption of EA. This research identifies seven key factors of public sector adoption of EA: clear communication, coercive pressure, expected benefit, good governance, mimetic pressure, normative pressure, and organizational size. In addition, the quantitative approach of model validation using PLS-SEM has made a significant contribution as empirical research in the EA research domain, because most EA studies use qualitative approaches such as case studies and interviews [21], [26]. This achievement is considered a significant contribution to the body of knowledge because quantitative approach is perceived as a structured way to generalize the population as a whole by examining the relationship between variables [132], [141]. Therefore, the findings of this research could be generalized by other public sectors in other countries that have a similar government structural composition as Malaysia.

Second, the context of this research is the MPS. The use of IT and IS in the public sector context has received continuous interest in past research, but most of the studies were conducted in developed countries such as Denmark, the United States, Finland, and Germany. Surprisingly, literature examining the adoption of IT/IS in developing countries is lacking. This research discussed the gap in knowledge by examining the determinants of EA adoption in a developing country such as Malaysia, particularly in the public sector context. Clear communication and good governance tend to be specific factors among the seven factors that influence the public sector's adoption of EA, particularly in the Malaysian context.

Third, the research results allow for useful practical contributions. The participation of EA and public sector practitioners as experts in this analysis has made the research findings sufficiently valid for identifying real-world phenomena. The findings of this research will support EA initiators in the MPS and other developing countries in designing new EA

TABLE 11. Measurement items of this research.

Variables	Code	Measurement items	Source
	EXT3	Agencies outside your organization provide training on EA.	
	EXT4	Technology vendors outside your organization actively market EA by providing incentives for adoption.	
	EXT5	Technology vendors outside your organization promote EA by offering free training–workshop sessions.	
Complexity	CPX1	Your organization believes that EA is complex to use.	[57]
	CPX2	Your organization believes that EA is a complex process.	
	CPX3	The skills required to use EA are too complex for your employees.	[204]
	CPX4	Integrating EA in your current work practices will be very difficult.	
Expected benefits	EB1	EA enables your organization to accomplish tasks more quickly.	[121, 205]
	EB2	EA improves the quality of your organization's work.	
	EB3	EA makes it easier to do your organization's job.	
	EB4	EA improves your organization's service delivery performance.	
	EB5	EA enhances your organization's effectiveness in service delivery.	
Organization size		Number of employees:	[191]

	< 100
	100–399
	400–699
	700– 999
	> 1000

Variables	Code	Measurement items	Source
Top management support	TMS1	The top management team is highly interested in using EA.	[204]
	TMS2	The top management team will allocate adequate resources for the adoption of the EA.	
	TMS3	The top management team is aware of the benefits of EA for the future success of the organization.	
	TMS4	The top management team has a vision as a leader to promote EA to the organization.	
Organizational readiness	OR1	Your organization gave its staff a formal explanation regarding halal supply chain services.	[206], [55]
	OR2	Your organization has knowledgeable staff to adopt EA.	
	OR3	Your organization has the financial resources to adopt EA.	
	OR4	Budget was the important factor that the organization had to deal with before adopting EA activities.	
Clear communication	COMM1	In your organization, everyone participates. In your organization, everyone has a chance to express their opinion.	[207]
	COMM2	Your organization listens to each organizational member.	
	COMM3	In your organization, employees feel free to make positive and negative comments.	
	COMM4	In your organization, even though organizational members do not have total agreement, organizational members do reach a kind of consensus that everyone in the organization accepts.	
	COMM5	You are comfortable with the roles that you play in the organization.	
Good governance	GVR1	The achievement of an EA comes from the persistent responsibility taken.	
	GVR2	The initiative of implementing an EA can definitely identify decision-making accountability.	[112]
	GVR3	You have thoroughly analyzed the outcome of adopting EA, which may cause some changes in the organization, suppliers, business partners, and customers.	
	GVR4	You have followed a systematic procedure for dealing with changes caused by the implementation of an EA.	
	GVR5	You have clearly defined the business cases for every initiative of EA.	
	GVR6	You have clearly defined a measure to evaluate the impact of adopting EA.	
Normative pressure	NP1	The organization believes that you should use EA.	[208]
	NP2	EA is the norm in your industry.	
	NP3	Using EA is beneficial to the organization.	
Mimetic pressure	MP1	Your main competitors who have adopted EA have greatly benefited.	[194]
	MP2	Your main competitors who have adopted EA are favorably perceived by others in the same industry.	
	MP3	Your main competitors who have adopted EA are more competitive.	
Coercive pressure	CP1	The government requires your organization to use EA.	[109]
	CP2	The industry association requires your organization to use EA.	
	CP3	Competitive conditions require your organization to use EA.	
Organization type		Organization type	[58]

	Federal
	Federal statutory body
	Local authority
	State
	State statutory body

initiatives. EA initiators can now identify the key factors that need to be considered for EA implementation to ensure that this initiative is widely accepted in the future by the public sector. Policy makers can use the research findings as inputs

in the creation of EA checklists to allow horizontal sharing and incorporation of knowledge across multiple public sector organizations. This research also assists the top management in public sector organizations in strategizing EA adoption by recognizing the important factors of EA adoption in their organization.

VIII. RESEARCH LIMITATIONS AND FUTURE WORK

The context of this research is restricted to the MPS, consisting of federal, federal statutory body, state, state statutory body, and local organizations. Although this research covered the population of MPS organizations, the generalizability of these results is subject to certain limitations. For instance, the results showed that the complexity of EA, ICT infrastructure, top management support, and external support have nonsignificant influences on EA adoption by MPS organizations. Given that these results are inconsistent with previous studies on public sector IT/IS adoption, the researcher suggests that any future work should include the moderation effect in the relationship between these variables in EA adoption because a moderator variable is usually added when the relationship between a variable and a criterion variable is unexpectedly weak or inconsistent [147].

IX. CONCLUSION

The benefits of EA include eliminating system duplication and silos [72], aligning IT and business in the organization for strategic planning and investment [98], [196], [197], reducing complexity in the IT infrastructure [198], [199], and improving business agility and dynamic change [66]. However, despite the perceived benefits of EA, public sector adoption remains sluggish, as demonstrated by scarce EA adoption studies in the existing literature. The goal of this research was to develop and validate a theoretical model that analyzed the influence of TOE factors on the adoption of EA by the MPS. An unanticipated finding was the weak influence of complexity of EA, ICT infrastructure, top management support, and external support on EA adoption by MPS organizations. Together, the research findings add to the knowledge base in the EA area and may contribute to better insights for EA initiators in their EA implementation plan and strategic planning to support EA implementation among MPS organizations.

APPENDIX A
See Table 10.

APPENDIX B
See Table 11.

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