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Using an extended technology acceptance model to predict enterprise architecture adoption in making cities smarter

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Abstract
Presently cities are undergoing changes and transformations due to the adoption of information and communications technology. Enterprise Architecture (EA) is one of the approaches adopted by practitioners and researchers to facilitate smart city development as it can enhance the effectiveness of cities' digital resources and sustainability capabilities. But, despite several literature on EA, studies on the adoption of EA to improve the sustainability of cities are still at the early stage. Besides, there are fewer studies that provided evidence on the adoption of EA to make cities sustainable grounded on established theoretical models and quantitative data. Therefore, this study aims to provide an understanding on the adoption of EA by different practitioners involved in a smart city project. Knowledge transfer and support services are integrated as new external variables needed to improve practitioners' behavior intention and actual adoption of EA in making cities smarter. A model is developed grounded on an extension of Technology Acceptance Model (TAM), and data were collected via a cross-country survey. Partial least squares-structural equation modeling was employed to analyze the data. Findings from this study offer implications for research and practice and provide opportunities for future research.

Keywords Sustainable cities · Smart cities · Enterprise architecture adoption · Extended technology acceptance model · Knowledge transfer · Support service

1 Introduction

Due to digital transformation, cities are increasingly deploying ICT systems to support in providing digital services to citizens (Cantelmi et al., 2021). However, for cities to become smarter they are faced with issues such as alignment, integration, and standardization (Adams et al., 2019; Petersen et al., 2019). Enterprise Architecture (EA) is suggested as an approach that can be adopted by cities in achieving the digitalization of urban environment (Anthony Jnr and Abbas Petersen, 2021). EA is defined as the representation of a high-level view of an institution's IT systems and business processes and, their interrelationships, and the degree to which these systems and processes are shared by different sectors within the organization (Tamm et al., 2011). EA is a blueprint of models, principles, and methods employed in the design and realization of an organizational structure, Information Systems (IS) business process, and digital service infrastructure (Al-Kharusi et al., 2017). EA outlines the documentation and explicit description of the present and anticipated relationships among information technology and business management processes (Espinosa et al., 2011). In urban context EA has become a strategic tool that aids the digital transformation of cities vision into becoming smart cities (Anthony et al., 2020). Prior studies (Espinosa et al., 2011; Ahlemann et al., 2021; Anthony Jnr, 2021a) suggest that EA helps institutions to cope with digitalization as well as the rapidly changing technological and business environments.

EA is mainly adopted either via the adoption of new or existing Enterprise Architecture Framework (EAF) such as Zachman, the Open Group Architecture Framework, federal enterprise architecture framework, etc. (Shanks et al., 2018; Jonnagaddala et al., 2020). EA adoption involves designing

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a structured and coherent model of the enterprise, which systematically captures the structures within the institution and their dependencies. This is performed using architectural layers and views to present and describe the institution at different levels and from different perspectives of stakeholders (Jonnagaddala et al., 2020). EA provide models for developing enterprise information systems that can help municipalities to align business processes with technologies and data deployed (Espinosa et al., 2011), thereby providing a general view of information systems within the city. The adoption of EA holistically aids cities to address and manage complexity, facilitating standardization, and consolidation of the city's ICT components. It also provides transparency to the city by simplifying internal interactions and organizational structure (Jonnagaddala et al., 2020). This, in turn, can aid policy makers and urban planner in making more informed decisions to making cities smarter for a sustainable society (Anthony Jnr, 2021b).

The adoption of EA can support cities in deploying social, technological, environmental and economic systems. Cities employs different approaches standards, and system such as ISO 26000, ISO 14001, and ISO 9001 to achieve economic, social, and environmental requirements of sustainability (Alves et al., 2016). In this study, EA is leveraged to develop innovative strategies to support smart cities into sustainability of cities. EA is employed in this study as it provides activities through which cities can align their IT and business capabilities with sustainability goals (Sutherland and Hovorka, 2014), acting as an enabler for sustainable digital transformation towards (Hussein et al., 2017; Anthony Jnr, 2021a). This is demonstrated based on the enterprise architecture framework developed in the literature (Bokolo and Petersen, 2020). EA helps at specifying the city's processes and provide alignment of city's sustainability goals with respect to environmental, social, and economic Key Performance Indicators (KPIs) set by the municipality (Sutherland and Hovorka, 2014).

In enterprise information system, technology adoption models can be employed to assess the adoption of an information system such as EA. One of such models is the Technology Acceptance Model (TAM), which is employed to evaluate user's acceptance of new technology. TAM has previously been employed to assess the adoption of EA in different domains such as application usage (Närman et al., 2012), building information modeling (Lee et al., 2015), security policy, e-government (Guo et al., 2019), e-health (Jonnagaddala et al., 2020), etc. TAM is grounded based on two constructs perceived usefulness and perceived ease of use (Närman et al., 2012). Although the usage of TAM has been shown to significantly explain difference in information system adoption, very little has been published about the usage of TAM to explore the adoption EAF by different practitioners that provide digital services within smart city context. Additionally, the success factors that may influence the practitioners to adopt EA is left mostly unexplained or being neglected (Ahlemann et al., 2021). Prior studies only explored EA adoption in other domain; thus, there is little evidence on adoption of EA in smart cities. Likewise, findings from the literature fails to discuss practitioner's perception towards the adoption of EAF in offering digital services to residents in smart cities. Addressing this gap, this study provides an inclusive, theoretically, and empirically grounded answer to the following research question:

- What are the factors that influence EA adoption by different practitioners in smart cities?

To explore the research question, a model is developed as a robust prediction framework to investigate the factors associated with EA adoption grounded on an extended TAM. This study is one of the first studies to investigate EA adoption in smart cities by considering knowledge transfer and support service as external variables that may influence practitioners' behavior intention and actual adoption of EA in making cities smarter. This paper is ordered as Sect. 2 is the review of the literature. Section 3 describes the research model and associated hypotheses development. Section 4 explains the research methodology. Section 5 is the survey results from the questionnaire. Section 6 is the discussion and implications. Lastly, Sect. 7 is the conclusion.

2 Literature review

This section provides a background of EA in smart cities, enterprise adoption theories, and review on prior studies that employed enterprise adoption theories to explore EA adoption.

2.1 The role of enterprise architecture in smart cities

Over the years, enterprise architecture has received increasing attention among academia and industry. EA is defined as a formal description of the current and future state(s) of an enterprise. The adoption of EA provides several benefits such as alignment of business and information technology, increased revenues, cost reduction, and better decision making. Therefore, the adoption of EA is viewed as important in facilitating the deployment of digital technologies and novel business models. Enterprise architecture is derived from the word "architecture" in enterprise context which refers to the fundamental organization of a systems components, their relationships to each other, and the environment in which they are deployed regarding the principles managing its design and evolution (IEEE, 2000).

The term enterprise architecture evolved as a domain within 1980s after Zachman had used the "architecture" concepts employed in constructional engineering to plan and design enterprise information systems (Petersen et al., 2019; Ahlemann et al., 2021). EA provides an integrated view of the organization from an IT and business perspective, in relation to its to-be state, and future state (Brosius et al., 2018; Bokolo and Petersen, 2020). Besides, EA presents the structure of the IT components within an enterprise, its information systems, the medium in which these IT components interconnect to achieve the enterprise objectives (Ahlemann et al., 2021). Enterprise architecture also captures how deployed information systems support existing and new business processes of the enterprise (Lange et al., 2016).

More recently, EA has been employed to facilitate and guide digital transformation in cities, thus, making it an important tool for cities embarking on digital transformation journey (Anthony et al., 2020; Ahlemann et al., 2021). To deal with issues such as the complexity associated in ICT system cities now employ enterprise architectures frameworks (Jnr et al., 2020a, b). These enterprise architectures frameworks such as Zachman (Zachman, 1987), TOGAF, etc. comprises of aligned and structured collections of design plans for the integrated deployment of business and IS landscape of the city, in its past, present, and future states (Lange et al., 2016; Anthony Jnr, 2020). EAF also captures the city`s data dictionary and data model providing a common conceptual model to be used by practitioners that provide digital services in smart city. It ensures that data used within the city have the same meaning across different systems and stakeholders regardless of data sources (Espinosa et al., 2011; Shanks et al., 2018).

2.2 Prior enterprise adoption theories employed in EA research

Over the decades, different theoretical models have been proposed in enterprise information system domain to examine individual's intention to adopt technologies. The enterprise adoption theories are mainly grounded in behavioral research from the fields of sociology and psychology. Enterprise adoption theories can be employed by researchers to predict the causal relationship between technology acceptance and its factors and can be utilized as a mechanism by enterprises to assess if the anticipated technology acceptance has been realized (Lee et al., 2015). In the context of this study, enterprise adoption theories previously employed to explore EA adoption are reviewed in this section. The identified enterprise adoption theories employed are shown in Fig. 1.

Figure 1 depicts the identified enterprise adoption theories employed by prior studies. Among the theories, there is the institutional theory which conceptualizes enterprises

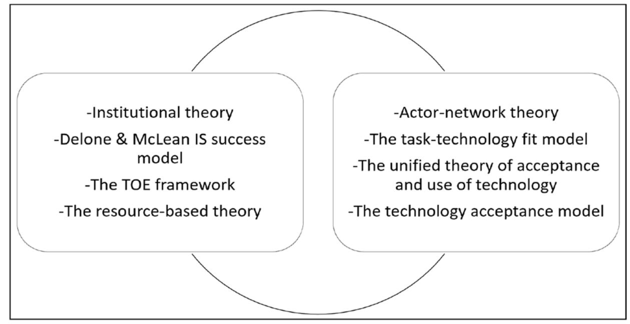

Fig. 1 The identified enterprise adoption theories previously employed

as social constructions that aims to gain legitimacy in their environment (Brosius et al., 2018). This theory maintains that different interactions and networks mainly determine the perception of individuals and groups (Ahmad et al., 2020). It is grounded on the responsibility of institutions in comprehending the actions and behaviors of stakeholders and provides a viewpoint that helps to explore both formal and informal rules that influences institutional attitudes and values, and behaviors of social actors (Brosius et al., 2018; Ahmad et al., 2020; Jnr, 2021). The Delone & McLean information systems success model is another model which was first proposed by DeLone in 1992 and revised in 2003 (DeLone and McLean, 2003). The revised model comprises six factors (system quality, information quality, service quality, user satisfaction, intention to use, and net benefits) that influences the success of information system adopted in enterprises (Espinosa et al., 2011). In the context of EA, these six factors proposed in Delone & McLean IS success model can serve as a guide to organizations to identify potential benefits to be derived from adopting EA (Espinosa et al., 2011; Lange et al., 2016).

The Technology Organization Environment (TOE) framework is an organizational-level-based theory that comprises technological, organizational, and environmental factors. According to TOE framework, the adoption of enterprise systems such as EA is determined by technological, organizational, and environmental contexts within the enterprise (Ahmad et al., 2020). The resource-based theory (RBT) conceptualized enterprises as resources (Barney, 1991). Resources may be intangible or tangible and comprises of assets and capabilities. Assets consist of data and people, IT hardware and software, whereas capabilities include organizational routines and processes that utilizes assets to achieve a task. Within the resource-based theory, organizational capabilities are regarded as a critical factor for firm performance (Shanks et al., 2018; Ahlemann et al., 2021). RBT has been employed in prior EA adoption studies (Shanks et al., 2018; Ahlemann et al., 2021) which investigated how EA is utilized to achieve strategic organizational change in achieving value in businesses. The RBT has been successfully applied to predict how value is produced through the utilization and management of IT and have been employed in the literature to explore EA Management (EAM) (Ahlemann et al., 2021).

Another theory is the Actor-network Theory (ANT) which was originally proposed by Callon and Latour who highlighted how the society and businesses are continuously changing because of collective action and interaction of components or actors such as human, non-human, or an integration of both (Gilliland et al., 2015). ANT was previously utilized as a reference theory to extract human factors or elements that could be related to explore use of EA (Gilliland et al., 2015), where the author employed ANT to specify human dimensions identified to examine the acceptance of EA. The Task-technology Fit (TTF) model is another theory that explains the deployment of technology (Goodhue and Thompson, 1995). TTF is deployed on the notion that if a user perceives a technology to have features which fit their work tasks, they are more likely to adopt the technology and implement their work tasks better (Närman et al., 2012). In TTF, the availability of an enterprise system depends on the matching capabilities of the enterprise system to the needs of the task (Goodhue and Thompson, 1995). TTF models comprise technology characteristics, task characteristics which impact technology fit, which also influence the outcome variable which is either performance or utilization (Lee et al., 2015). The Unified Theory of Acceptance and Use of Technology (UTAUT) was founded by Venkatesh et al. (2003) to integrate variables from TAM and the technology acceptance theories. The UTAUT model is presently one of the leading enterprise adoption models. The UTAUT model comprises four main constructs that are theorized to influence user acceptance. These constructs comprise social influence, facilitating conditions, effort expectancy, and performance expectancy (Hazen et al., 2014).

TAM is a theory that predicts how end users come to accept and utilize an information system (Bernaert et al., 2014). TAM was introduced by Davis (1989) as an adoption of technology model for predicting user acceptance of technology grounded on two variables, perceived ease of use and perceived usefulness which are theorized to be fundamental factors of user acceptance. Also, TAM is an adaptation of the Theory of Planned Behavior (TPB) and the Theory of Reasoned Action (TRA) which are other widely employed social psychology model that focuses on the factors that influences user behavior (Guo et al., 2019). According to TAM users incline to use or not utilize an application to the degree, they believe it will aid them to achieve their job better (Bernaert et al., 2014). Similar to the TRA, TAM argues that the actual system use is influenced by the behavioral intention which is influenced by the user's perception towards the use of enterprise system and perceived usefulness of the enterprise system (Guo et al., 2019). Over the years, TAM has been employed to explore EA acceptance in different sectors (Närman et al., 2012; Lee et al., 2015; Guo et al., 2019; Jonnagaddala et al., 2020) and is perhaps the most dominant theory in enterprise information systems domain (Närman et al., 2012). Moreover, Davis (1989) argued that external factors may be incorporated into TAM. In this study, the external factors comprise knowledge transfer and support service.

2.3 Related works from the lens of enterprise adoption theories

Due to the potential of EA to support digital transformation of enterprise process, EA has been adopted in several sectors grounded on enterprise adoption theories. One of the studies that explored EA adoption is Ahlemann et al. (2021) where the authors employed resource-based theory to achieve value generation through the adoption of EA management. Case studies were employed to examine if EA management creates benefits or only creates value in an organization based on EA modeling, planning, implementation, and governance. Another study by Ahmad et al. (2020) explored the factors that determine the adoption of EA within public sector enterprises. The TOE model and organizational theory were used to develop a conceptual model. Data were collected using survey and analyzed via Partial Least Squares-Structural Equation Modeling (PLS-SEM). Evidence from the study aimed to provide insights for EA adopted in planning and adopting EA implementation in public sectors.

Another study by Jonnagaddala et al. (2020) examined the adoption of EA within healthcare organizations. The study aimed to investigate the status of EA adoption by identifying the goals, challenges, and benefits associated with EA adoption in health sector. Also, an EA adoption evaluation framework based on TAM was developed which consists of EA, strategy, governance, and performance. Data were collected using questionnaire from 26 participants. Main findings from the study outlined that the main issues that impacts the adoption of EA comprise the lack of leadership, inadequate EA knowledge, and less involvement of senior management. Guo et al. (2019) conducted a review of the literature to identify the challenges faced by practitioners when they adopt EA in public sectors. The identified issues are clustered based on TAM perspective. Findings from the study aimed to provide in-depth insights to support practitioners to adopt EA in public sectors. Also, Brosius et al. (2018) explored EA assimilation grounded on institutional theory. The authors focused to address the institutional issues faced by enterprises to achieve intended EA outcome. First data were collected from 16 senior EA experts in a workshop. Secondly, data were collected from 134 EA practitioners via paper-based questionnaire and online survey.

The authors highlighted that the engagement of stakeholders within the enterprise significantly mediate the association between EA assimilation and institutional pressures.

Furthermore, Lange et al. (2016) investigated the factors and measures of EA management success based on an empirical analysis of data collected from a cross-sectional survey of 133 EA management practitioners. The authors aimed to address the lack of knowledge that impacts how EA management can be effectively adopted. Based on DeLone & McLean IS success model, findings from the study suggest that EA management is a core principle factors that mediate the impact of success factors such as infrastructure quality and service quality. Besides, Gilliland et al. (2015) researched on work level associated with human factors for EA as organizational strategy. The study focused to explore work level linked to human factors that impact acceptance of EA. Thus, a list of work-level-related human factors that enterprises can adopt to identify and resolve human factors that negatively impact the acceptance of EA as organizational strategy was presented by the authors.

In addition, Hazen et al. (2014) developed research model grounded on UTAUT to examine how training and performance expectancy impact the degree to which enterprises adopt EA. Data were collected via survey from senior managers, IT professionals, and consultants who have adopted EA. SEM was utilized for data analyses. Results from the study suggested that enterprises that adopt EA provide education and training program to users of EA. Moreover, Lange et al. (2012) evaluated the realization of benefits to be derived from EA management. A model is proposed based on the identified EAM success factors to assess the realization of benefits from EA management. Based on data collected from literature review and expert interviews from 11 informants, the EA management benefits and success factors were presented grounded on DeLone & McLean IS success model. The model aids enterprises to identify, assess, and benchmark their EA management initiatives been adopted. Lastly, Närman et al. (2012) employed EA and technology adoption models (the TTF model and TAM), to develop a framework to assess application portfolio management usage. Data were collected via survey from 55 respondents in five companies in maintenance management area. The framework is presented as an architecture metamodel that integrates variables from TAM and TTF model. The framework aids reuse of research results by architects, thus, supporting production.

Besides, other studies in the literature (Kakarontzas et al., 2014; Cox et al., 2016; Pourzolfaghar et al., 2020; Bastidas et al., 2021) also employed EA in smart city domain. However, none of the reviewed studies in this article are based on an established theoretical model as seen in Fig. 1 and also employed survey questionnaire data for validation of EA adoption in smart city domain simultaneously. Although prior studies related to the + CityxChange project (https://cityxchange.eu/) have published a few studies on EA in smart cities. Among these studies Jnr et al. (2021a) examined pluggability issues by modeling digital services and pervasive platforms integrated for smart urban transformation based on an EA framework. Similarly, Jnr et al. (2021b) explored how digital transformation can be achieved for smarter cities by using EA. Also, qualitative data were employed in the study. Jnr et al. (2021c) proposed a model grounded on DeLone and McLean information system success model to evaluate the acceptance and usefulness of EA for digitalization of cities. The work by Jnr et al. (2020a, b) explored how big-data-driven multi-tier architecture can be employed to promote electric mobility as a service within smart cities. Another interesting work from the project by Jnr and Petersen (2022) employed the original technology acceptance model to develop a model to examine EA Framework adoption for digitalisation of smart cities. The model was further validated based on a mixed-mode approach. This current study differs from the prior studies (Jnr et al. 2020a, b; Jnr et al. 2021abc; Jnr and Petersen, 2022), by proposing a model which extends the technology acceptance model by integrating two external variables (knowledge transfer, and support service) to explore if these variables influence actual EA adoption in making cities smarter.

Findings from the reviewed 10 studies suggest that empirical research for EA adoption has been researched in various areas with detailed purposes and findings. The studies also considered various factors that determine the adoption of EA. But to date, the adoption of EA in urban context is still minimal. Additionally, evidence from the discussed 10 studies indicates that the authors have explored the adoption of EA from the lens of enterprise adoption theories such as the UTAUT, TAM, TOE, DeLone & McLean IS success model, TTF model, institutional theory, and resource-based theory. However, none of the reviewed studies examined the adoption of EA in smart city context grounded on an enterprise adoption theory. Although the TAM theory has been employed in various domains, it has not been extensively applied to the domain of smart cities, mainly in relation to role of knowledge transfer, and support service for EA adoption. Therefore, this current study is added to the body of knowledge by providing an understanding on the adoption of EA in smart cities by developing a model grounded on an extension of TAM to include knowledge transfer and support service.

3 Developed extended technology acceptance model

As stated in the previous section, this study aims to employ an extended version of TAM theory to explore practitioner's perception of EA adoption in smart city context. As such, this section presents the factors that influence EA adoption by practitioners in smart cities and further presents the developed research model and associated hypotheses as discussed below;

3.1 Perceived ease of use of EA

This factor refers to the extent to which an end user trusts that utilizing a particular enterprise information system would be free from much effort (Davis, 1989; Guo et al., 2019). Findings from prior studies suggest that ease of use is one of the key factors for successful acceptance of enterprise information system (Bernaert et al., 2014; Jonnagaddala et al., 2020). Perceived ease of use defines the degree to which EA is ease or freedom from difficulty or great effort, in designing smart services in smart cities. Davis (1989) stated that a technology that is seen to be easier to be adopted than another will be more likely to be accepted and used (Bellini et al., 2020). In this article, the ease of use relates to the effort that is required to adopt EA (Bernaert et al., 2014). These observations suggest that there is a positive correlation between ease of use and practitioner's intention to adopt EA in modeling smart services in smart cities (Lee et al., 2015). Additionally, it is presumed that the belief that EA is easy to be adopted will directly influence practitioner's perceived usefulness and consensus on adoption of EA. In the context of this research, the perceived ease of use relates to the measure of ease of exchanging information among stakeholders, ease of learning relating to how practitioners can use EA, and ease of utilizing EA guidelines for collaboration (Lee et al., 2015). Therefore, this study proposes that a greater degree of perceived ease of use of EA will influence perceived usefulness of EA and also enhance the practitioner's perception of adopting EA. Therefore, this article proposes the hypotheses:

H1. Practitioners' perceived ease of use of EA will positively influence the perceived usefulness of EA in smart cities.

H2. A greater degree of perceived ease of use of EA will enhance the degree of practitioner's intention to adopt EA in smart cities.

3.2 perceived usefulness of EA

According to Davis (1989), the perceived usefulness refers to the extent to which a user believes that using a particular enterprise information system would improve his or her job performance. The user's view of usefulness has been seen an important determinant for technology acceptance (Guo et al., 2019). Thus, EA should be seen as useful and capable of being used advantageously by practitioners in designing digital services in smart city. Hence, the acceptance of EA is possible when a practitioner is willing to utilize an EAF. Findings from the literature suggested that perceived usefulness of enterprise information system strongly impacts user's acceptance intention (Närman et al., 2012; Jonnagaddala et al., 2020). Therefore, perceived usefulness is aligned with individual and organizational recognition that the adoption of EA improves working ability and productivity (Lee et al., 2015). Accordingly, this study posits that perceived usefulness will play a significant role within the relationship between behavior intentions of practitioners to adopt EA in smart city development. Based on the aforementioned observations, the following hypothesis is constructed;

H3. A greater degree of perceived usefulness will result in a greater degree of practitioner's intention to adopt EA in smart cities.

3.3 Behavior intention to adopt EA

Adoption is defined as the process of decision to utilize an initiative and the continuous actions of acquiring, planning, and deployment of such practice within an enterprise (Gilliland et al., 2014). Overall, behavioral intention is the assessment of the degree of an individual's intention to implement a particular behavior (Lange et al., 2016). The behavior intention to adopt a technology is both impacted by the perceived ease of use and perceived usefulness of the technology (Davis et al., 1989). But to completely adopt EA, practitioners must use EAF for their tasks in designing and deploying digital services. The degree to which practitioners intend to continue to use EA in smart city depends on their acceptance which is a prerequisite for actual EA use or adoption (Lee et al., 2015). In this study, EA adoption by different practitioners in smart cities is considered as a dependent variable. Therefore, this study posits that the extent to which practitioners expect that EA will enhance smart city development which will determine the degree to which they will actually adopt EA.

H4. A greater degree of practitioner's intention to adopt EA will result in a greater degree of actual EA adoption in smart cities.

3.4 Actual EA adoption

Actual adoption refers precisely to human acceptance of strategies and technology in an enterprise. The actual adoption of EA by practitioners is determined by his or her behavior intention to perform the behavior of using EAF in smart cities. In this study, actual adoption of EA refers to a mechanism for achieving the acceptance of EA in modeling of digital services in smart cities (Lee et al., 2015). Actual adoption is related to receptiveness and refers to human traits such as awareness, motivation, approval, acceptance, etc. (Gilliland et al., 2014; Hazen et al., 2014). As related to EA and smart cities, actual adoption refers to when practitioners are committed to the implementation of EA such that the EAF is actually used in providing digital services in smart city.

3.5 External variables

The external variables refer to objective factors or practice to be implemented in EA environment to improve actual EA adopting towards making cities smarter. In this study, the TAM model is extended to include external variables which comprise knowledge transfer and support service.

3.5.1 Knowledge transfer

Knowledge transfer in context of this study refers to the quality of information delivered through EA to improve smart city development. The knowledge transferred by any EAF should be understandability and sufficient to practitioners who adopts EAF. Moscoso-Zea et al. (2016) pointed out that if EAF offers practitioners with well-designed models and design contents, then EA will be considered as easy and simple to practitioners. Findings from the literature (McNabb and Barnowe, 2009) suggested that knowledge transfer is an important factor that influences practitioners' perceived usefulness and perceived ease of use of EAF. This is because the available of knowledge as information may help in enhancing practitioners' perceived ease of use and acceptance of EAF (Nabiollahi et al., 2011). Moreover, this factor encompasses how knowledge on the use of EA can be transferred to all practitioners involved within smart city development. This helps ensure that all partners from different disciplines can understand the usefulness and applicability of EA to improve IT, business, and sustainability of the city.

3.5.2 Support service

Support service quality involves the quality of service provided to practitioners who adopts enterprise architecture to support smart city development (Assar and Hafsi, 2019), based on the availability of responsive offline and online technical support (Šaša and Krisper, 2011). This variable refers to the "service quality" supports as highlighted by DeLone and McLean (2003); Espinosa et al. (2011); Lange et al. (2016) that practitioners receive such as hands on training on how to adopt enterprise architecture. The availability of these supports may also be a crucial determinant that influences practitioners' perception towards accepting enterprise architecture (Braun and Winter, 2007). This assumption is supported by results from Šaša and Krisper (2011) where the authors highlighted that the quality of service positively impacts the performance of business process within organization.

Based on these observations on knowledge transfer and support service, the following hypotheses were proposed:

H5: Knowledge transfer and support service will positively influence perceived usefulness of EA by practitioners.

H6: Knowledge transfer and support service will positively influence perceived ease of use of EA by practitioners.

H7: Knowledge transfer and support service will positively influence practitioners' behavior intention to adopt EA.

H8: Knowledge transfer and support service will positively influence actual EA adoption by practitioners.

Based on an extension of TAM adopted by including knowledge transfer and support service. This study aims to explore the factors that influence EA adoption by different practitioners in smart cities. The extended technology acceptance model developed is depicted in Fig. 2. The model is conceptualized based on the TAM`s main variables (perceived ease of use of EA, perceived usefulness of EA, behaviour intention to adopt EA, and actual EA adoption)

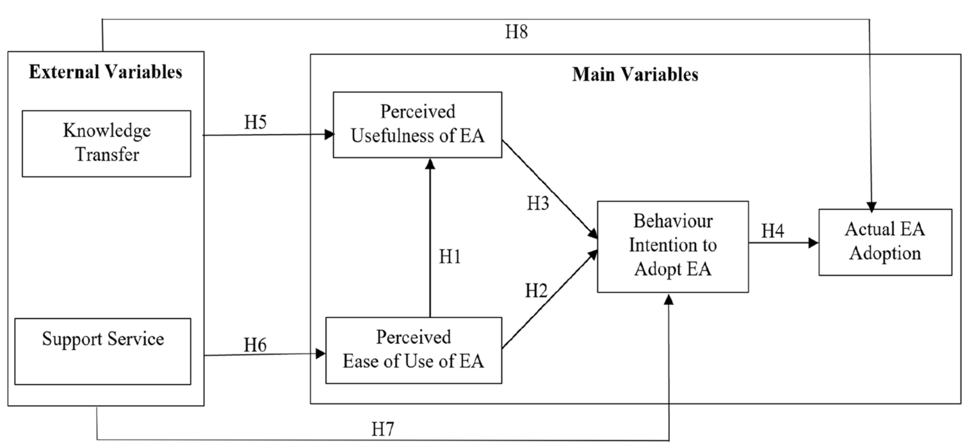

Fig. 2 Developed extended technology acceptance model

and external variables (knowledge transfer and support service) derived from the literature.

4 Research methodology

This research employs a positivist paradigm which adopts a quantitative cross-sectional survey method using a questionnaire instrument. The questionnaire was developed from prior EA studies that employed TAM and from the authors as seen in appendix Table A1. As previously stated, the model and associated hypotheses presented in Fig. 2 are developed based on TAM and secondary data from the literature. First the main variables were derived from the original TAM (actual EA adoption, behavior intention to adopt EA, perceived ease of use of EA, and perceived usefulness of EA) and then the external variables (knowledge transfer and support service) were incorporated next within the model. To validate the model, quantitative data were collected from organizations in Norway and Ireland involved in a smart city project (+CityxChange (+CxC) (https://cityxchange.eu/)) that developed an EAF (Bokolo and Petersen, 2020). Practitioners in these organizations provided data regarding their perception on EA as regard to design of digital services in smart cities.

4.1 Data collection

Purposive sampling was used analogous to prior EA studies (Gilliland et al., 2015; Shanks et al., 2018). Most participants were familiar with EA. Quantitative data collected were utilized to validate the developed research model using a cross-sectional survey and data were collected from practitioners (researchers, technical architects, full-stack developer, managing director, IT manager, software developers, and project engineers) who had experience in using EA or are familiar with EAF adoption in smart city context. The perceptions of practitioners provide a valid source for collecting data about the value of EAF. In early November 2020, a pilot test was conducted, and few EA experts were employed to check the face and content validity for understandability, clarity, and wording of the questions formulated. For construct validity, all the factors and their respective items are theory driven and adapted from prior studies on EA and TAM and from the authors. Next, the questionnaire was slightly revised based on the feedbacks from the pilot test and was deployed as a web-based survey.

The data collection took place between November 2020 and January 2021 by the means of the online survey questionnaire. Invitations were sent in November 2020, and in January 2021, additionally reminder was sent to participants to partake in the survey. The first section of the questionnaire provides an introduction of the research to prospective participants and consent was obtained from the eligible respondents. The second section collect data as regard to the demographic information of the respondents (gender, age, organization type, type of services primarily provided, primary role, years of experience with EA, and familiarity with the developed EAF), based on ordinal scale. The third section of the questionnaire collected data based on the respondent's perception towards the adoption of EA in smart city to support the development of digital services. The question items were measured based on a 5-point Likert scale ranging from strongly disagree to strongly agree. The demographic data of the respondents are shown in Table 1.

4.2 Data analysis

To analyze the survey data, Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) method was used similar to prior EA studies (Aier, 2014; Brosius et al., 2018). PLS-SEM is an appropriate approach to validate our research model as it is well suitable for theory testing and exploratory research such as in this research (Hair Jr et al., 2016). PLS-SEM method is suitable with research with modest or low sample size (Hair Jr et al. 2014). Thus, SmartPLS version 3 was used for data analysis (Lange et al., 2016). The bootstrapping resampling procedure with 5000 resamples was employed analogous to prior studies (Brosius et al., 2018; Bokolo and Petersen, 2019), to stabilize the estimates. Based on the resampling, significance levels were assessed by the (two-tailed) *t*-value (Brosius et al., 2018). Descriptive analysis was carried out using Statistical Package for Social Science (SPSS) version 26. SmartPLS 3.0 was used to assess the SEM for exploratory and inferential analysis (Shanks et al., 2018).

5 Findings

Data analysis in Partial Least Squares-Structural Equation Modeling (PLS-SEM) is using SmartPLS software. The statistical analysis comprises demographic data, the analysis of measurement model, and structural model.

5.1 Demographic data

The demographic analysis of the survey participant is shown in Table 1. The data comprise datasets from different practitioners in 18 organizations based within Norway

Table 1 Profile of the survey respondents

Profile	Options	Percentage
Gender	Male	92.2
	Female	7.8
Age	20–30 years	29.1
	31–40 years	24.3
	41–50 years	38.8
	51–60 years	7.8
Type of Enterprise	University	23.3
	Research organization	16.5
	City council or municipality	7.8
	Private organization	52.4
Type of Services Enterprise Primarily Provides	Energy related	7.8
	Data related	24.3
	Innovation related	23.3
	ICT Infrastructure related	15.5
	Other	29.1
Experience with Enterprise Architecture	Just knew about EA recently	31.1
	Less than 1 year	36.9
	1–3 years	24.3
	4–5 years	7.8
Experience with Smart City Projects	Just knew about smart city recently	5.8
	1–3 years	78.6
	4–5 years	15.5
Familiarity with the developed EAF for + CxC smart city project (Bokolo and Petersen, 2020)	I have seen a presentation of it	36.9
	I have provided feedback	24.3
	I have provided input and / or feedback to one or more models based on the EAF	31.1
	I am not familiar with it	7.8

and Ireland involved in a smart city project + CxC smart project (https://cityxchange.eu/).

5.2 Analysis of measurement model

Analysis of measurement model assesses the reliability and validity of the research model. Validity assesses the degree to which a variable in a research model differs from other variables in the same research model. Reliability measures the degree to which the variables give same results that are consistent and free from error (Hair Jr et al., 2016; Bokolo and Petersen, 2019). The validity is measured based on the convergent validity which assess whether indicators can proficiently reflect their conforming variable. Convergent validity involves the assessment of construct validity and reliability, where the reliability of the model constructs was assessed by considering the internal consistency reliability, and validity which were measured grounded on the Average Variance Extracted (AVE) value, which comprises the totality of variance, a construct measured from its indicators. Generally, the AVE should be much higher or equivalent to 0.5 as posited by Hair Jr et al. (2016). Similarly, for the internal consistency reliability, the Construct Reliability (CR) should be higher than 0.70 and the Cronbach's alpha (α) value should also be higher than or equal to 0.70 (Lange et al., 2012).

The factor loadings of each indicator are assessed to offer evidence which measure the convergent validity of all indicators which should be greater than the benchmarked value of 0.70 as posited by Hair Jr et al. (2016). Results from Table 2 suggest that the factor loadings of each indicator are higher than 0.7 apart from 3 indicators (PerceivedUsefullness1 = 0.489, PerceivedEaseOfUse3 = 0.425, and ActualEAAdoption2 = 0.640). Each of the items were removed from the model. Additionally, Findings from Table 2 depicts that the model constructs' reliability (CR and α) is higher than 0.7 and AVE (higher than 0.5) is above the recommended values for all factors. Table 2 also shows the mean and standard deviations (SD) of the variables, where the mean score for the Likert scale gathered from the respondents suggests that the mean scores are greater than 2.5 as suggested by Bokolo and Petersen (2019) based on the

Table 2 Exploratory and descriptive statistics

Factors	Indicators	Factor Loadings	Cronbach's Alpha (α)	CR	AVE	Standard Mean	SD
Perceived Usefulness of EA	PerceivedUsefullness1	0.489	0.885	0.896	0.676	3.83	0.635
	PerceivedUsefullness2	0.874					
	PerceivedUsefullness3	0.917					
	PerceivedUsefullness4	0.927					
Perceived Ease of Use of EA	PerceivedEaseOfUse1	0.803	0.728	0.834	0.572	3.32	0.564
	PerceivedEaseOfUse2	0.860					
	PerceivedEaseOfUse3	0.425					
	PerceivedEaseOfUse4	0.850					
Behavior Intention to Adopt EA	BehaviourIntention1	0.848	0.890	0.924	0.752	3.26	0.563
	BehaviourIntention2	0.877					
	BehaviourIntention3	0.842					
	BehaviourIntention4	0.899					
Actual EA Adoption Use	ActualEAAdoption1	0.891	0.723	0.843	0.647	3.66	0.614
	ActualEAAdoption2	0.640					
	ActualEAAdoption3	0.858					
Knowledge Transfer	KnowledgeTransfer1	0.876	0.907	0.930	0.768	3.95	0.507
	KnowledgeTransfer2	0.888					
	KnowledgeTransfer3	0.910					
	KnowledgeTransfer4	0.829					
Support Service	SupportService1	0.837	0.863	0.906	0.708	3.73	0.616
	SupportService2	0.863					
	SupportService3	0.772					
	SupportService4	0.888					

5-point Likert scale which is greater than 3.00 which is reflected as a significant criteria to determine the respondents acceptance and adoption of EA.

Moreover, the SD values are close to 0 and lower than 1; thus, the responses from the respondents are not widely distributed (Jnr, 2020; Jnr et al., 2020a, b). Furthermore, the discriminant validity is assessed whether two factors are statistically different from each other. The discriminant validity is the degree to which an indicator reflects its variable in oppose to all other indicators within the measurement model. The cross loading on all other factors shows discriminant validity. Also, Fornell and Larcker (1981) posited the use of AVE to assess discriminant validity. To assess the discriminant validity of all constructs, Fornell and Larcker (1981) proposed that the square root of AVE of each variable should be higher than the correlations shared between the factors and other factors in the research model. Moreover, the value should be greater than 0.5 as posited by Hair Jr et al. (2016).

Results from Table 3 indicates that the cross loadings are much lower than the factor loadings showing the discriminant validity for the indicators. Moreover, the AVE value is greater than 0.5, it is recommended that the factor establishes a minimum of 50% of the measured variance

Table 3 Inter-determinants correlation

	Actual EA Adoption	Behavior Intention to Adopt EA	Knowledge Transfer	Perceived Ease of Use of EA	Perceived Usefulness of EA	Support Service
Actual EA Adoption	**0.804**					
Behavior Intention to Adopt EA	0.390	**0.867**				
Knowledge Transfer	0.449	0.257	**0.876**			
Perceived Ease of Use of EA	0.393	0.656	0.313	**0.756**		
Perceived Usefulness of EA	0.140	−0.113	0.032	0.297	**0.822**	
Support Service	0.476	0.369	0.599	0.481	0.098	**0.841**

Bold signifies that the values are higher than 0.5 as recommended in the literature (Hair Jr et al., 2016)

(Bokolo and Petersen, 2019). Based on these results, it is determined that the constructs show a satisfactory convergence and discriminant validity as well as the reliability (Lange et al., 2012).

5.3 Structural model analysis

After the items of the variables are confirmed to be valid and reliable, the next step is to carryout structural model analysis. The structural model validates the developed research model (see Fig. 2), in terms of predictive abilities and relationships between the model variables. Thus, this sub-section examines the model fitness, relationships between constructs and hypotheses confirmation (H1-H8). Thus, the structural model was validated by computing the path coefficients and the values of R^2. The path coefficient reflects the impact or strength of the correlation between the independent variables (knowledge transfer, support service, perceived usefulness of EA, and perceived ease of use of EA) and mediating variable (behavior intention to adopt EA), and dependent variable (actual EA adoption). To verify the factors that influence EA adoption by practitioners in smart cities, the hypotheses developed are to be tested (see Fig. 2). The empirical analysis is presented in Table 4 and Fig. 3.

Therefore, the structural model assessment is assessed by checking the path coefficients *(β)* value which is based on the value of the significant levels (*p* value) which is significant when $p = < 0.05$ assessed using PLS path modeling method which measures the impact of the variables. Moreover, the coefficient of determination term R^2 value is used to measure the predictive impact or effect of the research model hypotheses. Next, *t-value* which is the path coefficient is utilized to test the impact of the model hypothesis, which is grounded on the regression coefficients and related significances as shown in Table 4. A

Table 4 Summary of the structural model

Hypotheses	Path Description	Standard Error (*SE*)	*Beta (β)*	R^2	*t-value*	Significance Level (*p* value)	Decision
H1	Perceived Ease of Use of EA—> Perceived Usefulness of EA	0.341	0.920	0.090	8.802	0.000	Supported
H2	Perceived Ease of Use of EA—> Behavior Intention to Adopt EA	0.060	0.795	0.633	13.186	0.000	Supported
H3	Perceived Usefulness of EA—> Behavior Intention to Adopt EA	0.087	−0.183	0.033	− 1.868	0.065	Unsupported
H4	Behavior Intention to Adopt EA—> Actual EA Adoption	0.080	0.580	0.336	7.149	0.000	Supported
H5	Knowledge Transfer & Support Service- > Perceived Usefulness of EA	0.110	0.910	0.080	6.657	0.000	Supported
H6	Knowledge Transfer & Support Service- > Perceived Ease of Use of EA	0.496	0.060	0.000	0.650	0.948	Unsupported
H7	Knowledge Transfer & Support Service- > Behavior Intention to Adopt EA	0.110	0.620	0.040	6.814	0.000	Supported
H8	Knowledge Transfer & Support Service- > Actual EA Adoption	0.120	0.114	0.013	6.534	0.000	Supported

Decision: Accept a null hypothesis if *t-value* lower than 1.96 and *p value* greater than 0.05

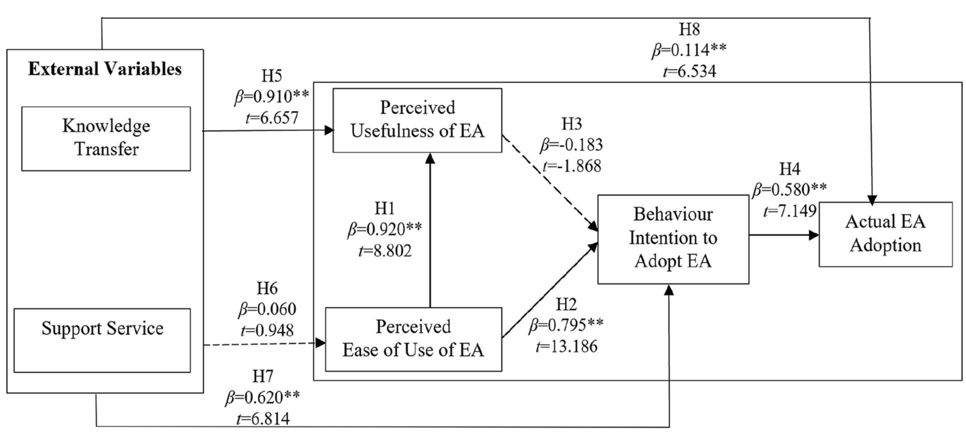

Fig. 3 Results of the structural model. Note: $^{**}p < 0.05$

bootstrapping approach of 5000 samples was employed in PLS to assess the significance level, and a null hypothesis is accepted if *t-value* lower than 1.96 and *p value* greater than 0.05 (Hair Jr et al., 2016).

Results from Fig. 3 and Table 4 depict the significance testing of the model hypotheses presented in Fig. 2. H1 states that practitioners' perceived ease of use of will positively influence the perceived usefulness of EA in smart cities. Results from Table 4 show that (H1) path coefficient is ($t = 8.802$, $\beta = 0.920$, $p = 0.000$), therefore supporting (H1), since *t-value* is greater than 1.96 benchmark and path coefficient "β" is higher than "0" (Bokolo and Petersen, 2019). Similarly, (H2) states that a greater degree of perceived ease of use of EA will enhance the degree of practitioner's intention to adopt EA adoption in smart cities. Results from Table 4 further suggest that (H2) path coefficient is ($t = 13.186$, $\beta = 0.795$, $p = 0.000$), therefore, supporting H2. Next, (H3) states that a greater degree of perceived usefulness will result in a greater degree of practitioner's behavior intention to adopt EA adoption in smart cities. Accordingly, results from Table 4 disclose that the hypothesis is not significant as path coefficient is ($t = -1.868$, $\beta = -0.183$, $p = 0.065$). Similarly, results from Table 4 reveal that greater degree of practitioner's intention to adopt EA will result in a greater degree of actual EA adoption in smart cities (H4) with path coefficient of ($t = 7.149$, $\beta = 0.580$, $p = 0.000$).

Further results from Table 4 indicate that (H5) path coefficient is ($t = 6.657$, $\beta = 0.910$, $p = 0.000$), therefore, supporting (H5), confirming that knowledge transfer and support service positively influence perceived usefulness of EA. Similarly, (H6) states that knowledge transfer and support service will positively influence perceived ease of use of EA. Results from Table 4 further suggest that (H6) path coefficient is ($t = 0.650$, $\beta = 0.060$, $p = 0.948$), therefore, rejecting H6. Next, (H7) states that knowledge transfer and support service will positively influence practitioners' behavior intention to adopt EA. Accordingly, results from Table 4 disclose that the hypothesis is significant as path coefficient is ($t = 6.814$, $\beta = 0.620$, $p = 0.000$). Likewise, results from Table 4 reveal that knowledge transfer and support service will positively influence actual EA adoption by practitioners (H8) with path coefficient of ($t = 6.534$, $\beta = 0.114580$, $p = 0.000$). In addition, the results empirically confirm that (H2) the perceived ease of use of EA influences behavior intention to adopt EA has the strongest effect. Whereas (H3) perceived usefulness of EA impact on practitioner's behavior intention to adopt EA in smart cities has the least effect.

It is assumed in this study that the external variables (knowledge transfer and support service), are factors that may impact EA adoption (see Fig. 2). As supported by the results, knowledge transfer and support service positively influence perceived usefulness of EA. This result suggests that if city administration provides more knowledge (such as best practices) on the usefulness of EA and provides support services such as training is provided to practitioners, the adoption of EA within smart city project will improve sustainability of the city. Conversely, the results suggest that knowledge transfer and support service do not positively influence perceived ease of use of EA. Practically, this result is useful for policy development suggesting that even if training and support services are provided to practitioners, this will not simplify usage of EA for practitioners who will utilize EA for modeling IT, business, and sustainability aspects of the city. This is because the practitioners involved in smart city projects are mostly from diverse fields working collaboratively to make cities smarter and sustainable.

Furthermore, the results suggest that the perceived usefulness of EA does not influence practitioners' behavior intention to adopt EA. This result states that within the smart city project, most practitioners were involved in the use of EA even if they do not perceive it to be useful as first. This is because they already have other approaches, they previously used to model sustainable and digital services in making cities smarter. But they eventually participated in the use of EA as it was proposed within the smart city project. Overall, the original TAM is valid as supported by the literature. Although findings from this study suggest that the unsupported links ((H3) "Perceived Usefulness of EA" influence on "Behavior Intention to Adopt EA" and (H6) "Knowledge Transfer & Support Service" influence on "Perceived Ease of Use of EA"), needs to be addressed for successful implementation and the theoretical model as seen in see Fig. 3 is still valid.

6 Discussion and implications

6.1 Discussion

Cities are faced with issues related to data alignment and system interoperability as they digitalize urban systems and services. EA is an approach that enterprises in smart cities can leverage on to systematically address some of the issues faced in urban environment. Therefore, this study extended the technology acceptance adoption model to explore the factors that influence practitioner's adoption of EA in terms of increasing the EA acceptance rate among participating enterprises involved in a smart city project. This study examines practitioners' perception on EA adoption and acceptance in a smart city project for modeling of digital services in smart cities. A research model was developed grounded by extended TAM. Data were collected using survey instrument from practitioners in Norway and Ireland to empirically test the model, and PLS-SEM was employed to analyze the survey data. The result from this study shows that six hypotheses embodied in the research model were supported by the data and two hypotheses were not supported. These results produce several significant findings that advance the adoption of enterprise architecture and understanding of how enterprise architecture can be used in enterprises that provided digital services in smart city context.

The results from this study show a significant relationship between perceived ease of use of BL and perceived usefulness of BL. The results support the conclusion made by Bernaert et al. (2014); Jonnagaddala et al. (2020) that perceived ease of use of EA significantly influence perceived usefulness of EA. This result seems quite reasonable since perceived ease of use of EA relates to the degree to which the practitioners expect that EA use will comprise less effort or free of difficulty when modeling digital services in smart cities (Anthony Jnr, 2021a). In addition, the results indicate that the perceived ease of use of EA has a positive effect on practitioner's behavior intention to adopt EA. This result is similar to findings from prior studies (Närman et al., 2012; Lee et al., 2015) which confirmed that the perceived ease of use of EA impacts the intention to use, and attitude of users towards using EA in their enterprise. Also, in accordance with Gilliland et al. (2014), results suggest that the perceived ease of use has a direct effect on users' attitude towards use of EA in improving security policies and blockchain technology. This result is also in line with findings from Jonnagaddala et al. (2020), where the authors found that EA supports health practitioners to apprehend the easiness of EA and feels relaxed to adopt EA in reducing complexity associated in healthcare.

Additionally, findings suggest that the perceived usefulness of EA does not impacts practitioners' intention to adopt EA. A possible interpretation is that the perceived usefulness measures the degree to which practitioners believe that their enterprise activities will be enhanced by using EA and may not necessarily change their perception towards EA adoption (Lange et al., 2016). This result is not aligned with findings from previous studies (Gilliland et al., 2014; Hazen et al., 2014) which suggested that the perceived usefulness of EA significantly determines the extent to which users believe that using EA approaches would improve their organizational productivity. Moreover, the results confirm that practitioners' intention to adopt EA is found to be a significant factor that influences actual EA adoption by practitioners. This result is consistent with the study undertaken by Jonnagaddala et al. (2020) where the authors highlighted that intention to use embodies the extent and manner in which EA is utilized within the organization.

Findings reveal that knowledge transfer and availability of support service positively influence perceived usefulness of EA. This result is in line with findings from prior studies (Jnr, 2020; Jnr et al., 2020a, b) where the authors suggested that knowledge as information availability positively determines IS use by practitioners in collaborative enterprise. Likewise, Moscoso-Zea et al. (2016); Assar and Hafsi (2019) stated that knowledge management and service support plays a substantial role in the use of EA in relation to business intelligence. Moreover, the study suggest that knowledge transfer and support service does not influence perceived ease of use of EA. This result does not support findings from prior studies (McNabb and Barnowe, 2009; Nabiollahi et al., 2011) where the authors suggested that knowledge management positively determines EA use for IT management and public sector development. Likewise, Moscoso-Zea et al. (2016) stated that availability of knowledge as support plays a substantial role towards user adoption of EA.

Further results from Assar and Hafsi (2019) report that knowledge transfer and support service positively influence practitioners' behavior intention to adopt EA. Likewise, prior studies also stated that service quality influence users' satisfaction in adopting EA to improve IT service management and business process (Braun and Winter, 2007; Šaša and Krisper, 2011). Thus, good service quality and availability of knowledge supports practitioners to understand EA use to improve modeling of digital services in smart cities (Jnr et al., 2021a). Finally, the result confirms what Šaša and Krisper (2011); Moscoso-Zea et al. (2016) concluded in their research suggesting that knowledge transfer capability and support service accessibility will positively influence actual EA adoption by practitioners. This is supported by results from Braun and Winter (2007); Nabiollahi et al. (2011) where the authors specified that IT service quality and knowledge dissemination positively predicted user satisfaction of IS deployed in an organization. Basically, if the practitioners are satisfied with the service offered by EA approach, then their behavior towards EA will increase based on the benefits derived which in turn influence the actual use of EA to improve enterprise process (Assar and Hafsi, 2019).

Findings from Table 1 regarding the participants experience with EA indicate that 31.1% recently just knew about EA, 36.9% have less than 1 year experience with EA. Also, another 24.3% have 1–3 years' experience with EA and lastly 7.8% have 4—5 years' experience with EA. Overall this demographic data did not affect the outcome of the results as all participants were introduced to the role of EA and why it was used within the + CityxChange project as published in the report on the on “the Architecture for the ICT Ecosystem” (Petersen et al., 2021). Besides, in the project, it was perceived as normal that 31.1% of respondents just learned about EA as most of the respondents are from different disciplined involved in the smart city project. Moreover, the response rate was low, but this was due to the fact participation in the survey within the smart city project was voluntary and most partners were not interested to participate in providing their opinion regarding adoption of EA to making cities smarter.

6.2 Theoretical implications

Findings from this study offer several theoretical implications. This research employs an extension of technology acceptance model as a research lens. This study contributes to the literature in the areas of enterprise architecture and technology acceptance. The findings provide insight to IT managers and enterprise system users who aims to further promote the adoption of EA to enhance the digitalization of services provided by their enterprises in smart cities. The study also provides a complete measurement instrument that provides insights into feasible factors and associated indicators that supports the adoption of EA in smart cities. The developed model can be employed in future studies to explore the acceptance of EA in urban context in other countries. Hence, insights from this research could, therefore, serve as a basis for researching the use of enterprise architecture from the lens of different stakeholder (researchers, technical architects, full-stack developer, managing director, IT manager, software developers, and project engineers), perspectives.

EA modeling provides a communication tool within the city’s administration to illustrate how IT, business, and sustainability components are deployed in improving the livability of the city. This helps the city with coordinating environmental opportunities to coordinate and guide supporting activities to create more benefits with reduced costs. It also helps cities to explore new opportunities and respond to new requirements of their citizens. Evidently, cities can employ the model to evaluate how to optimize legacy systems within the city into an integrated and interoperable digital environment that can be open to corporate sustainability and business strategy through reduced use of natural resources. EA can be leverage as an approach to articulate a city’s future direction and its sustainability goals, while serving as an instrument to aid actual transformation of urban services.

Furthermore, the model can be employed by IT manager to provide direction and guidance to further understand the factors that determine the adoption of EA in smart cities. Prior EA studies are mostly grounded on qualitative methods such as interviews, workshops, and case studies. This study provides a quantitative approach which is perceived as a structured approach to generalize the population by investigating the relationship between factors. This current study complements prior studies by empirically demonstrating the applicability of technology acceptance model in smart city as this is one of the first studies to employ TAM to examine the adoption of EA in urban context. This research offers significant contribution as empirical research in EA research domain and provides a cross-sectional survey evidence based on results from two countries (Norway and Ireland) for model validation using PLS-SEM.

6.3 Managerial and practical implications

A significant managerial implication of this research is that for EA adoption to bring benefits to enterprises in urban environment, an effective EA adoption model must be developed. Therefore, the developed model can be used to evaluate the readiness of different practitioners as well as the entire enterprise business and IT alignment. This can provide guidance to enterprises management and enterprise system users to come up with an effective improvement plan as organizations are currently digitalization their business operations (Anthony Jnr, 2022). Practically, this study provides a model to be employed as a tool to evaluate the adoption of EA in smart cities. This study is significant in providing value-added services to citizens in smart cities. Moreover, as highlighted by Hazen et al. (2014), this research helps extend a main tenet of technology acceptance to city and societal context, as there is a dearth of research regarding EA adoption in urban context from technology acceptance perspective.

This research complements extant research to help fill this gap. Specifically, the findings suggest that factors such as knowledge transfer, support service, perceived ease of use of EA, perceived usefulness of EA, behavior intention to adopt EA, and actual EA adoption remain pertinent to promoting adoption even after an innovation such as EA has been adopted by an enterprise. By means of a cross-sectional survey, this study validated the research model, targeting different practitioners in Norway and Ireland. Furthermore, the findings from this study provide IT managers with evidence that EA adoption enables both IT-driven and business-driven change opportunities within an enterprise or in a city. Business manager and IT manager involve in providing data-driven services in cities can use the research findings from this study as inputs in the actualization of an EA checklists to supports the dissemination of knowledge across multiple stakeholders in urban environment. This research also assists policy makers in municipalities in strategizing EA adoption by recognizing the significant factors and key metrics of EA adoption needed for digital transformation of city services.

Findings from this study reveal that EA modeling supports the sustainable development of cities into smart cities. In this study, the author developed a research model conceptualized from an extension of TAM to assess practitioners' perception towards the adoption of EA to support cities in becoming sustainable smart city. A questionnaire is designed (as seen in Table A1) to be used in practice to guide EA adoption in smart city projects to improve the decision support of practitioners to improve their environmental goals. Cities can employ the measurement instrument (see appendix Table A1) as a benchmarking to measure how their EA adoption can be improved based on the model factors. Practically, EA can help cities to ensure credibility, transparency, consistency, and comprehensiveness for corporate sustainability. EA modeling can be communicated to the entire city to be used as a standard towards improve sustainability of the city. It gives practitioners a mutual insights and action towards environmental, economic, and social target of the city which is so crucial for the corporate sustainability (Pankowska, 2013).

7 Conclusion

Generally, enterprise architecture adoption aims to address system interoperability and data silos, aligning IT and business strategic planning and investment within the enterprise, decreasing complexity in IT infrastructure, and fostering organizational agility and dynamic change. However, notwithstanding the benefits of EA, its adoption is low in urban context in making cities smarter. Therefore, this research develops and validates a model grounded on an extension of TAM that investigate the factors that influence enterprise architecture adoption by different practitioners in smart cities. Findings from this research add to the existing knowledge in EA adoption and provides insights for cities to digitalize their urban operations. The findings aid practitioners by serving as a guide for decision making to plan and strategically deploy EA in their organizations.

Therefore, in this article, we argue that EA approaches (such as modeling tools, frameworks, and management) can systematically provide guidance and consistency in actualizing a smart sustainable city. The identified factors as seen in Fig. 2 can contribute to the understanding and orchestrating of urban services to support sustainability goal which remains an untapped area with several opportunities (Sutherland and Hovorka, 2014). This study contributes to existing body of knowledge by presenting the factors that influence EA adoption from the lens of practitioners in smart city context. The findings provide both practitioners in industry and researchers in academia with a more realistic and accurate understanding of EA to aid in digital transformation of cities into smarter cities.

7.1 Limitations and future works

A few limitations were identified in this study. First, this study only extends the body of knowledge of EA adoption to smart cities context by underpinning the TAM theory. However, the extension of TAM in this study provides an avenue to gain insights into the adoption of EA by different practitioners in smart city project. In this study, data were only provided by participants from 18 organizations in 2 countries to validate the develop model. Data were provided by more male respondents as compared to female respondents. Further work may include exploring EA adoption from a different enterprise adoption theory such as the IS success model to establish further evidence.

Also, data collected as regarded to gender will be improved in future as 92.2% of the respondents were male and only 7.8% were female. More female respondents will be encouraged to participate in future smart city projects. Besides, there is need to conduct a longitudinal study and collect data from more participants from other countries where EA is adopted in smart city projects in delivering digital services provided by enterprises to stakeholders in smart cities. Future research will also conduct proper interviews or conduct a case study from the lens of different practitioners in smart city context to help provide future evidence. Also, citizens participation will be explored in future studies. This will help engage citizens and provide means for them to participate in the smart city process.

Appendix

Table A1 Questionnaire items

Factors	Items	Sources
Perceived Usefulness of EA	PUA1—Enterprise architecture is relevant for my work, PUE2—Enterprise architecture is relevant for CxC smart city project, PUE3—The developed EAF is useful for my work, PUE4—The EAF is useful for the CxC smart city project	(Närman et al., 2012; Gilliland et al., 2014)
Perceived Ease of Use of EA	PEU1—The CxC EAF is easy to understand, PEU2—The CxC EAF is easy to use, PEU3—The designed CxC EAF use case models are easy to understand, PEU4—I find it easy to describe a scenario using the designed EA use case models	(Lee et al., 2015; Jonnagaddala et al., 2020)
Behavior Intention to Adopt EA	BIEA1—I will recommend the framework to colleagues in my organization, BIEA2—I will use the framework for my work in the future, BIEA3—I will use the use case models for my work in the future, BIEA4—I will recommend the use case models to colleagues in my organization	(Bernaert et al., 2014; Jonnagaddala et al., 2020)
Actual EA Adoption	AEAA1—The use case models are useful for my work AEAA2—The use case models are useful for the + CxC project, AEAA3—The use case models have helped me clarify details about our use case	(Authors own)
Knowledge Transfer	KNTF1—The CxC EAF could help in discussions with colleagues and / or collaboration partners within my organization, KNTF2—The CxC EAF could help when explaining use cases and solution architectures to colleagues, KNTF3—The CxC EAF could help with capturing knowledge, KNTF4—The CxC EAF could help with sharing knowledge within my organization and / or project partners	(Authors own)
Support Service	SUAE1—The CxC EAF could support collaborative activities, SUAE2—The CxC EAF could support reflection on use cases, SUAE3—The CxC EAF could support identifying potential value-added services, SUAE4—The CxC EAF could support shared understanding to support decision making	(Authors own)

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Declarations

Conflict of interest The author(s) declare that they have no conflict of interest.

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