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A Model to Evaluate the Acceptance and Usefulness of Enterprise Architecture for Digitalization of Cities

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Abstract

Purpose

Enterprise Architecture (EA) is usually adopted as an approach for managing enterprise complexities and aligning business and Information Technology (IT) capabilities. Although IT practitioners and researchers agree about the potential applicability and benefits of EA in smart cities, little is known about the factors that influences the acceptance and usefulness of EA in smart cities. Thus, EA acceptance and usage remains a central concern of urban research and practice. Similarly, there are fewer studies that explored EA adoption from the context of enterprises that provide digital services in cities grounded on empirical evidence. Therefore, this study assesses the acceptance and usefulness of EA in smart cities context by developing an EA adoption model drawing on the DeLone & McLean Information System (IS) success model.

Design/methodology/approach

Based on the identified factors survey questionnaire was designed and sent out to participants which includes IT professionals, senior managers, and consultants from 18 organizations in Norway and Ireland involved in a smart city project (+CityxChange) (https://cityxchange.eu/)). Statistical Package for Social Science (SPSS) and structural equation modeling using partial least square was applied for data analysis.

Findings

The results suggest that service quality and system quality positively impact user satisfaction of EA and user's intention to use EA. More importantly, information quality does not influence user satisfaction of EA, and the user satisfaction of EA and user's intention to use EA significantly influences the net benefit of EA.

Originality/value

This study provides a complete understanding for academicians and IT practitioners regarding the factors and impacts on EA acceptance and use in smart cities. Finally, this study discusses the implications of this research and provides recommendations for future research.

Keywords: Enterprise information systems; Enterprise architecture adoption; Technology acceptance and use; IT practitioners; Information system management; Smart cities.

1. Introduction

Cities continues to experience digital transformations by deploying Information Technology (IT) to support services offered to citizens and stakeholder (Jnr *et al*., 2021). A smart city is an urban location that deploys Information Communications Technology (ICT) and other associated technologies to enhance services offered to citizens (Silva *et al*., 2018). Smart cities deploys an interconnection of digital technologies to provides solutions that enhance the performance and quality of urban services, while ensuring that the natural resources are available for current and imminent generations in terms of environmental, economic, and social aspects (Heo *et al*., 2014). Smart city aims to offer value added services and proficient resource management for stakeholders through the usage of available data (Jnr *et al*., 2020a). In a continually changing and dynamic urban environment digitalization is desirable to be able to

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address the goals and effectively manage changes for urban development. One of the key initiatives to support the successful digitalization of cities is the adoption of Enterprise Architecture (EA) (Anthony Jnr, 2021a). EA aims to guide the development of an organization's operation of ICT systems, i.e., the digitized enterprise processes and IT systems that digitalized the organization's main capabilities (Al-Kharusi et al., 2021). This facilitating role is geared to provide a sustainable institutional-wide vision of IT systems and enterprise processes (Tamm *et al*., 2011).

EA directs Information Systems (IS) alignment, administrative processes, and business strategy and is widely adopted in institutions to improve structural alignment, improved decision-making, decrease costs, and improve performance (Hazen *et al.,* 2014). EA provides descriptive artefacts that aid cities to understand and manage complexity and change management of digital transformation (Gilliland *et al*., 2015). EA describes the important structure and key components of an enterprise, its information system, the ways in which these systems and data interacts to realize defined enterprise objectives, and the medium in which IS supports business processes within the organization (Lange *et al*., 2016). Large enterprises across various industries adopts EA for various reasons such as for technology management, enterprise strategic management, management and guide of IT deployment, enterprise-IT alignment, and business compliance assessment (Jonnagaddala *et al*., 2020). Researchers such as Lange *et al*. (2016) argued that EA can be used as an instrumental for governing enterprise's continuous development process by establishing the connection between business strategy and its deployment, and secondly supporting the implementation of solution architectures. EA builds on a comprehensive set of tools, models, and concepts for the holistic management of an enterprise's information systems (Lange *et al*., 2016; Anthony Jnr and Abbas Petersen, 2021).

Unfortunately, despite the benefits of EA, cities do not adopt EA to such a degree that it achieves these positive outcomes (Hazen *et al*., 2014; Jnr *et al*., 2021). Hence, there is a need to investigate the factors that impact the acceptance and use of enterprise architecture for digitalization within the context of cities. While EA is a tool for decreasing institutional complexity, effectively usage of EA is not without limitations in urban context (Ahlemann *et al*., 2021). As there are factors that may influence IT practitioners, IT architects, and stakeholders to effectively accept and use EA for formal governance and collaboration (Van Der Raadt *et al*., 2018), in digitalization of cities. Although, findings from the literature (Espinosa *et al*., 2011) have explored factors that influences the perceived benefit of EA in organizations (Lange *et al*., 2016), these studies failed to examine how these factors significantly impact the digitalization of cities (Härting, 2018). In addition, quantitative research method might be useful to provide deeper insights on the factors in relation to the digitalization of cities. Accordingly, in this study the following research questions are raised:

- What model can be adopted to explicate factors that impacts EA acceptance and use for digitalization of cities?
- What factors impacts EA acceptance and use for digitalization of cities?

To this end this research use one of the EA acceptance theories, the DeLone & McLean IS success model as underpinning theory in developing the proposed model and associated hypotheses. A quantitative method was employed using survey questionnaires to collect data from purposively selected respondents. Next, Statistical Package for Social Science (SPSS) and Structural Equation Modeling based on Partial Least Squares was used for data analysis. Findings from this study can assist top management involved in digital transformation of cities in identifying the significant factors that impacts EA usage in their cities. This research provides a theoretical underpinning, and empirical evidence on related factors impacting the acceptance of EA. To the knowledge of the author there exist no prior study that explicitly examined the effect of factors on the acceptance and usefulness of EA for digitalization of cities. This paper is structured as follows: Section 2 is the theoretical background. Section 3 describe the research model. Section 4 details methodology. Subsequently, findings from the survey are captured in Section 5. Section 6 presents the discussion of findings and related implications for researchers and IT practitioners. Section 7 is the conclusion, limitations, and future works.

2. Theoretical Background

This section presents the significance of EA for digitalization of cities, review of prior studies that employed enterprise adoption theories to explore EA usage, and provide an overview of DeLone & McLean IS success model.

2.1. Significance of Enterprise Architecture for Digitalization of Cities

In the ISO/IEC/IEEE standard architecture is refers to the central organization of a system, constituted in its components, the relationships and the embodied environment, and the principles orchestrating its development and evolution. Weiss *et al.* (2013) refer to EA as the establishing lucidity for IT systems and business processes, reflecting the standardization and integration requirements of the enterprise. According to Ajer and Olsen (2018) EA can be a seen as a process, a method, or strategy. EA provides an architecture to support enterprise by enabling agility and integration of how business processes, data, and applications interconnect to support enterprise in developing from inaccessible silos to unified solutions within the enterprise towards an efficient, robust, and flexible ICT eco-system (Gilliland *et al*., 2015). Over the decade EA has been employed in large institutions to manage complex IT systems (Ajer and Olsen, 2018).

EA uses artifacts such as modelling languages for modelling up-to-date and imminent states of an institution, its governing principles for design and evolution, frameworks for overarching reference, good practices, and applications to facilitate software designers' work (Weiss *et al*., 2013). EA provides a medium to get a complete view of the city's present state, a clear description of the proposed situation, and a road map to employ an integrated, well-structured plan for digitalization of urban services (Anthony Jnr, 2021a). Hence, EA provides a means of conceptualizing the current state, aiding decisions making about the future state of the city (Van Der Raadt *et al*., 2018). EA offers a model-driven administration method to set the restrictions at city and enterprise level for IT designers and enterprise architects ensuring the delivery of digitalized solution, which can be integrated into the current city strategy (Anthony Jnr, 2021b). EA provides a medium to facilitate planning and overall structuring of city`s services provided to citizens by offering standardization and specifying a definite direction for the future (Van Der Raadt *et al*., 2018).

Generally, EA provides the establishing lucidity for an enterprise's corporate processes and IT infrastructure. IT practitioners and enterprise architect employ EA in urban context to categorize key data, technology, and system applications that must be connected across multiple departments of the enterprise (Bradley *et al.*, 2012). In the context of this study, EA refers to a plan (or set of plans) that guides urban planners management strategies and responsibilities, including the use and identification of IS resources (Bradley *et al*., 2012). According to Ahmad *et al*. (2020) EA is used by enterprise architects to achieve organizations plan and design technological innovation toward deployment of digital services. Evidently, EA benefits IT practitioners and decision-makers by actualizing desired technology solutions, reducing duplication of systems and applications, aiding interoperability, and improving seamless integration across the city services. But, despite the substantial benefits EA is not widely adopted in urban context (Ahmad *et al.*, 2020). Traditionally EA is within an enterprise, when used on city-scale one need to cover both city management, but also parts of the services of a number of other public and private organizations. This might make it more complex.

2.2.Related Works that Adopted Enterprise Architecture

Digitalization has led to the deployment of information systems modelling approaches such as EA to aid digital transformation in the city. As such a few studies has examined EA use across several sectors. One of these studies is Pattij *et al.* (2019) where the authors developed a model to investigate the mediation influence of IT capabilities on the correlation between agility and enterprise architecture management. The model comprises of enterprise architecture management, IT capabilities, and organizational agility. Survey data was collected from 110 EA stakeholders and structural equation modeling based on partial least squares was used to analyze the model. Also, Rouhani *et al.* (2019) presented critical success factor required for EA implementation based on extensive literature review and evidence from practitioners based on a proposed model.

Another study by Sallehudin *et al.* (2019) explored EA modelling deployed in the public sector grounded on the HOT-Fit framework. The study examines EA implementation in Malaysian public sector's by assessing the factors that impacts EA. The model comprises of human, organization, and technological factors. Data was collected from 92 participants and structural equation modeling based on partial least squares was utilized for data analysis. Also, Härting *et al.* (2018) developed a research model to assess the benefits of enterprise architecture management. The researchers identified factors and their significance on enterprise architecture management. Besides, data was collected from a case of an industrial digital transformation. Hazen *et al.* (2017) suggested a competence-based theory to achieving agility and firm performance during EA adoption. Hence EA assimilation and EA strategic orientation are employed as operational and dynamic capabilities. Data was collected from a total of 190 manufacturers and regression test was used to validate the model hypotheses related to EA assimilation, agility, EA strategic orientation, and firm performance.

Additionally, Niemi and Pekkola (2016) conducted a review of prior models and case study via 14 semi-structured interviews from EA stakeholder in a public organization to explore EA benefit realization. The authors focused to investigate how EA benefits impacts public organizational process and how related factors impacts each other. Syynimaa (2015) modelled the dynamics of EA adoption process. The study proposed a conceptual model to explicate the complexity of EA adoption based on EA and resistance literature and organizational change. The conceptual model comprises of strategic level of EA, objectives, resistance during planning, resistance during execution, and outcomes. Data was collected from 11 Finnish higher education institutions to empirically validate the model. Iyamu and Mphahlele (2014) investigated the effect of organizational structure on EA deployment. The study explored the relationship between EA and organizational structure. The identified factors that determines EA deployment comprises of resources, knowledge, hierarchy, policies, and communication. Case-study approach was adopted using semi-structure technique to provide qualitative data towards exploring the effect of enterprise structure in the use of EA in businesses.

Bradley *et al.* (2012) investigated the effectiveness of IT, EA, and the intermediating impact of IT alignment. Their study is based on the advance Ross four-stage model of EA maturity as a useful IT resource for aiding medical care institutions to achieve competitive advantage. The model comprises of EA maturity stage, IT alignment, operational IT effectiveness, and enterprise agility. Data was collected from 164 US hospitals and structural equation modeling based on partial least squares was utilized for data analysis. Ojo *et al.* (2012) explored how to enhance government EA practice based on a maturity factor analysis. The study was aimed at specifying the main factors for achieving the maturity of government EA practice to guide policymakers in improving their EA capabilities within their agencies. The EA practice maturity model comprises of EA maturity, EA effectiveness, EA stakeholder satisfaction, EA environment, and EA function design. By means of data collected from 33 agencies factor analysis was employed for analyzing the identified factors. Lastly, Kluge et al. (2006) studies how to achieve corporate value from adopting EA. The researchers employed the D&M IS success model for the development of a realization model specific to EA domain. Data was collected from two major case studies involving a Swiss insurance organization and an Australian utility firm. Findings from their study suggest that actual use and service quality as two major factors that impacts EA general success.

Evidence from the review studies suggest that EA has been the theme of diverse experimental research with explicit domain and findings. The reviewed studies also explored various factors that impacted the implementation of EA. To date, the acceptance and usage of EA to support digitalization in city context is minimal. Besides, EA studies conducted in urban area are fewer than those conducted in other sectors, such as in manufacturing enterprises and health sector. Thus, there is need to explore the factors that influence EA acceptance and use for digitalization of cities.

2.3.Theories of Enterprise Architecture Acceptance and Usefulness

EA acceptance and usage refers to the action of EA being used or in use. Hence EA acceptance is defined as IT practitioners choose to follow or take up the adoption of EA (Syynimaa, 2015). EA acceptance reflects the usage of EA by IT practitioners and stakeholders. Also, in organization there are other practitioners that either adopts EA or IT architecture (Lee *et al*., 2015). In this research acceptance and usage denotes the activities which are incorporated in the design and development of EA (Iyamu and Mphahlele, 2014). Findings from Iyamu and Mphahlele (2014) revealed that the usage of EA in organization was a significant strategic approach towards realizing the goals and objectives of businesses. The authors argued that enterprises intend to adopt EA to support and reach its mission on delivering better technological driven solutions and services, while decreasing operational costs and improving productivity. Respectively, over the years several theories have been employed to explore the acceptance and use of IS, such as Technology Acceptance Model (TAM) which was previously employed by Närman *et al.* (2012) where the researchers developed a framework to evaluate application usage. Another theory is the institutional theory which was adopted by Weiss and Winter (2012) to explore institutionalization of enterprise architecture management in businesses.

The DeLone and McLean (D&M) IS success model is another theory that is previously employed to explore the acceptance of technology over time. The DeLone and McLean (D&M) IS success model was first designed in 1992. The first D&M IS success model comprises of system quality, and information quality as factors that influences use, and user satisfaction factors, which determines the individual impact, and organizational impact factors. But, in 2003 the model was updated as designed by DeLone and McLean (2003). The updated DeLone and McLean (D&M) IS model comprises of a set of factors (information quality, service quality, system quality, and system success) that influnces IS use and user satisfaction. The IS use and user satisfaction factors influnces the overall net benefit factor. The main constructs from the D&M IS success model are summarized in Table 1.

Table 1 Main constructs from the D&M IS success model

Main Constructs	Description	Sources
System quality	Entails how EA framework is employed to support physical and online enterprise operations for different practitioners to communicate, collaborate, and interact in digitalization of services.	(DeLone and McLean, 2003; Kluge et al., 2006).
Information quality	Involves the quality of information and resources content delivered through EA framework based on the timeliness, accessibility, understandability, sufficiency, accuracy, and completeness to practitioners within enterprise operations.	(Lange *et al.*, 2016; Niemi and Pekkola, 2016).
Service quality	Involves the quality of assessment and feedback support services provided to practitioners to assess the adoption of EA framework for digitalization of services.	(DeLone and McLean, 2003; Lange *et al.*, 2016).

Although the model was initially developed for the IS domain, it basically captures value realization process of business practices (Kluge *et al.*, 2006). While the D&M IS success model has been implemented in prior IS studies, it has not been widely adopted to the area of EA and digitalization of city particularly in EA and smart cities. From the theoretical perspective, the acceptance and use of EA requires a technology theory to explain EA adoption in cities. Although EA for digitalized cities can be seen as a macrolevel decision, only few studies have examined the factors from the viewpoint of a city. Prior research on the use of EA in city context suggest that there is a scarcity of factors related to the perception of IT practitioners who utilized EA to digitalization of city services (Härting, 2018; Van Der Raadt *et al*., 2018). Therefore, this study deems that D&M IS success model is relevant in investigating the acceptance and usefulness of EA in the context of influential factors within the scope digitalization of cities. IT practitioners' views can impact decision making at the macro level towards the digitalization of city services as they partake in co-creation of innovative services and are also involved in suggesting digital services provided to citizens and stakeholders towards to improvement of urban environment (Ahlemann *et al.*, 2021; Jnr *et al*., 2021). The aforementioned IT practitioners involved in digitalization of cities comprises of professionals, IT designers and developers, senior managers, and consultants.

3. Research Model

The factors that influence EA acceptance and use for digitalization of cities grounded on DeLone and McLean IS success model and related hypotheses are presented as discussed below;

3.1.1. System Quality

System quality refers to characteristics, technical success, accuracy, and efficiency of EA in facilitating digitalization of city services (Niemi and Pekkola, 2016). Thus, system quality is an important factor that determines the acceptance of any technology (DeLone and McLean, 2003). Moreover, it is included in the capability of EA to support collaboration between IT practitioners and stakeholders limiting the number of systems generated errors that impact usage (Kluge *et al.*, 2006). In context of EA, system quality was found to positively influence the acceptance of information systems (Lange *et al.*, 2016). Moreover, Espinosa et al. (2011) stated that the quality of EA is related to its capability to offer IT practitioners with access to resources to support IT and business alignment. Findings from Lange *et al.* (2016) revealed that the system quality is a significant factor that determines use intention and satisfaction of user. Based on these observations, it is evident that IT practitioners and stakeholders who perceive EA offers quality information systems modelling of technological infrastructures and data may also influence their perceptions towards the actual use of EA. Thus, this study hypothesized the following:

H1: *The system quality of enterprise architecture will positively influence IT practitioners and urban stakeholder's intention to use EA for digitalization of cities.*

H2: *System quality of enterprise architecture will positively influence IT practitioners and urban stakeholder's satisfaction when adopting EA for digitalization of cities.*

3.1.2. Information Quality

Information quality denotes the quality of EA resources and information delivered through EA to support digitalization of cities (Anthony Jnr, 2021a). The information quality of EA should be accessibility, completeness, accuracy, understandability, sufficient to IT practitioners and stakeholders. Thus, information quality is essential for stakeholders in order to access accurate and precise information regarding city development (Kluge *et al.*, 2006). Findings from the literature (Lange *et al.*, 2016; Niemi and Pekkola, 2016) suggested that information quality is an important factor that influences IT practitioners and stakeholder's intention to use EA as well as their satisfaction derived from using EA. This is because the quality of information available may help in enhancing their perceived ease of use and acceptance of EA (Kluge *et al.*, 2006). Moreover, Niemi and Pekkola (2016) pointed out that if EA offers IT practitioners and stakeholders with well-designed models and tools, then it will be considered as easy and simple to the users. Based on this, the following hypotheses are formed:

H3: *The information quality of enterprise architecture will positively influence IT practitioners and urban stakeholder's intention to use EA for digitalization of cities.*

H4: *Information quality of enterprise architecture will positively influence IT practitioners and urban stakeholder's satisfaction when adopting EA for digitalization of cities.*

3.1.3. Service Quality

Service quality entails the value of services and support provided to IT practitioners and stakeholders who adopts EA for digitalization of cities (Lange *et al.,* 2016), based on the availability, effectiveness, responsiveness, reliability, and assurance of offline and online support (Anthony Jnr, 2021a). Service quality provided to users may also be a crucial determinant that influences their perception towards accepting and using EA (Espinosa *et al.,* 2011). This is supported by results from Niemi and Pekkola (2016) where the authors specified that service quality positively predicted stakeholders satisfaction of EA. Basically, if IT practitioners and stakeholders are satisfied with the service offered by EA towards digitalization of cities then their intention to use and satisfaction will increase based on the benefits derived which in turn determines the actual use of EA (Espinosa *et al.,* 2011). Further results from Anthony Jnr *et al.* (2020) reported that the technical support and guidance provided statistically influences stakeholders' behavioral intention toward the acceptance of EA. Based on these observations the following hypotheses were proposed:

H5*: The service quality of enterprise architecture will positively influence IT practitioners and urban stakeholder's intention to use EA for digitalization of cities.*

H6*: Service quality of enterprise architecture will positively influence IT practitioners and urban stakeholder's satisfaction when adopting EA for digitalization of cities.*

3.1.4. Intention to Use EA

In this study intention is denoted as the prospect that IT practitioners and stakeholders will use EA for digitalization of city services (Anthony *et al.,* 2020). Moreover, intention to use entails the prospect of IT practitioners and stakeholders to use EA before they truly use it and it's mostly projected to occur in future (Lee *et al.,* 2015). As IT practitioners use EA their intentions to continue to use EA is centered by the fact that EA approach can improve the digitalization of cities. Researchers such as Närman *et al.* (2012); Jonnagaddala *et al.* (2020) examined the association between intention and actual use in EA and argued that intention plays an imperative role in the actual use of a new technology. This finding is analogous with results from Gilliland *et al.* (2014) where the author found that users who have a strong intention to use EA resources would accept EA modelling than stakeholders with lower intentions. Based on this, the following hypothesis is formed:

H7: *IT practitioners and stakeholders' intention to use EA will positively influence actual benefit of EA.*

3.1.5. User Satisfaction of EA

User satisfaction refers to the extent of cognitive spontaneity of user fulfillment with usage of EA. User satisfaction can be achieved by introducing IT practitioners and stakeholders' to how EA can be integrated to improve the digitalization of city services (Jnr, 2021; Jnr *et al.*, 2021). Moreover, the satisfaction can be referred to as a complex factor which may be based on IT practitioners and stakeholders' interest, psychological stimulation, and pleasure derived from EA models and tools (Gilliland *et al.,* 2014). Moreover, user satisfaction is considered influenced by the intrinsic belief of the user of EA which is centered on prior experiences with EA based tools (Hazen *et al.*, 2014; Lee *et al.*, 2015). Thus, the following hypothesis is formed:

H8: *IT practitioners and stakeholders' satisfaction of EA will positively influence actual benefit of EA.*

Based on DeLone and McLean IS success model adopted in this study to explore the factors that influence EA acceptance and use for digitalization of cities. The theoretical model is developed as shown in Figure 1.

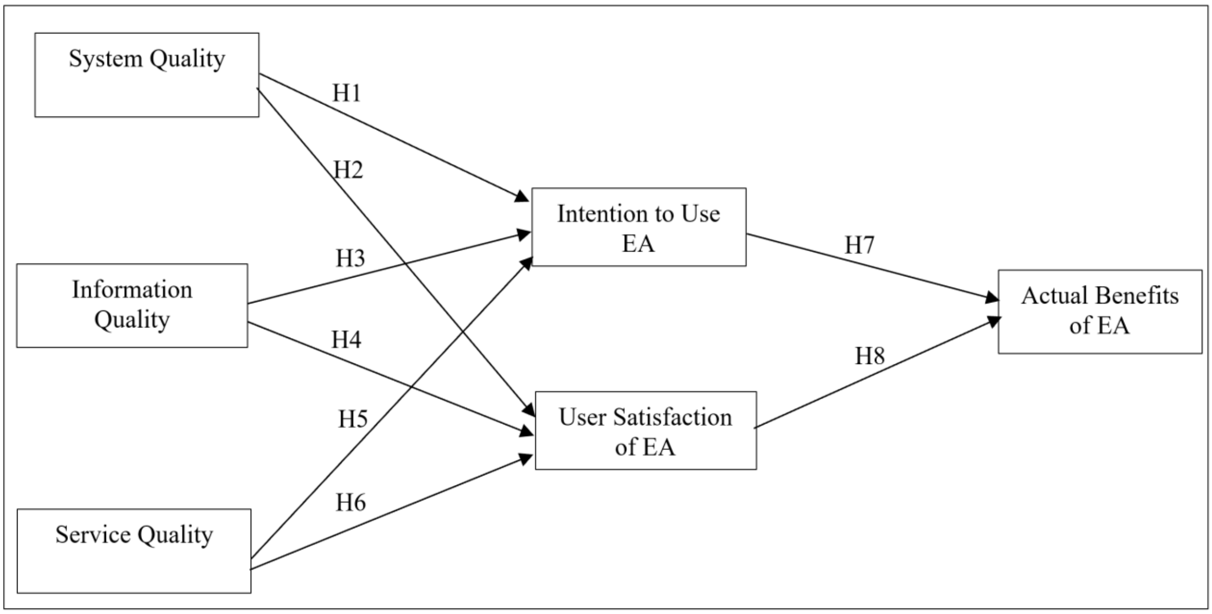

Figure 1 Developed theoretical model

4. Methodology

4.1.Sample and Procedure

To validate the developed model hypotheses a quantitative empirical approach was employed by means of a survey questionnaire conducted among 40 participants from 18 organizations in Norway and Ireland involved in a sustainable urban project (+CityxChange) (https://cityxchange.eu/)). The +CityxChange smart city project aims to support the co-creation of a future for cities to integrate smart sustainable energy solutions. Through the utilization of digital services to progress the quality of life citizens, achieving energy production and less consumption, and transferring the experiences to other cities across Europe and the world. Purposive sampling was used analogous to prior EA studies (Gilliland *et al.*, 2015; Shanks *et al.*, 2018). Most participants were familiar with EA. Targeting IT practitioners, senior managers, experienced consultants, and researchers who had experience in using EA or are familiar with EA model adoption in smart city context. The questionnaire was developed from prior EA studies that employed D&M IS success model as seen in appendix (Table A1).

Figure 1A and Figure 1B in Appendix shows results of IBM SPSS SamplePower test and results of GPower test to demonstrate the statistical relevance using power analysis in determining the minimum sample size. The results of IBM SPSS SamplePower test (see Figure 1A) for sample size indicates that a minimum of 17 samples are required for each group. Where this study has two group of samples in Norway and Ireland thus 17*2=34 samples are needed to have a valid result. As seen in Figure 1A the mean of group A (Norway) is between 3 and the mean of group B (Ireland) is between 4, whereas the standard deviation is given as 1, since the mean value as seen in Table 2 is below 1. Similarly, the results of GPower test (see Figure 1B), suggest that using an estimated effect size of 0.62 for two groups a total of 36 samples are required. However, we acknowledge that 40 participants who were involved in the smart city project (+CityxChange) (https://cityxchange.eu/)) use and validation of the developed EA framework were limited and is one of the limitations of this study and is considered as small sample size. But we were faced with the challenges of collecting more data required as the overall population of participants involved in the use of the developed EA framework was low.

The questionnaire was administered online via https://nettskjema.no which is a platform approved by the Norwegian Centre for Research Data (NSD) to collect data as the platform adheres to EU General Data Protection Regulation (GDPR) data privacy of respondents. The practitioners in these organizations involved in using the EA framework received a personalized link to the survey via the survey system to provide data regarding their perception on EA as regards to digitalization of city services as regards to the +CityxChange smart city project. The questionnaire was distributed in English between November 2020 to January 2021. The first section of the questionnaire provides an introduction of the research to prospective respondents and permission was attained from the qualified participants. The second section collect data as regards 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) which is specifically developed for the +CityxChange smart city project, based on ordinal scale.

The developed EAF provides an architecture that is being used in Limerick, Ireland and Trondheim, Norway to design and capture digital services, open data, and system applications deployed to achieved sustainable energy services in smart cities. Also, the developed EAF provides an ICT ecosystem that establishes how the +CityxChange smart city project partners collaborate in offering virtual services to citizens and urban stakeholders while at times utilizing same data sources and systems. The third part of the questionnaire collected response based on the respondent's perception towards the acceptance and usefulness of EA in digitalization of city. The question items were measured based on a 5-point Likert scale ranging from strongly disagree to strongly agree. The demographic data of the participants are shown in Table 1.

4.2.Data Analysis

The research model (see Figure 1) was designed into a structural equation model which was confirmed using a structural equation modelling partial least squares approach similar to prior study (Bradley *et al*., 2012; Weiss *et al.*, 2013). The PLS-SEM was employed because it has less rigid distributional expectations and is more appropriate for exploration of variable relationships. Also, PLS-SEM has lower sample size requirements as it uses estimates to assess via bootstrapping resampling method with 500 resamples. Based on this, the significances of each hypothesis are evaluated by means of two-tailed *t*-tests. Descriptive analysis was executed using Statistical Package for Social Science (SPSS) v. 26. SmartPLS 3.0 was used to assess the PLS-SEM for model testing (Shanks *et al*., 2018).

5. Findings

The findings comprise demographic data analysis and analysis from SPSS and PLS-SEM. The data was analyzed in SEM-PLS-SEM using SmartPLS comprises of two main phases, the examination of measurement model and structural model.

5.1.Respondents Data

The analysis of the survey participants profile is shown in Table 2.

Table 2 Profile of the participants

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

5.2.Analysis of Measurement Model

All variables were measured in reflective method in PLS-SEM to validate the developed research model (see Figure 1). The measurement model needs to be calculated grounded on the validity and reliability. Validity measures the extent to which a variable in a model differs from other variables in the same model (Jnr, 2021). Reliability measure the extent to which the variables give same results that are consistent and error free. The validity is measured based on different validity measures such as convergent validity which assesses whether items can proficiently reflect their corresponding variable (Shanks *et al*., 2018). Convergent validity involves the assessment of construct validity and reliability, where the reliability of the model factors was assessed by considering the internal consistency reliability, and validity which were measured grounded on the Average Variance Extracted (AVE) value. Which is defined based on the totality of variance a variable capture from its indicators (Bokolo and Petersen, 2019).

The AVE value ought to be higher than or equivalent to 0.5 as suggested by Hair *et al*. (2021). Similarly, for the internal consistency reliability the Construct Reliability (CR) ought to be greater than 0.70 and the Cronbach's alpha value should be larger than or equivalent to 0.70 (Cronbach, 1951). The factor loadings of the questionnaire indicators are also measured, which offer a medium to assess the convergent validity of questionnaire indicators ought to be greater than 0.50 as advised by Hair *et al.* (2011).

Table 3 Analysis of measurement model

Factors	**Indicators**	**Factor Loadings**	**Cronbach's Alpha (α)**	**CR**	**AVE**	**Standard Mean**	**SD**
System Quality	SystemQuality1	0.749	0.882	0.920	0.745	3.85	0.658
	SystemQuality2	0.906					
	SystemQuality3	0.969					
	SystemQuality4	0.851					
Information Quality	InformationQuality1	0.855	0.902	0.922	0.748	3.92	0.521
	InformationQuality2	0.748					
	InformationQuality3	0.866					
	InformationQuality4	0.790					
Service Quality	ServiceQuality1	0.693	0.751	0.845	0.586	3.21	0.691
	ServiceQuality2	0.898					
	ServiceQuality3	0.949					
	ServiceQuality4	0.883					
Intention to Use EA	IntentionToUseEA1	0.933	0.723	0.840	0.601	3.15	0.681
	IntentionToUseEA2	0.948					
	IntentionToUseEA3	0.984					
	IntentionToUseEA4	0.754					
User Satisfaction of EA	UserSatisfaction1	0.692	0.598	0.775	0.541	3.67	0.609
	UserSatisfaction2	0.761					
	UserSatisfaction3	0.881					
Actual Benefit of EA	ActualBenefitOfEA1	0.885	0.899	0.922	0.667	3.67	0.660
	ActualBenefitOfEA2	0.897					
	ActualBenefitOfEA3	0.676					
	ActualBenefitOfEA4	0.953					
	ActualBenefitOfEA5	0.911					
	ActualBenefitOfEA6	0.845					

The survey results reveal that factor loading are greater than 0.5 for all items. Table 3 shows that the model constructs' reliability values greater than or approximately equal to 0.7 and AVE is higher than 0.5 are above the recommended values for all factors. Table 3 also suggest the standard deviations (SD) and mean value of the factors, where the mean value is greater than 2.5 as suggested by Jnr (2020) when employing a 5-point measurement. Additionally, the SD score are near to 0 and lesser than 1, hence the responses from the participants are not widely distributed.

5.2.1. Discriminant Validity

Discriminant validity assess if two variables numerically differs one another. Thus, Fornell and Larcker (1981) recommended the use of AVE to test for discriminant validity. According to the Fornell-Larcker-criterion, discriminant validity is confirmed if the square root of a latent construct's AVE (see Table 3), is higher than correlations of this latent construct with any other constructs in the model. This holds true for all factors measured in the model (Weiss *et al.,* 2013). Also, Hair *et al.* (2011) recommended that the value should be higher than 0.5 explaining that the variable establishes a minutest of 50% of the assessed variance (Jnr, 2021). Results presented in Table 4 suggest that the factor meets up to the required benchmark of 0.5 (Henseler *et al.*, 2015).

Table 4 Inter-determinants correlation

	Actual Benefits of EA	Information Quality	Intention to Use EA	Service Quality	System Quality	User Satisfaction
Actual Benefits of EA	**0.817**					
Information Quality	0.686	**0.865**				
Intention to Use EA	0.266	0.230	**0.775**			
Service Quality	0.367	0.422	**0.853**	**0.765**		
System Quality	0.268	0.245	-0.196	0.030	**0.863**	
User Satisfaction	0.569	0.538	0.321	0.481	0.439	**0.735**

5.3.Structural Model Analysis (Hypotheses Testing)

This sub-section validates the model fitness, relationships between constructs and hypotheses testing. Thus, the testing of the structural model is deployed to test the hypotheses in the developed research model presented in Figure 1.

Table 5 Test of research model

Hypotheses	**Hypothesis Path**	**Path Coefficient *Beta (β)***	R^2	***t-value***	**Significance Level (*p*-value)**	**Decision**
H1	System Quality --> Intention to Use EA	0.268	0.720	3.602	0.004	Supported
H2	System Quality --> User Satisfaction of EA	0.243	0.590	2.617	0.022	Supported
H3	Information Quality--> Intention to Use EA	0.220	0.400	2.230	0.048	Supported
H4	Information Quality--> User Satisfaction of EA	0.263	0.069	1.832	0.094	Unsupported
H5	Service Quality--> Intention to Use EA	0.866	0.749	5.724	0.000	Supported
H6	Service Quality--> User Satisfaction of EA	0.363	0.132	3.253	0.008	Supported
H7	Intention to Use EA --> Actual Benefits of EA	0.124	0.150	3.524	0.005	Supported
H8	Satisfaction of EA --> Actual Benefits of EA	0.346	0.120	2.013	0.049	Supported
Conclusion: Hypothesis is valid if *t-value* = > 1.96 and *p-value* = <0.05						

Results from Figure 2 and Table 5 depict the testing of the model hypotheses as illustrated in Figure 1. H1 states that the system quality of EA will positively influence IT practitioners and stakeholder's intention to use EA for digitalization of cities. Results from Table 5 show that H1 path coefficient β = 0.268 (t=3.602, p=0.004), therefore supporting H1 since *t-value* is greater than 1.96 yardstick and path coefficient is more than 0 (Jnr, 2021). Similarly, H2 states that system quality of EA will positively influence the satisfaction of employing EA for digitalization of cities. Results from Table 5 further show that H2 path coefficient β = 0.243 (t=2.617, p=0.022), therefore supporting H2. Next, H3 states that information quality of EA will positively influence IT practitioners and stakeholder's intention to use EA for digitalization of cities. Therefore, results from Table 5 reveal that the hypothesis is positive where path coefficient β = 0.220 (t=2.230, p=0.048).

Conversely, results indicate that information quality of enterprise architecture does not positively influence the satisfaction of employing EA for digitalization of cities (H4) with path coefficient β = 0.263 (t=1.832, p=0.094). Similarly, the results confirm H5 which suggest that the service quality of enterprise architecture will positively influence IT practitioners and stakeholder's intention to use EA for digitalization of cities with path coefficient β = 0.866 (t=5.724, p=0.000). Furthermore, results reveal that H6 which posit that service quality of enterprise architecture will positively influence the satisfaction of employing EA for digitalization of cities is statistically significant with path coefficient β = 0.363 (t=3.253, p=0.008). Results from Table 5 further confirms H7 that IT practitioners and stakeholders' intention to use EA will positively influence actual benefit of EA with a path coefficient β = 0.124 (t=3.524, p=0.005). Next, the results support H8, IT practitioners and stakeholders' satisfaction of EA will positively influence actual benefit of EA with path coefficient β = 0.346 (t=2.013, p=0.049).

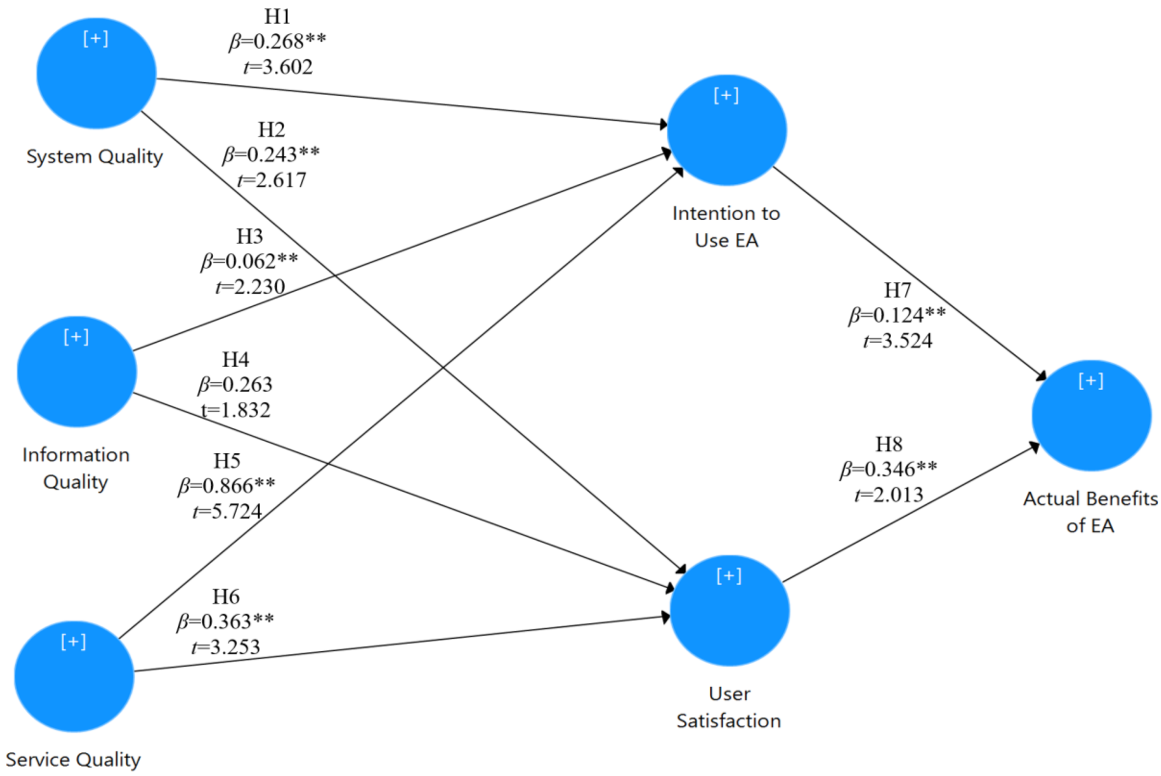

Figure 2 Results of the research model. Note: **$p < 0.05$

Interestingly, the results suggest that (H5) "service quality of EA impact on IT practitioners and stakeholder's intention to use EA for digitalization of cities" is the most significant relation with *t-value* = 5.724 suggesting that the easiness of EA is the most important factor that influences IT practitioners and urban stakeholder's to accept and use EA for digitalization of cities into smart cities as suggested by the DeLone & McLean IS success model. In addition, the evidence from prior study (Baragash and Al-Samarraie, 2018) suggested that R^2 score of 0.67, 0.33, and 0.19 were regarded as outstanding, normal, and small, individually. Likewise, Bokolo Jr *et al.* (2020); Jnr *et al.* (2020b) advised that the R^2 score should be more than 0.10 to be valid.

5.3.1. Test of Effect and Common Method Variance

Table 5 show the effect size measured based on the R^2 score. Where H1= 0.720 interpreting an effect size of 72% and H2= 0.590 interpreting an effect size of 59%. Also, H3= 0.400 interpreting an effect size of 40%, and H4= 0.069 interpreting an effect size of 6.9%. Likewise, H5= 0.749 interpreting an effect size of 74.9%, and H6= 0.132 interpreting an effect size of 13.2%. Lastly, H7= 0.150 interpreting an effect size of 15%, and H8= 0.120 interpreting an effect size of 12%. The results indicate that all R^2 values are much greater than 0.1 as endorsed by Anthony *et al.* (2019) and ranges from 0.749 (74.9%) for H5 and 0.120 (12%) for H8 indicating that an excellent to low R^2 values (Jnr, 2020). The results empirically confirm that H5 has the strongest effect size. Thus, service quality of EA impact IT practitioners and stakeholder's intention to use EA for digitalization of cities and H8 has the least positive effect indicating that IT practitioners and stakeholders' satisfaction of EA slightly influence actual benefit of EA in digitalization of cities services provided to citizens.

Given that data were collected from a single source, common method variance could influence the results. Therefore, Table 6 depicts the results of common method variance analyzed in SPSS using factor analysis to demonstrate the extent to which this might affect the results.

Table 6 Test of total variance explained

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.398	39.960	39.960	2.398	39.960	39.960
2	1.747	29.119	69.079			
3	0.900	14.996	84.074			
4	0.555	9.254	93.329			
5	0.331	5.512	98.841			
6	0.070	1.159	100.000			
Extraction Method: Principal Component Analysis.						

The components column in Table 6 comprises of all the six factors (actual benefits of EA, information quality, intention to use EA, service quality, system quality, and user satisfaction). Results from Table 6 indicates that the percentage of variance which is the total variance explained is given as 39.960 (39.96%) which is lower than is less than 60%, thus this study conclude that there is no common method bias and the data collected is valid (Tehseen et al., 2017).

5.3.2. Test of Predictive Relevance

Besides, assessing the magnitude of the R^2 values as a criterion of predictive accuracy, researchers may desire to also examine Stone-Geisser's Q^2 value as a criterion of predictive relevance. The predictive relevance is estimated using Blindfolding Test in SmartPLS3 to assess the total effect. The blindfolding is a samples re-use technique. It allows calculating Stone-Geisser's Q^2 value, which represents an evaluation criterion for the cross-validated predictive relevance of the PLS path model. The Q^2 value of variables in the PLS path model is obtained by using the blindfolding procedure (Hair Jr *et al.*, 2021). Similarly, the Stone-Geisser's Q^2 value, which represents an evaluation criterion for the cross-validated predictive relevance of the PLS path model as suggested by Hair *et al*. (2011), thus results from blindfolding (Q^2 value) are presented in Table 7 and Figure 3.

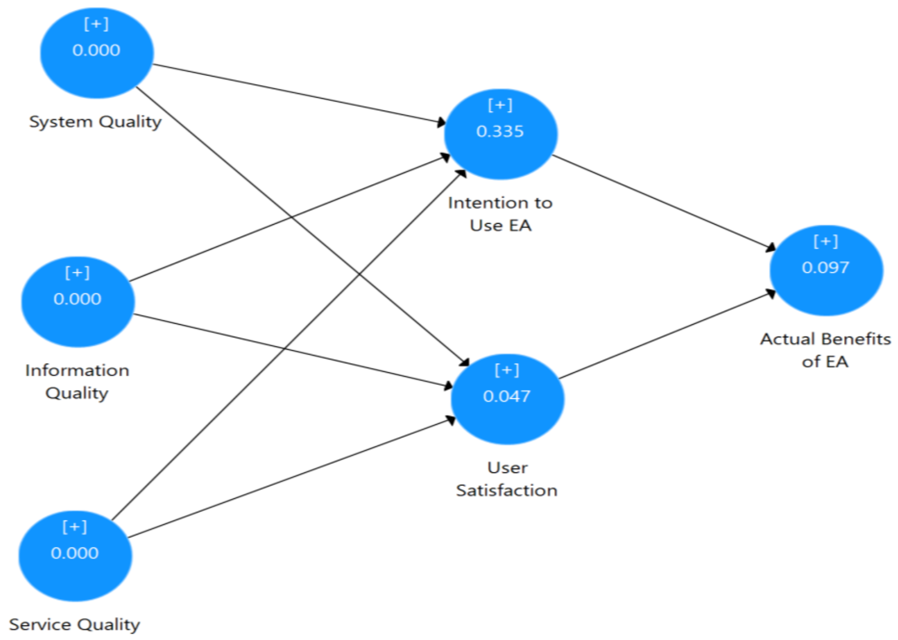

Figure 3 Results of test of predictive relevance

Table 7 Blindfolding procedure for test of predictive relevance

Factors	Sum of Square of the Observation (SSO)	Sum of Square in Predicting Errors (SSE)	Q^2 (=1-SSE/SSO)
Actual benefits of EA	78.000	70.424	0.097
Information quality	52.000	52.000	-
Intention to use EA	52.000	34.573	0.335
Service quality	52.000	52.000	-
System quality	52.000	52.000	-
User satisfaction	39.000	37.177	0.047

Figure 3 and Table 7 depicts the test of predictive relevance, where the Q^2 value in the PLS path model is obtained by using the blindfolding procedure (Hair Jr *et al*., 2021), to check for the path coefficient of IT practitioner's intention to use EA, user satisfaction, and actual benefits of EA based on the R^2 percentage variance. Results from blindfolding (Q^2 value) as seen in Table 7 suggest that intention to use EA has more effect on actual benefits of EA with a value of 0.335 (33.5%).

6. Discussion and Implications

6.1.Discussion

This study builds upon the DeLone & McLean IS success model to develop and empirically test a theoretical model that supports to understand the factors that influence EA acceptance and use for digitalization of cities. This study is original and adds to the body of knowledge because its conceptualizations is grounded on DeLone & McLean IS success model, enterprise architecture, and digitalization of cities which is still not widely explored in the literature. The developed model was successfully validated with structural equation modeling based on partial least squares approach on survey data collected from participants in 18 organisations based in Norway and Ireland. The model validation yields several interesting findings which are discussed in this sub-section. The results from this study show a significant relationship between system quality of EA and IT practitioners and stakeholder's intention to use EA for digitalization of cities. This result is in line with findings from prior studies (Kluge *et al.,* 2006; Lange *et al.,* 2016). One possible explanation is that system quality is based on the IT practitioners' perception regarding the flexibility, ease of use, interactivity, responsiveness, user-friendliness, and stability of EA which determines the useful of EA (Al-Kharusi *et al.,* 2017; Ajer and Olsen, 2018).

In addition, the results indicate that system quality of EA has a positive effect on the satisfaction of employing EA for digitalization of cities. This result is analogous with findings in the literature (Espinosa *et al.,* 2011; Niemi and Pekkola, 2016) which confirmed that the system quality of any information system impacts both perceived usefulness, and attitude towards acceptance and usage of EA. Also, IT practitioners and stakeholder's intention to use EA for digitalization of cities is influenced by information quality which provides quality resources delivered through EA should also be accessible in different format. Thus, our result confirms what Weiss and Winter (2012) concluded in their study suggesting that the adoption of EA in organizations will influence stakeholder's perception towards actually using EA models for digitalization purpose. Likewise, the results suggest that the quality of information provided by EA does not improves the satisfaction derived from employing EA for digitalization of cities. Although this result is not consistent with results from prior studies (Lange *et al.,* 2016; Niemi and Pekkola, 2016), which indicated that information quality influences user's intention to use EA as well as their satisfaction derived from using EA. This interesting observation suggest that the magnitude of information quality provided by EA to users of EA does not impact user satisfaction. One possible explanation is that user's experiences may be negative or positive feelings encountered and this will impact the satisfaction derived. As the quality of information available may not help IT practitioners in improving their perceived ease of use and acceptance of EA. Since EA can be seen as not being easy and simple to some IT practitioners.

Additionally, the results confirm that service quality which requires provision of quality influences the user's intention to use EA to support digitalization process. The result is parallel to findings from Lee *et al.* (2015) where the researchers confirmed that quality of service improves the acceptance of users to use EA in relation to their perceived ease of use and perceived usefulness. Similarly, our results is also analogous with findings from DeLone and McLean (2003) who revealed that the availability of miscellaneous support that assists in a timely manner to address problems originating from the use of IS do influence users intention to use an IS. Another finding indicates that service quality of EA has a positive effect on IT practitioners and stakeholder's satisfaction derived from adopting EA for digitalization of cities. A possible interpretation is that the service quality measures the degree to which users believe that usage of EA provides quality tools, models, and blueprints that enhances digitalization of cities into smarter cities (Anthony *et al.,* 2020).

In this study, intention to use EA determines the weight of actual benefit of EA. This result is consistent with the studies undertaken by Lange *et al.* (2016); Niemi and Pekkola (2016) where the authors highlighted that intention to use embodies the extent and manner in which EA is utilized by stakeholders in the organization. Similarly, our results suggest that IT practitioners and stakeholders' satisfaction of EA is significantly influenced by actual benefit of EA. This result is also analogous with findings from Espinosa *et al.* (2011); Aier (2014) which suggested that practitioners are more likely to continue adopting EA if their level of success with EA and the perceived usefulness of EA are high. Likewise, IT practitioners and stakeholder's intention to accept and use EA to a large extent is influenced by their current use satisfaction (Närman *et al.*, 2012; Jonnagaddala *et al.*, 2020).

6.2.Implications of Study

The findings of this study have some theoretical significance for enterprise architecture theory and practice for managers and policy makers towards digitalization of cities.

6.2.1. Theoretical Implications

Enterprise architecture entails the collection of enterprise modelling documents, typically referred to as artifacts which describes various facets of an institution from an integrated IT and business perspective (Kotusev and Kurnia, 2020). Organizations employing EA involves using these EA artifacts to support planning and digitalization of business and IT alignment in cities. This is one of the first studies to present a theoretically designed and statistical tested model of factors and indicators of EA acceptance and usefulness grounded on the DeLone & McLean IS success model towards the digitalization of cities. This study provides new theoretical insights into EA acceptance and usefulness, thereby contributing to the convergence of EA and digitalization of cities.

The theoretical model presented in this research offers a novel perspective to advance EA adoption in urban context. By considering the factors in the developed model, the current state of a city's readiness can be assessed and thus the envisioned state can be managed to transition from the present state to the desirable state. The findings from this study provide academicians and practitioners with significant insight into factors that facilitate EA acceptance and usefulness for digitalization of cities. In addition, the developed theoretical model can be useful for IT practitioners and enterprise architects interested in developing digital services in smart cities as it provides them with insights on the factors that increases acceptance and usefulness of EA. Overall, the results from this study suggest that the beliefs and practices of EA framework among researchers and practitioners is mostly influenced by the service quality and system quality of EA has a positive effect on the satisfaction of employing EA for digitalization of cities. Whereas the quality of information provided by EA does not influence if EA will be adopted towards the digitalization of cities.

By understanding these factors from the beginning of a smart city project, IT practitioners and stakeholders can strategize and concentrate on how to achieve the desired smart cities goals. Besides, findings from this study can inform enterprises operating or providing services in smart cities about how EA can be employed to improve and provide value added services to citizens. The findings of this study yield actionable suggestions for improving successful EA acceptance in institutions. The developed questionnaire measurement instrument presented in Appendix Table A1 offers a starting point for IT consultants and stakeholders to assess the extent to which EA deployment is effective in their cities. This provides a clear view of the present state of digitalization of city services in general and also allows for evaluation of the insights of EA benefits specifically in smart cities.

6.2.2. Practical and Managerial Implications

This study provides some recommendations to understand the role and value of EA in cities for digitalization. Survey data was utilized to verify the developed theoretical model. Practically, this research provides a better understanding of the role of EA in guiding the digitalization of cities. The results are practically relevant in exploring the potential value of EA, and how cities can maximize the prospect of deriving these potential benefits from EA adoptions. This research offers foundation for additional research on EA adoption in smart cities by providing understanding of the factors and key metrics for success usefulness of EA for digitalization of cities into smart cities. Findings from this research focuses on the ways in which EA enables IT driven change and business driven opportunities in cities to support digital transformation and development of cities.

Evidence from this study can be used as a foundation for future academic studies to further validate the developed model in other public sector context and to generalize the factors and test their applicability. The developed model is expected to support IT practitioners because it provides a comprehensive understanding on the potential of EA to minimize the chances of possible misalignment challenges among different stakeholders involved during smart city development. As a managerial implication, the developed model can be deployed as an instrument to envisage the likely sources of modernization towards the usage of EA in digitalization of cities. The model can be employed to track benefits of digitization of cities over time. This study has key findings which has implications for both IT practitioners and researchers by providing insight as to how EA adds value to smart cities. The findings suggest that EA adds value directly by means of its influence on both IT and business alignment thereby improving interoperability of business and enterprise systems deployed in urban environment.

The results suggest that IT practitioners and stakeholders are often hesitant to accept and do not see the usefulness of EA due to factors such as the system quality, information quality, and service quality as regards to EA initiative in their enterprise. This is because EA can be time consuming and costly, and they are mostly unsure of the value EA would add to their organization compared to deployment cost. By identifying the usefulness EA adds, it is hoped that empirical evidence from this study will motivate enterprises that provides digital services in cities to adopt EA and invest their tangible and intangible resources to advance the adoption of EA to foster digitalization operation in urban context.

7. Conclusion

Digitalization is an important topic for both practitioners and researchers as it is seen as a tool towards modernization of public sector (Ajer and Olsen, 2018). Hence, digitization is a determinant for the development of innovative services in sectors such as in cities which are deploying digital technologies to become smart cities. Presently, information systems approach such as enterprise architecture is now being employed to facilitate the digitalization of cities.

The adoption of the enterprise architecture is often intended to bridge the gap between business and IT by aligning their respective goals within an institution. In smart cities, EA is a process and method used to manage the complex ICT landscape in enterprises as it is perceived as an enabler for developing isolated silos into integrated seamless systems across cities. Thus, EA is seen as an important requirement for successful digitalization of cities. However, EA acceptance and usage remains a central concern of urban research and practice.

Similarly, there are few studies that explored EA adoption from the context of enterprises that provide digital services in city context grounded on empirical evidence. Therefore, this study assesses the acceptance and usefulness of EA in smart cities by developing an EA adoption model based on the well-established DeLone and McLean IS success model as theoretical foundation to develop a model to examine the factors that influence EA acceptance and use for digitalization of cities. Based on the identified factors survey questionnaire was designed and sent out to IT professionals, senior managers, and consultants in 20 organisations based in Norway and Ireland. Structural equation modelling based on partial equation modelling and SPSS was applied to evaluate the data. Overall, findings from this study presents theoretical models that can be used to explain factors that influence EA acceptance and use for digitalization of cities. The findings can provide recommendations to EA designers about the challenges related to EA adoption as related to digitalization of cities.

7.1.Limitations and Future works

As with any study this current research has a few limitations. First the results cannot be generalized beyond the urban context in Norway and Ireland, although literature on studies that adopt EA in several sectors were used in this study. The context of this EA research is aligned to digitalization in making cities smarter. Likewise, this study utilized data from only 18 organization which resulted in a limited sample size with lower statistical power in this study which may have impacted the reduced significance values. The current study employs a cross section design with the focus on behavioral intentional and actual usage suggesting a causal study which is one of the limitataion of the study.

To address the issue of causality we plan to collect data on actual usage from the respondents in the follower cities (Estonia, Czech Republic, Spain, Romania, and Bulgaria) within the +CityxChange smart city project to compare the previous data from light house cities (Norway and Ireland) on the intention with usage. Therefore, there is need for further studies with results of similar studies in other countries. To get more insight to further validate the model there is need to collect data on a larger scale, the sample needs to be broadened and increased further to other countries. Furthermore, qualitative data can be collected to gain additional insights. Despite these limitations, this research makes several contributions to the literature in the areas of enterprise architecture and digitalization in cities context.

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Appendix

Table A1 Questionnaire items

Factors	Indicators	Source
System Quality	SystemQuality1- Enterprise architecture is relevant for my work.	(Lange et al., 2016; Al-Kharusi et al., 2017; Ajer and Olsen, 2018)
	SystemQuality2- Enterprise architecture is relevant for smart city projects.	
	SystemQuality3- EA models are useful for my work.	
	SystemQuality4- EA models are useful for smart city projects.	
	InformationQuality1- EA could help with capturing knowledge.	

Information Quality	InformationQuality2- EA could help with sharing knowledge within my organization and / or project partners.	(Espinosa et al., 2011; Weiss and Winter 2012; Niemi and Pekkola, 2016)
	InformationQuality3- EA could help when sharing knowledge across cities.	
	InformationQuality4- EA could help with reusing knowledge.	
Service Quality	ServiceQuality1- EA models are easy to understand for digitalization.	(Kluge et al, 2006; Lange et al., 2016; Al-Kharusi et al., 2017)
	ServiceQuality2- EA models are easy to use for digitalization.	
	ServiceQuality3- EA models are easy to understand towards digitalization.	
	ServiceQuality4- I find it easy to describe a scenario using the EA models.	
Intention to Use EA	IntentionToUseEA1- I will recommend EA models to colleagues in my organization.	(Lee et al., 2015; Lange et al., 2016; Niemi and Pekkola, 2016)
	IntentionToUseEA2- I will use EA models for my work in the future.	
	IntentionToUseEA3- I will use EA use case models for my work in the future.	
	IntentionToUseEA4- I will recommend the use case models to colleagues in my organization.	
User Satisfaction of EA	UserSatisfaction1- The use case models were useful for my work.	(Espinosa et al., 2011; Aier; 2014)
	UserSatisfaction2- The use case models were useful for the smart city projects.	
	UserSatisfaction3- The use case models have helped me clarify details about our use cases.	
Actual Benefit of EA	ActualBenefitOfEA1- EA could support participatory design activities.	(Närman et al., 2012; Jonnagaddala et al. 2020).
	ActualBenefitOfEA2- EA could support collaborative activities.	
	ActualBenefitOfEA3- EA could support reflection on use cases.	
	ActualBenefitOfEA4- EA could support identifying potential value-added services.	
	ActualBenefitOfEA5- EA could support creative activities such as brainstorming.	
	ActualBenefitOfEA6- EA could support shared understanding to support decision making.	

Figure 1A Results of IBM SPSS SamplePower test

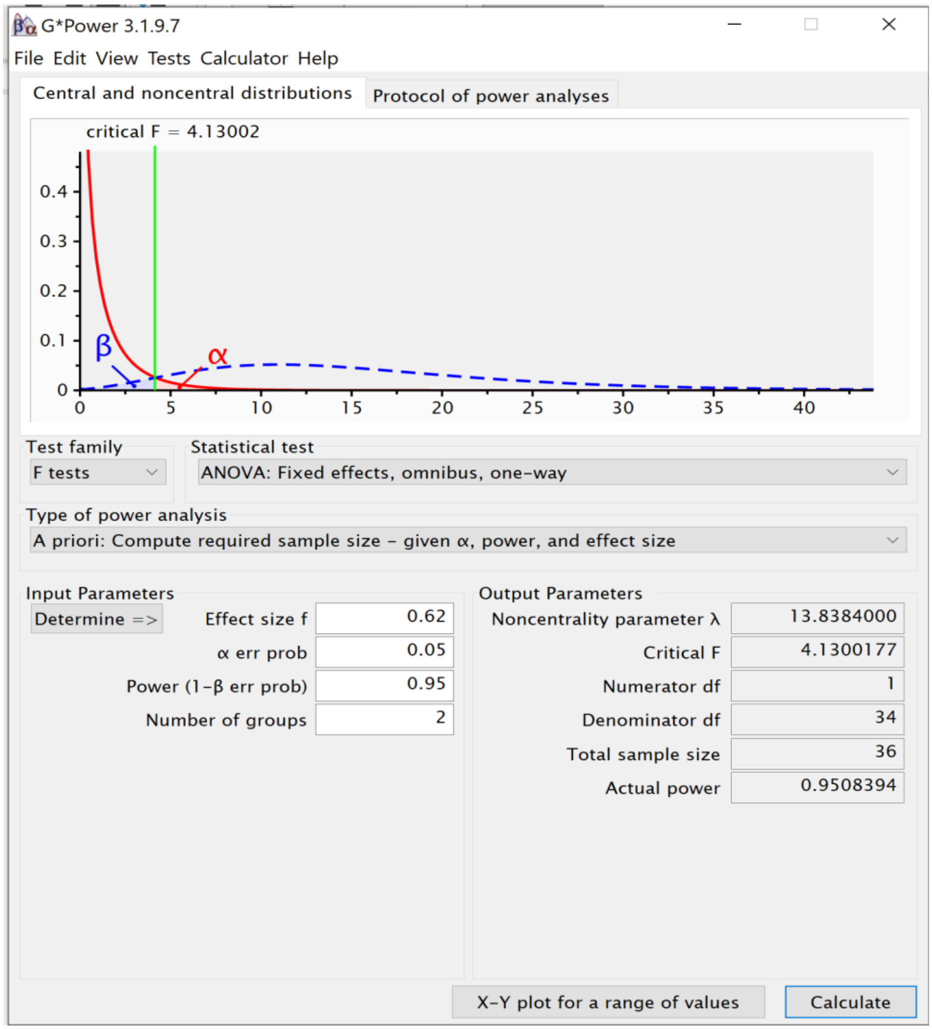

Figure 1B Results of GPower test