Master of Science

Quantification Model of Smart City Development Dynamics Using Structural Equation Modeling

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Abstract

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In recent years, smart city projects have drawn significant attention as initiatives for enhancing urban development and regeneration. Many studies have incorporated technical and non-technical enablers to better control the design, planning, and progress management of smart cities. However, despite considerable efforts and achievements, the direct and indirect effects of smart city enablers on urban performances have not been quantified comprehensively. Thus, due to this lack of in-depth quantification and understanding, urban leaders encounter difficulties in establishing proper strategies and policies for the successful development of smart cities. To address this issue, the present study has used Structural Equation Modeling (SEM) to identify the critical enablers of smart cities and to quantify their dynamic effects (i.e., direct and indirect effects) on the performances of such cities. More specifically, the authors applied SEM to test and estimate the relationships between four enabler clusters (i.e., technological infrastructure, open governance, intelligent community, and innovative economy) and four performance objectives (i.e., efficiency, sustainability, livability, and competitiveness) using the actual data of 50 smart cities. The statistical results demonstrated that non-technical enabler clusters (i.e., open governance, intelligent community, and innovative economy), as well as the technical drivers (i.e., technological infrastructure), have significant impacts on the performances of smart cities with their highly interrelated, synergetic dynamics. The high percentage of variance explained for performance objectives, which varied from about 71% to 91%, was indicative of good explanatory power. Based on those mathematical findings, urban leaders can enhance strategic planning for smart city transitions through proper policy management.

Keywords: Smart City, Project Management, Urban Development, Urban Regeneration, Development Enablers, Performance Objectives, Structural Equation Modeling

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Chapter 1. Introduction

1.1 Research Background

In recent years, smart city projects have received considerable attention from urban leaders (Figure 1.1). Researchers have also paid high attention to smart city developments (Figure 1.2). This is because, with mass urbanization as the new normal, cities worldwide are under constant pressure to provide better quality services, revitalize economic opportunities, address social and environmental issues while reducing operational costs (Ahvenniemi et al., 2017; Silva et al., 2018). Metropolitan infrastructures and utilities are implacably being stretched to their breaking point (Maccani et al., 2013). As reported by the United Nations (2016), 67% of the world's population will be living in urban areas by 2050, against 50% back in 2008. These projections are increasingly urging urban authorities to engage in smart city projects.

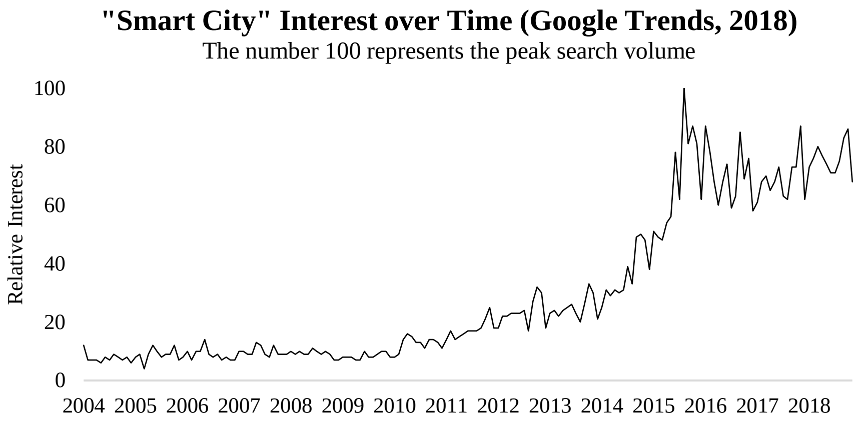


Figure 1.1 Growing Interest in Smart City

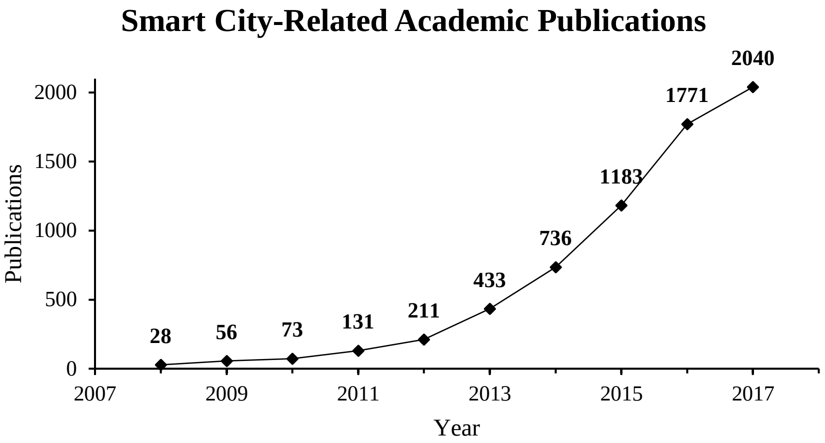


Figure 1.2 Academic Attention Devoted to Smart Cities

(Adapted from Li, Wang, Luo, & Li, 2018)

Even though the idea of smart cities was introduced in the early 1990s, there is still no universal agreement concerning how to define them (Albino et al., 2015; United Nations, 2016; Lin et al., 2019). From the beginning, urban thinkers agreed to characterize them as innovative platforms that improve urban performances, such as quality of life, the efficiency of urban functions, and economic competitiveness (Caragliu et al., 2011; Silva et al., 2018).

However, despite numerous attempts, the definition has yet to be fully accepted. Due to the lack of in-depth acknowledgment of fundamental enablers and the unclarified influence of technology in smart cities (Chourabi et al., 2012; Hollands, 2008; Nam & Pardo, 2011a), there are numerous interpretations of smart cities and the debate remains particularly fragmented (Meijer & Bolívar, 2016). In 2014, the International Telecommunication Union reported that 116 definitions of smart cities were used in practice. For this reason, the difficulty to implement and govern smart city programs has been generally acknowledged in academia (Neirotti, De Marco, Cagliano, Mangano, & Scorrano, 2014a; Ruhlandt, 2018). Thus, the leaders of smart cities encounter difficulties in enhancing urban regeneration in developed countries and urban development in developing countries (United Nations, 2016; Ruhlandt, 2018).

1.2 Problem Statement

To harness the full potential of smart city initiatives through the development of coherent management strategies, it is essential to identify key enablers comprehensively (e.g., urban digitization, economic dynamism, human and social capital, and open governance) and quantify their dynamic effects (i.e., direct and indirect effects) on the performances of smart cities (United Nations, 2016; Maccani et al., 2013; Ruhlandt, 2018).

However, since smart cities originated from technological advancements (e.g., smart grids and the Internet of Things can allow optimized energy use), early studies overlooked the importance of non-technical enablers and focused rather on the evaluation and planning of technology implementation (Aurigi, 2006; Batty, 1997; Kitchin, 2014). For this reason, according to Nam and Pardo (2011), 85% of technology-driven public sector projects have not attained their objectives in practice. This indicates that a given smart digital solution (e.g., intelligent surveillance with video analytics) cannot be transplanted simply from one urban area to another without addressing the influences of local factors, such as urban policies and the levels of empowerment of the citizens (Nam & Pardo, 2011b; Neirotti et al., 2014; Stratigea et al., 2015).

Therefore, in order to avoid the failure of smart city initiatives that can be caused by stakeholders' resistance to change, many researchers have recently considered the effects of non-technical enablers that collaborate with technological drivers in their attempts to support the maturation of smart city policy management (Angelidou, 2015; Bibri et al., 2017; Calzada et al., 2015).

For example, in 2014, the British Standards Institution acknowledged the importance of integrating physical, digital, and human systems for successful smart city development.

Despite the extensive efforts to understand the influences of various enablers, the previous methods did not fully quantify the direct and indirect effects of smart city enablers on urban performances. For example, the use of technology in smart cities (e.g., Internet of Things) leads directly to a higher quality of life (Braun et al., 2018; Jain et al., 2017), but it also can improve the living environment indirectly by first enhancing government initiatives (e.g., data generation and management). However, those effects have not been integrated for comprehensive quantification of enablers' effects on smart city performance objectives. Thus, it is still challenging to understand the development dynamics of smart city projects.

Due to this lack of complete understanding, urban leaders face difficulties in establishing proper strategies for the successful development of smart cities.

1.3 Research Objective

The primary objective of this paper is to quantify the dynamic effects (i.e., direct and indirect effects) of smart city enablers on urban performances by applying Structural Equation Modeling (SEM) technique.

The specific objectives to achieve the primary objective are as follows:

1. Identify a range of technology, policy, and society-related enablers that can control the key performances of smart cities.
2. Collect corresponding urban data to create a dataset for model development.
3. Develop an SEM-based quantification model to assess the dynamic effects of smart city enablers on urban performances.
4. Evaluate the model and discuss the results for applications in smart city planning, design, and progress management.

The developed assessment model is expected to provide practical insights (e.g., investment prioritization on smart city projects), which can help urban strategists manage the smart city policy implications in order to enhance their preparedness for the transitions to smart cities. This will allow smart cities to reach their target performance objectives through appropriate development strategies.

1.4 Research Scope

This study was conducted on a sample of 50 smart cities in 37 countries, as depicted in the geographical distribution in Figure 1.3. Those aspiring next-generation cities, which are among the smartest cities in the world (Easy Park, 2017), were selected for incorporating diverse demographic, geographic, and economic characteristics. For instance, according to the International Monetary Fund’s World Economic Outlook Database (October 2018), the scope comprises 12 cities in developing countries (e.g., Medellin in Colombia, Kuala Lumpur in Malaysia, and New Delhi in India) in which complete awareness of the smart city concept has yet to be established. Also, of the 50 cities, 21 are in Europe, 12 are in America, 9 are in Asia, 4 are in the Middle East, 3 are in Oceania, and 1 is in Africa.

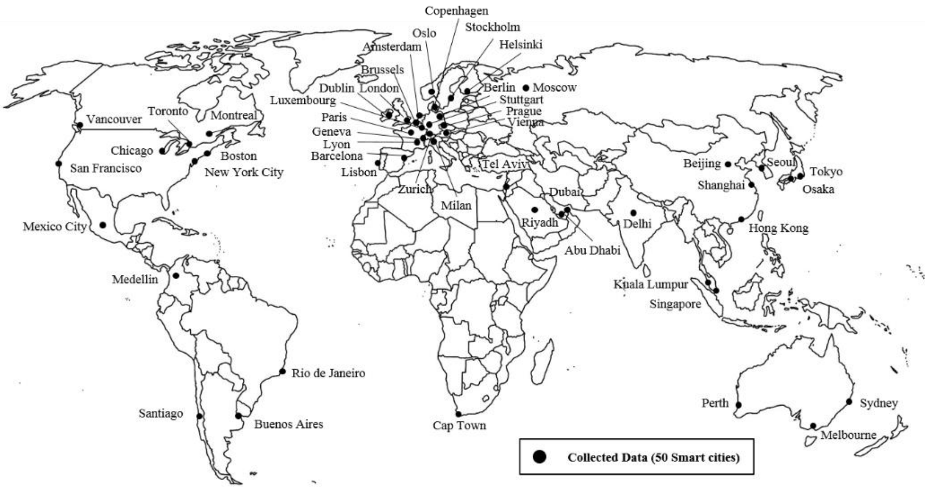


Figure 1.3 Cities Included in the Research Scope

1.5 Research Process

The rest of the paper is structured as follows. Chapter 2 explores and reviews the existing studies that are relevant to both the identification of smart city development enablers and the quantification of their effects on urban performances. Next, the research framework that quantifies enablers' effects on smart city performances using Structural Equation Modeling (SEM) is described in Chapter 3. Then, Chapter 4 analyzes and discusses the experimental results of the SEM analysis, and model applications are presented in Chapter 5. Finally, Chapter 6 concludes the paper with contributions and future studies as well as the limitations of this study.

Chapter 2. Literature Review

2.1 Identification of Smart City Enablers

Smart city projects have unique characteristics with different development conditions and performance objectives. For this reason, the comprehensive identification and quantification of enablers' effects on the performances of smart cities are fundamentally important and essential for their coherent planning and development. Thus, many researchers and practitioners have attempted to identify the principal enablers of smart cities.

In the early stages, the corporate sphere (e.g., Cisco, IBM) only focused on the significance and benefits of new disruptive Information and Communication Technologies (ICTs) to modernize urban infrastructures, as critiqued in Albino et al. (2015), Hollands (2008), and Simonofski et al. (2017).

However, although technology is recognized as a central enabler of smart cities (Zygiaris, 2013), it should not be considered as exclusive (Nam & Pardo, 2011a). In previous studies (Chourabi et al., 2012; Odendaal, 2003), it was even found that the impacts of ICTs on urban development and on the quality of the citizens' lives are unclear and questionable. It was also reported that, without careful preparation of urban contexts (e.g., democratic and inclusive governance), ICTs could increase information inequalities and amplify the digital divide. In practice, corporate-designed smart cities, such as Songdo in South Korea and Masdar City in the United Arab Emirates, have missed their growth objectives despite undeniable technological advances (e.g., telematics, sensor networks, RFID systems, smart card applications and so on in Songdo) because they failed to consider the wider effects of culture, governance, and civic engagement (Albino et al., 2015; Calzada & Cobo, 2015).

Based on those findings, researchers collectively acknowledged the importance of incorporating smart city enablers comprehensively including technical and non-technical drivers when planning and developing strategies for smart cities (Maccani et al., 2013; Nam & Pardo, 2011a; Simonofski et al., 2017). The important roles of citizens as end-users (Braun et al., 2018; Oliveira & Campolargo, 2015; Simonofski et al., 2017) and the influences of urban management, policy, and innovation (Azevedo Guedes et al., 2018; Nam & Pardo, 2011b) especially were highlighted.

2.2 Quantification of Enablers' Direct Effects

Recent studies have also paid greater attention to extracting quantifiable information from current trends in the development of smart cities. Researchers have made special efforts to quantify enablers' effects on the performances of smart cities in order to support the maturation of policy management for such cities.

Recent studies have independently quantified the direct effects of technical and non-technical enablers on urban performances. For example, Tahir et al. (2016) used the Analytical Hierarchy Process (AHP) to quantify the relative importance of six dimensions that influences the performances of smart cities. A hierarchy between smart environmental practices, mobility, living, people, economy, and governance was found to incorporate the technologies that are required for making a smart city a reality (Tahir & Abdul Malek, 2016). Another approach, proposed by Caragliu et al. (2011), used statistical and graphical analyses to understand the direct influences of numerous factors (e.g., demographic and social variables) on the economic performance of smart cities in Europe. This study acknowledged the effects of non-technical enablers, such as creativity and the levels of education of the citizens. Neirotti et al. (2014) applied linear regression analysis to identify how contextual variables, such as geographical, urban, demographical, social, environmental, and technology-related proxies, directly affect the deployment of smart city solutions. The results indicated that technology development alone is insufficient to build a successful smart city.

Recently, in line with the “100 Smart Cities Mission” launched by the Indian government (Arora, 2018), Kumar et al. (2019) quantified the relative importance of smart city development factors for use in planning an effective smart city. They used Total Interpretative Structural Modeling (TISM) to classify the selected factors (e.g., capital resources, socio-economic potential, multimodal accessibility, and public participation) based on their hierarchical interrelationships, and they used the findings for further analysis of smart city eligibility. Yadav et al. (2019) used hybrid Best Worst Method (BWM) – Interpretative Structural Modeling (ISM) to identify the intensity of influences of smart city enablers and justify their interrelationships. The results revealed that sustainable resources management, development of smart buildings, advanced research, and intelligent transportation are the key enablers of the developed framework. The successful execution of the developed framework can assist smart city practitioners in developing countries (e.g., India and China).

2.3 Limitations of Quantification Strategies

The existing studies have shown promising results in the quantification of the effects of smart city enablers for practical applications in policy management. However, despite remarkable findings, significant research questions must be addressed in order to comprehensively quantify the development dynamics within smart cities.

One major issue is that researchers have mainly considered the effects of the individual relationships (i.e., direct relationships) of development enablers on the overall performance of smart cities without taking into account the complex dependencies (i.e., indirect effects) that result from the internal relations between the enabler clusters and between the performance objectives. For instance, government initiatives are often implemented to improve the living environment (i.e., direct effect). In smart cities, those initiatives can be enhanced by ICT (e.g., social media communities can allow more participative forms of governance and greater democracy) (Chourabi et al., 2012; Kitchin, 2014). Therefore, technology indirectly influences the quality of life of citizens through open governance as the mediator (i.e., indirect effect). However, those dynamic effects (i.e., direct and indirect effects) have not been integrated for comprehensive quantification. This issue limits the practicality and applicability of the previous findings to the actual smart city policy management since the aforementioned indirect effects are vital for understanding the dynamics of smart city growth.

Those limitations have led previous studies to make only partial advancements in the formulation of a new policy agenda to better control the design and planning of smart cities. To fill this knowledge gap, this paper proposes an assessment model that incorporates the direct and indirect effects of the enablers of the development of smart cities.

Chapter 3. Quantification Model Development

3.1 Research Overview

Figure 3.1 shows the research framework that was built to mathematically investigate how enablers, directly and indirectly, influence the performances of smart cities. The framework comprises two main processes.

First, the research model was established; the authors conducted an extensive literature review, specified the latent variables (LVs) of interest, and then established possible causal paths among the variables. In this study, the research team strategically distinguished two layers of LVs (i.e., (1) enabler clusters and (2) performance objectives) to further discriminate internal relationships (i.e., within a layer) and external relationships (i.e., between the two layers).

Next, to test the hypothesized research model, the research team collected and processed the actual data of 50 smart cities for use in performing SEM analysis. After model estimation (e.g., estimation of path coefficients) was completed, fit assessments were conducted to identify any potential data-model inconsistencies among the LVs. The validation step, in which the model was modified and updated, was repeated until the data-model fit was good enough to represent the possible dynamics of smart city development (Aibinu & Al-Lawati, 2010).

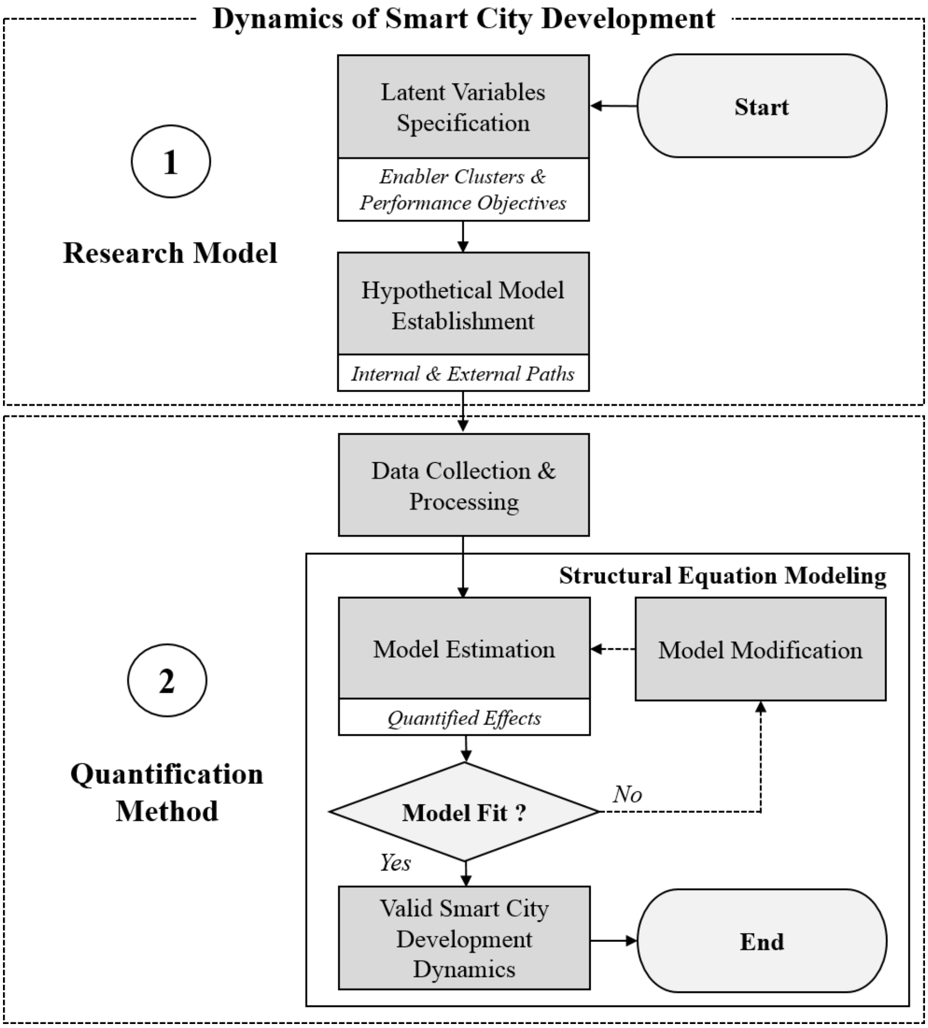


Figure 3.1 Research Overview

3.2 Latent Variables Specification

In this section, the authors conducted a bibliographic analysis to identify two layers of central LVs in smart city development, i.e., enabler clusters and performance objectives. In SEM terminology, LVs are unobserved variables that are inferred from observed variables through correlational models.

3.2.1 Smart City Enabler Clusters

To understand and identify practical enablers of the development of a smart city, the research team conducted an extensive literature review. A commonly applied search engine, Scopus, was used to retrieve 155 scholarly peer-reviewed publications that provided relevant information. The search was limited to subject areas that were highly related to this research, such as engineering, project management, decision sciences, and social sciences. From the exploratory screening of titles and abstracts, the authors retained for further analysis 35 papers that discussed the desirable characteristics of smart cities. To identify smart city enablers, these papers mostly proceeded to comparative literature analysis and combined the findings of numerous prior studies (Gil-Garcia, Pardo, & Nam, 2015). To detect redundancy of content (e.g., repetitive enablers) and reach information saturation, a selective reading was performed over the 35 papers (Azevedo Guedes et al., 2018). As a result, 21 articles that were aligned with the purpose of this research were read thoroughly, and, consequently, 17 potential smart city enablers were extracted. Since dimensionality reduction was required to establish the upcoming structural modeling (Hair et al., 2017), the research team semantically linked 17 identified enablers to four principal latent variables that were developed by previous studies (Chourabi et al., 2012; Maccani et al., 2013; Silva et al., 2018). They were Technological Infrastructure, Open Governance, Intelligent Community, and Innovative Economy.

The four principal constructs could be explained with the identified enablers, as summarized in Table 3.1. First, Technological Infrastructure was decomposed into the following five technical enablers, i.e., *ICT availability, ICT performance, ICT affordability, ICT security*, and *ICT adoption*. A United Nations report (2016) also supported our findings by arguing that urban digitization requires available, efficient, affordable, secure, and accessible Technological Infrastructure. Second, Open Governance, which refers to a governance model that actively engages citizens in government decision-making (United Nations 2016), is built upon *government transparency*, *administration efficiency*, and *stakeholder participation*, as well as contextual strategies and perspectives (e.g., *green* and *digital* interests for smart city transition) (Ruhlandt, 2018; Silva et al., 2018). Third, Intelligent Community can be divided into five enablers, i.e., *eco-consciousness*, *education*, *creativity*, *digital proficiency* (i.e., digital skills and awareness), and *social cohesion* of citizens (Maccani et al., 2013). Fourth, Innovative Economy is characterized by the urban *innovation ecosystem* (e.g., regulatory framework for innovation) and the innovation changes brought in the industry by the *fourth industrial revolution* (e.g., digitization and artificial intelligence). The term innovation refers to the capacity to exploit local creativity and social capital to enhance urban vitality and growth; it is noteworthy that technology itself does not make any contribution to innovation (Chourabi et al., 2012).

Table 3.1 Smart City Development Enablers in Literature

Enabler Cluster	**No.**	**Smart City Enabler**	Nam	Fistola	Zygiaris	Neirotti	Maccani	Albino	Gil-Garcia	Oliveira	Simonofski	Silva
			2011	2013	2013	2014	2014	2015	2015	2015	2017	2018
Technological Infrastructure	1	ICT Availability	●	●	●	●	●	●	●	●	●	●
	2	ICT Performance	●		●		●	●	●			●
	3	ICT Affordability		●	●							
	4	ICT Security			●	●	●				●	
	5	ICT Adoption	●	●	●	●	●	●	●	●	●	●
Open Governance	6	Gov. Transparency	●	●	●	●		●		●	●	●
	7	Admin. Efficiency	●	●		●	●	●	●	●	●	●
	8	Env. Interest			●	●			●			
	9	Public Participation	●		●		●	●	●	●	●	●
	10	Digital Interest	●	●	●	●	●	●	●		●	●
Intelligent Community	11	Eco Consciousness		●	●					●		
	12	Education	●		●	●	●	●	●		●	●
	13	Creativity	●		●	●	●	●	●	●	●	
	14	Digital Proficiency	●	●	●	●	●	●			●	●
	15	Social Cohesion	●	●	●	●	●	●	●	●		●
Innovative Economy	16	Innov. Ecosystem		●				●		●	●	●
	17	4^{th} Industrial Rev.	●	●	●	●	●	●	●	●	●	●

3.2.2 Smart City Performance Objectives

According to the European Investment Bank (2008), urban analysts faced difficulties in evaluating smart cities holistically because it is challenging to convert the benefits of a smart city into direct revenue streams. To ease the conceptualization and performance quantification, smart city performance can be decomposed into more quantifiable performance objectives. For instance, as remarked by Chourabi et al. (2012), it is intuitive to characterize a smart city as an icon of sustainability and livability.

However, such reflection is not exhaustive. To identify the key performance objectives of a smart city extensively, the research team conducted a bibliometric analysis over 116 operational definitions of 'smart city' extracted from academic and practical studies, consistent with the procedure above (i.e., using Scopus). Thereby, the authors were able to review and integrate the various perspectives of different stakeholders.

As summarized in Table 3.2, it was observed that researchers mainly emphasized the need for Environmental Sustainability, Economic Competitiveness, Urban Livability, and Urban Efficiency in their conceptualization of the performance of a smart city. First, Environmental Sustainability is attained through wiser management of natural resources (e.g., low-carbon economy) (Antrobus, 2011). Second, Economic Competitiveness designates the urban capacity to thrive (e.g., job creation, increased productivity, and economic growth) (Lombardi, Giordano, Farouh, & Yousef, 2012). Third, Urban Livability characterizes the quality of life (e.g., affordable education, healthcare, and housing) and the well-being of citizens in metropolitan areas (Lin et al., 2019). Fourth, Urban Efficiency comprises the performance of regular city operations (e.g., traffic flow and traffic safety) (Silva et al., 2018).

Through this analysis, the research team was able to identify the performance objectives that primarily are targeted by urban leaders in smart cities.

Table 3.2 Smart City Performance Objectives in Literature

No.	**Performance Objective**	Toppeta (2010)	Caragliu (2011)	Nam (2011a)	Chourabi (2012)	Zygiaris (2013)	Neirotti (2014)	Stratigea (2015)	Meijer (2016)	Jain et al. (2017)	Arora (2018)	Braun (2018)	Ruhlandt (2018)	Silva (2018)	Lin (2019)
1	Sustainability	●	●	●	●	●		●	●		●		●	●	●
2	Competitiveness		●			●		●	●		●		●	●	●
3	Livability	●	●	●	●		●	●	●	●	●	●	●	●	●
4	Efficiency		●	●	●					●		●		●	●

3.3 Hypothetical Model Establishment

In order to integrate both the direct (i.e., unmediated) and indirect (i.e., mediated) effects of enabler clusters on performance objectives, it is essential to identify the causal relationships between the eight aforementioned LVs (i.e., four enabler clusters and four performance objectives). Thus, in this study, 28 direct relationships labeled from H1 to H28, were hypothesized; the path diagram in Figure 3.2 graphically displays such a priori influences with straight arrows. Specifically, the research hypotheses include three types of relationships as follows: (1) 16 external effects directed from enabler clusters to smart city performance objectives, (2) 8 internal effects among smart city enabler clusters, and (3) 8 internal influences among performance objectives.

By definition, it is believed that enablers have a positive influence on the attainment of smart city performance objectives. Therefore, it was legitimate to establish 16 external causal relationships (i.e., H1 to H16 in Figure 3.2) oriented from the four enabler clusters towards the four performance objectives.

Then, a comprehensive literature review was conducted to capture the directions of the six internal effects between enabler clusters (i.e., H17 to H22) selectively. For instance, Paskaleva (2009) posited that the use of technology (e.g., open data, e-governance) creates a progressive, transparent, and participatory government-public partnership (H17). The use of technology (e.g., e-learning) also empowers citizens by establishing an environment that improves cognitive skills and abilities to learn (H18) and to innovate (H19) (Komninos, 2006). Then, the policy context that is derived from open governance creates conditions that enable innovative urban development (H20) (Ruhlandt, 2018). In addition, a smart city can be characterized as a platform in which the creativity and intelligence of citizens can drive open governance (H21) (Kitchin, 2014), and a city's ability to raise innovation is based mainly on knowledgeable and creative human capital (H22) (Zygiaris, 2013).

It is believed that the six remaining internal effects among smart city performance objectives can be classified as common sense (i.e., H23 to H28). For example, citizens normally expect to live better in a city with efficient functions (e.g., transportation system) (H24), sustainable living environment (H26), and dynamic economy (H28). Smart city programs can also simultaneously pursue conflicting goals; cities around the world encounter difficulties in reconciling the needs of immediate competitiveness with long-term sustainable development (Monfaredzadeh & Berardi, 2015). In this regard, a negative influence can be assumed (H27).

To represent the indirect effects, both internal and external effects must be constructed and integrated into the model. The indirect effect of an enabler cluster A to a performance objective B is equal to the sum of the effects of the pathways that connect A to B by involving at least one mediator variable (i.e., the direct effect is excluded). The effect of each contributing pathway is computed by multiplying the path coefficients along that pathway. For instance, the indirect effect of Technological Infrastructure to Urban Efficiency is calculated by summing effects of the following paths, i.e., H17 - H5, H17 - H20 - H13, H18 - H9, H18 - H22 - H13, H18 - H21 - H5, and H19 - H13 while, the direct effect is simply represented by H1 (Figure 3.2).

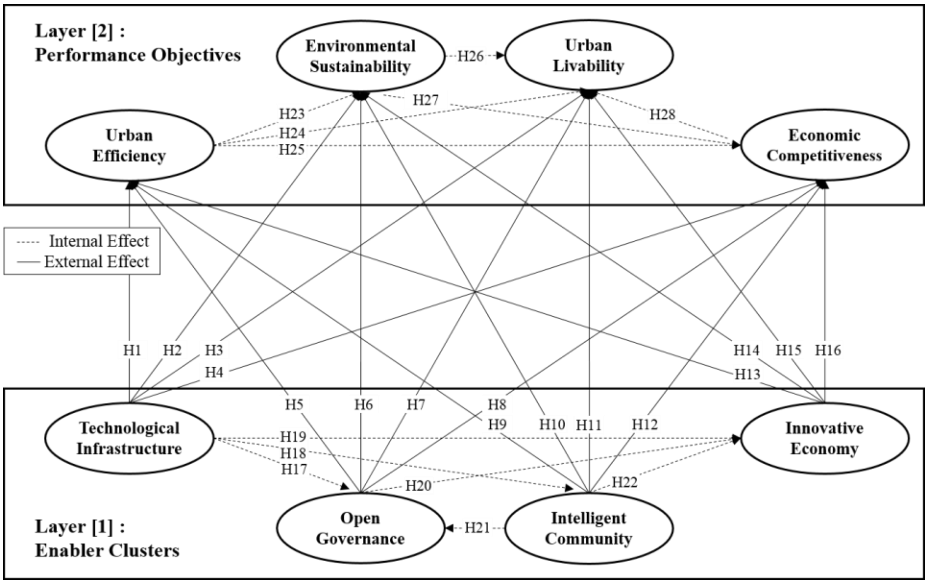


Figure 3.2 Hypothesized Structural Research Model

3.4 Structural Equation Modeling (SEM)

Since the eight LVs shown in Figure 3.2 are LVs rather than observed variables, SEM was used in this study to test the proposed model. In this chapter, the research team reviews the general approach to SEM and then describes the specific SEM strategy implemented in this research, i.e., the Partial Least Squares (PLS-SEM) iterative algorithm.

3.4.1 SEM Process

In recent years, SEM has become increasingly popular in project management and engineering research (Aibinu & Al-Lawati, 2010) as a statistical process used for quantifying relationships hypothesized between various unobserved LVs that can be inferred from measurable variables. Initially developed by sociologists and psychologists, SEM is a powerful statistical method that has been acknowledged particularly for its ability to quantify complex effects among multiple variables and to address measurement errors effectively (Molwus et al., 2017; Qureshi et al., 2015).

By definition, the parameters in SEM are (1) factor weights to measure unobserved variables (LVs) from measurement variables and (2) path coefficients to indicate the direct effect of an LV assumed to be the cause of another LV assumed to be an effect. Those parameters are computed using the collected data through an alternative application of confirmatory factor analysis (CFA) and path analysis respectively, on two sub-models (i.e., the measurement model and the structural model, Figure 3.3), until convergence is achieved.

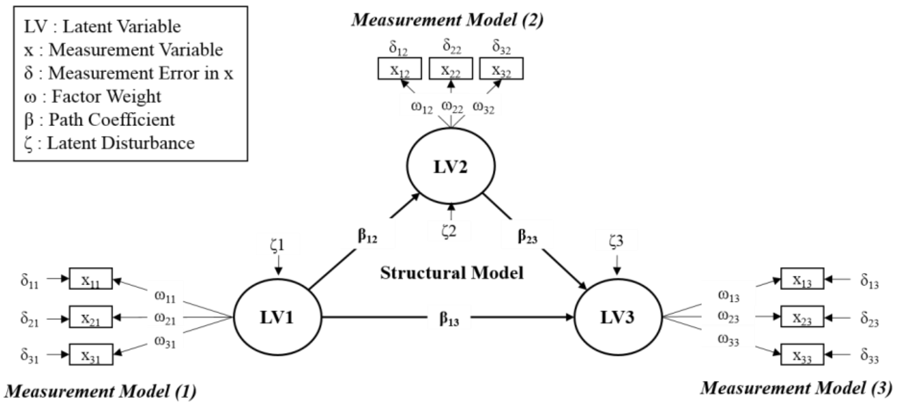


Figure 3.3 Simplistic SEM Process

The measurement model (also referred to as the outer model) computes the scores of LVs by linear combinations between computed weights, ω, and standardized data of reflective measurement variables. In this framework, the scores of the eight LVs is iteratively estimated for each city. For example, the score of Technological Infrastructure (TI) was initially estimated based on the weights of 11 sub-enablers from TI1 to TI11 (Table 4.1). And, the structural (or inner) model quantifies the strengths of relationships (i.e., path coefficients β) among the LV scores through path analysis.

It is noteworthy that SEM does not provide unquestionable proof of influences among LVs; rather, it mathematically supports or disconfirms the propensity of such influences. Hypothesized relationships can be rejected as being good approximations of reality, but they cannot be confirmed as being the exclusive representation of the actual underlying processes. One of the strengths of SEM is its disconfirmatory power (Mueller, 1999; Qureshi et al., 2015).

3.4.2 SEM Strategy

In this paper, the SEM technique called Partial Least Squares (PLS-SEM) was chosen for analyzing the hypothesized model using SmartPLS 3.2.8 application software. To be specific, PLS-SEM was selected because it has both confirmatory and exploratory abilities; i.e., it can both confirm a theory-based model and develop a new theory (Hair et al., 2017).

In PLS-SEM (Figure 3.4), the idea is to first construct each LV based on its measurement variables using initialized weights. Then, using the structural model, each LV is reconstructed by means of its predicting LVs. Next, in the measurement model, the best linear combination to express these LV scores through their measurements variables (MVs) is calculated; the coefficients are referred to as outer weights. Finally, each LV is constructed as such weighted sum of its MVs. The loop is repeated until the relative change of all weights from one iteration to the next become smaller than a predefined tolerance (Equation (1)). Then the algorithm stops and the last estimation of LV scores computed is taken to be definitive (Monecke & Leisch, 2012).

$$\left|\frac{\widehat{w}_{kg}^{i}-\widehat{w}_{kg}^{i+1}}{\widehat{w}_{kg}^{i}}\right| < tolerance \qquad (1)$$

where $\widehat{w}_{kg}^{i}$ is the weight of the k^{th} measurement variable of the g^{th} LV at the i^{th} iteration.

Otherwise, it is required to go back to the inner calculation (i.e. structural model). In the experiments, the tolerance was set to 10^{-7} and the maximum number of iterations to 300.

Moreover, PLS-SEM allows the user to apply three structural model weighting schemes: (1) centroid, (2) factor, and (3) path weighting schemes. While the results differ little for the alternative weighting schemes, path weighting was applied in this study. Indeed, this weighting scheme provides the highest R^2 value for endogenous variables.

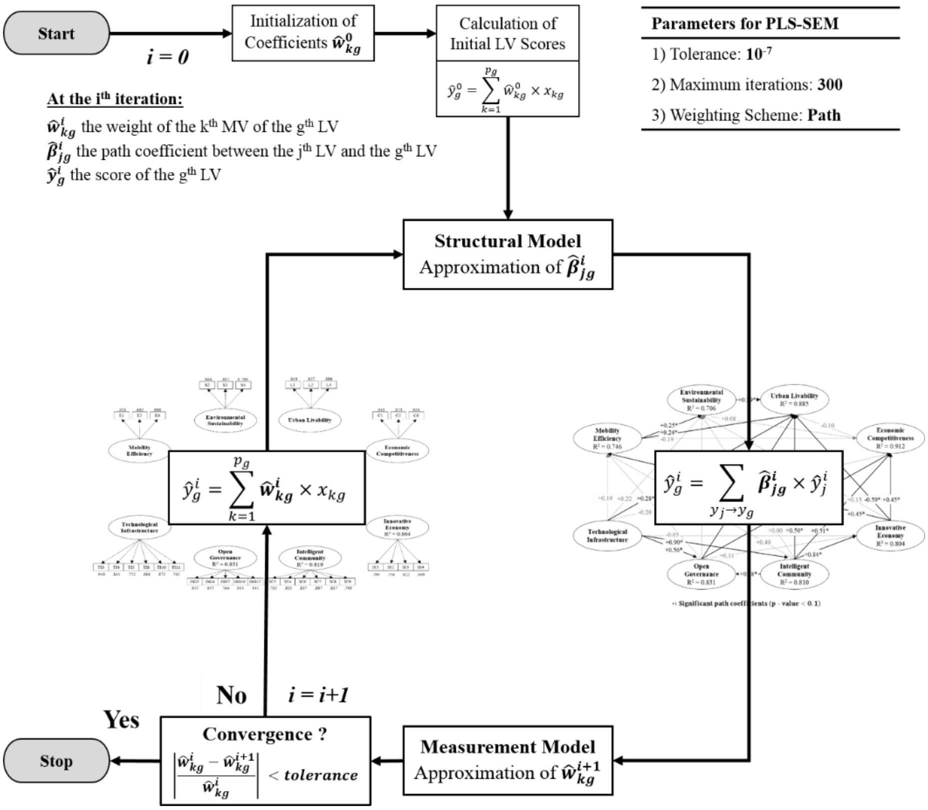


Figure 3.4 PLS-SEM Algorithm

Also, the authors preferred PLS-SEM over covariance-based SEM algorithms due to its high statistical power with relatively small sample sizes (i.e., 100 or fewer observations as reported in Table 3.3) (Hair et al., 2017; Raymond & Bergeron, 2008). Despite its having this ability, the research team conducted oversampling using a bootstrapping technique to ensure the stability of results (Aibinu & Al-Lawati, 2010). Bootstrapping is a statistical method of inference about a population using sample data. This method relies on random sampling with replacement from sample data.

Given the limited number of observations (i.e., 50 cities) considering the large number of variables, 1,000 bias-corrected and accelerated (BCa) bootstrap subsamples were generated to validate the estimated model and to determine the confidence interval of the model's parameters.

Table 3.3 Rules of Thumb for Choosing SEM Method (J. Hair et al., 2017)

No.	Criteria	PLS-SEM	CB-SEM
1	**Philosophy**	Exploratory/Confirmatory	Confirmatory
2	**Objective**	Prediction Oriented	Parameter Oriented
3	**Methodology**	Variance-based	Covariance-based
4	**Sample Size**	Small (30-100 Cases)	High (100-800 Cases)
5	**Model Complexity**	Complex Models (Many LVs=6+ and many Indicators=50+)	Simple Models (5 or fewer LVs and 50 of fewer indicators)
6	**LVs Construction**	Reflective or Formative	Reflective
7	**Data Distribution**	Non-Parametric	Normal Distribution
8	**Preferred Sub-model**	Measurement Model	Structural Model
9	**Validation**	R^2 ; Significance, value, and sign of path coefficients	GFI[1], AGFI[2], RMSEA[3], NNFI[4], NFI[5], CFI[6]
10	**Available Software**	SmartPLS, PLS-Graph, XLSTAT	LISREL, AMOS, SAS, EQS

N.B. [1]GFI: Goodness-of-Fit Index. [2]AGFI: Adjusted Goodness-of-Fit Index. [3]RMSEA: Root Mean Square Error of Approximation. [4]NNFI: Non-Normed Fit Index. [5]NFI: Normed-Fit Index. [6]CFI: Comparative Fit Index.

Chapter 4. Model Testing and Results

4.1 Data Collection and Preparation

4.1.1 Data Collection

The data collection for the 50 smart cities identified in Figure 1.3 was methodically organized through open-data portals (Tenenhaus et al., 2009). The interested reader is directed to Appendix A and Appendix B for a detailed description of data sources.

First, the 17 smart city enablers extracted in Table 3.1 were measured by subdividing them into several accurate measurement variables, which were referred to as sub-enablers, as detailed in Table 4.1. For example, the performance of public technological infrastructure was assessed through two sub-enablers, i.e., *broadband latency* (in milliseconds) (TI4) and *network bandwidth* (in megabits per second) (TI5).

Similar work was conducted to quantify the performances of smart cities. Each performance objective was assessed based on the measurement variables, which are referred to as sub-objectives in this paper, as shown in Table 4.2. For instance, Economic Competitiveness was measured through manifest performance sub-objectives, such as *urban wealth* (i.e., GDP per capita) (C2) and *average salary* (C6) (Lombardi et al., 2012).

The four principal enabler clusters were assessed through 40 sub-enablers and the four performance objectives were evaluated through 20 sub-objectives.

Table 4.1 Results of CFA - Smart City Sub-Enablers

Enabler Cluster		Code	Measurement Sub-Enabler	Loading	VIF[a]	Cronbach's α	CR[b]	AVE[c]
No.	Enabler			Fig. 4.1	(<5)	(>0.7)	(>0.7)	(>0.5)
Technological Infrastructure (TI)						0.890	0.916	0.650
1	ICT Availability	TI1	Public Wi-Fi Coverage	~~-0.180~~				
		TI2	Fiber Coverage	~~0.185~~				
		*TI3	ICT Sophistication	0.919	4.565			
2	ICT Performance	*TI4	Broadband Latency	0.841	3.049			
		*TI5	Network Bandwidth	0.752	2.057			
3	ICT Affordability	TI6	Local Call Tariff	~~-0.397~~				
		TI7	Internet Tariff	~~-0.376~~				
4	ICT Security	*TI8	Internet Security	0.684	1.531			
		TI9	Cyber Security Effort	~~0.534~~				
5	ICT Adoption	*TI10	Internet Usage	0.872	3.584			
		*TI11	Smartphone Penetration	0.742	1.804			
Open Governance (OG)						0.885	0.917	0.692
6	Government Transparency	OG1	Government Honesty	0.972	~~20.935~~			
		*OG2	Government Stability	0.832	2.511			
7	Admin. Efficiency	OG3	Bureaucratic Quality	0.964	~~15.669~~			
		*OG4	Urban Policies	0.837	2.756			
		OG5	E-Governance	~~0.630~~				
8	Environment Interests	OG6	Pollution Control Policy	~~-0.117~~				
		*OG7	Green Policies	0.764	2.026			
9	Public Participation	OG8	Civic Activism	~~0.348~~				
		OG9	Citizen Participation	~~0.365~~				
		*OG10	E-Participation	0.813	2.899			
10	Digital Interests	OG11	Data Privacy Policy	~~0.681~~				
		*OG12	ICT Regulations	0.911	3.638			
Intelligent Community (IC)						0.908	0.930	0.690
11	Eco Conscious.	IC1	Water per capita	~~-0.111~~				
		IC2	Electricity Per Capita	~~-0.683~~				
		*IC3	Energy Savings	0.755	2.212			
12	Education	*IC4	Affinity for Studies	0.855	3.129			
		IC5	Students' Abilities	~~0.677~~				
13	Creativity	*IC6	Creative Ideas	0.837	2.551			
		*IC7	Scientific Creativity	0.887	3.703			
14	Digital Proficiency	*IC8	Digital Skills	0.837	2.470			
		*IC9	Cyber-Vigilance	0.799	2.299			
15	Social Cohesion	IC10	Social Equality	~~0.618~~				
		IC11	Ethnic Diversity	~~0.415~~				
		IC12	Elderly People	~~-0.692~~				
Innovative Economy (IE)						0.849	0.900	0.698
16	Innovation Ecosystem	*IE1	Public R&D Investment	0.799	2.293			
		*IE2	Regulatory Environment	0.756	1.851			
		*IE3	Start-Up Ecosystem	0.822	2.105			
17	4th Industrial Revolution	*IE4	Smart Factories	0.949	4.900			
		IE5	Business Intelligence	0.935	~~8.730~~			

[a] VIF: Variance Inflation Factor. [b] CR: Composite Reliability. [c] AVE: Average Variance Extracted
* These sub-enablers were retained selectively [i.e., Loading satisfies the selection criteria (Figure 4.1) and VIF<5].

Table 4.2 Results of CFA – Smart City Sub-Objectives

Performance Objective		**Load**	**VIF**	**Weight (%)**	**Cronbach's α**	**CR**	**AVE**
Code	Sub-Objective	Fig. 4.1	(<5)	-	(>0.7)	(>0.7)	(>0.5)
Urban Efficiency (E)					0.774	0.865	0.691
*E1	Smart Parking	0.911	2.293	0.379			
*E2	Car Sharing Services	0.682	1.435	0.208			
E3	Public Transport Reliability	~~0.609~~					
E4	Public Transport Use	~~0.429~~					
E5	Traffic Flow	~~0.487~~					
*E6	Traffic Safety	0.888	1.910	0.414			
Environmental Sustainability (S)					0.802	0.884	0.720
S1	Renewable Energy	~~0.136~~					
*S2	Energy-Efficiency	0.864	3.071	0.307			
*S3	Waste Recycling	0.897	3.339	0.319			
*S4	Clean Air	0.789	1.342	0.374			
Urban Livability (L)					0.865	0.918	0.791
*L1	Quality of Social Services	0.919	2.979	0.350			
*L2	Happiness	0.857	1.848	0.343			
*L3	Feeling of Security	0.888	2.658	0.307			
L4	Public Safety	0.907	~~5.093~~				
Economic Competitiveness (C)					0.899	0.937	0.833
*C1	Business Competition	0.941	3.945	0.337			
*C2	Urban Wealth	0.873	2.293	0.303			
C3	Employment	~~0.585~~					
C4	Attractiveness	~~0.574~~					
C5	Diplomatic Power	~~0.133~~					
*C6	Average Salary	0.924	3.299	0.359			

N.B. *These sub-enablers were retained selectively [i.e., Loading satisfies the selection criteria (Figure 4.1) and VIF<5].

4.1.2 Data Preparation

General data processing was performed to prepare the raw data for SEM analysis; i.e., missing values were handled and standardization was conducted.

Statistical analysts are repeatedly confronted with dealing with missing data, e.g., the absence or unavailability of one or more variables for one or more cities. To address this issue, the process of replacing missing data with substituted values was considered by applying two types of imputations, i.e., hot-deck imputation and regression imputation (Ericsson, 2014). If the data were not available at the city level (e.g., government transparency), the data were collected from a larger region that includes the city, such as a region or country (i.e., hot-deck imputation). Also, when the variables showed correlation with other variables, this relationship was used to obtain an estimate of the missing value (i.e., regression imputation). For instance, since the affinity for studies in smart cities (IC4 in Table 4.1), calculated using the city population mean years of schooling, is correlated strongly with urban wealth (C2 in Table 4.2) (Caragliu et al., 2011), linear regression was used when inputting the missing data.

Next, the research team standardized the data (Table 4.3) using the Z-scoring technique as follows. For measurement variables that are correlated positively to the latent variable, Equation (2) was used to standardize the data to represent better outcomes with higher scores (e.g., *digital skills*, IC8). However, some variables have an undesirable effect on the related latent variable; for example, the lower the *latency of ICT broadband network* (TI4), the more performant the Technology Infrastructure. In that case, Equation (3) was used.

Depending on the raw data x, the standard score z was calculated by using the appropriate equation:

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

$$z = \frac{\mu - x}{\sigma} \tag{3}$$

where z is the standardized score, x is the original raw data, and μ and σ are the mean and standard deviation of the sample, respectively. The standardized data were used to perform the SEM analysis.

Table 4.3 Details of Data Standardization

Code	Sub-Enabler (Unit)	Raw Data		Standardized Data			
		Mean	**StDev**	**Mean**	**StDev**	**Min**	**Max**
TI4	Broadband Latency (ms)	67.59	18.90	0.00	1.00	-2.68	1.41
TI5	Network Bandwidth (Mbps)	22.87	9.42	0.00	1.00	-1.80	2.75
TI10	Internet Users (%)	80.09	14.25	0.00	1.00	-3.55	1.22
TI11	Smartphone Penetration (%)	64.30	24.70	0.00	1.00	-1.95	1.45

4.2 SEM Analysis

4.2.1 Measurement Model

To ensure that the LVs are within an acceptable level of error, it is imperative to evaluate and validate the reflective measurement model. First, the authors performed reliability analyses for all individual measurement variables (i.e., unidimensionality and collinearity tests). Such analyses can detect the propensity for multiple items to reflect the exact score of LVs. Internal consistency tests of the LVs were then conducted, including construct reliability, convergent validity, and discriminant validity (Götz et al., 2010).

The standardized loadings and the variance inflation factors of the sub-enablers and sub-objectives were calculated, and they are reported in Table 4.1 and Table 4.2, respectively. Data unidimensionality is usually satisfied by retaining items that have factor loadings greater than 0.7 (Fornell et al., 1981), but the selection process can be extended, as shown in Figure 4.1. The loadings computed from CFA indicated the level of variance that was shared with their related LV. The variance inflation factor (VIF) was also computed to quantify the severity of multicollinearity. Given a set of predictors, for the k^{th} predictor:

$$VIF_k = \frac{1}{1 - R_k^2} \tag{4}$$

where R_k^2 is the R^2 value obtained by regressing the k^{th} predictor on the remaining predictors (Hair et al., 2017). Götz et al. (2010) suggested that if an item's VIF is below 5.0, the absence of redundant information could be assumed in the set of predictors.

Since the SEM results were initially not satisfactory in terms of internal consistency, the authors modified and adjusted the research model by eliminating offending variables until the aforementioned conditions were met. First, 13 of the 60 measurement variables with loadings less than 0.50 were eliminated. For instance, TI2 (*fiber coverage*) was removed because of its loading value of 0.185. Next, 12 out of the 47 selected measurement variables had loadings between 0.50 and 0.70, but only two of them (i.e.,TI8 and E2 with loadings of 0.684 and 0.682) were retained based on the decision-making process described in Figure 4.1. At this stage, 37 sub-enablers were selected. The authors then eliminated four out of the 37 remaining items whose VIFs exceeded 5.0; OG1, OG3, IE5, and L4 did not meet such standards because their VIF values, calculated using Equation (4), were 20.9, 15.7, 8.7, and 5.1.

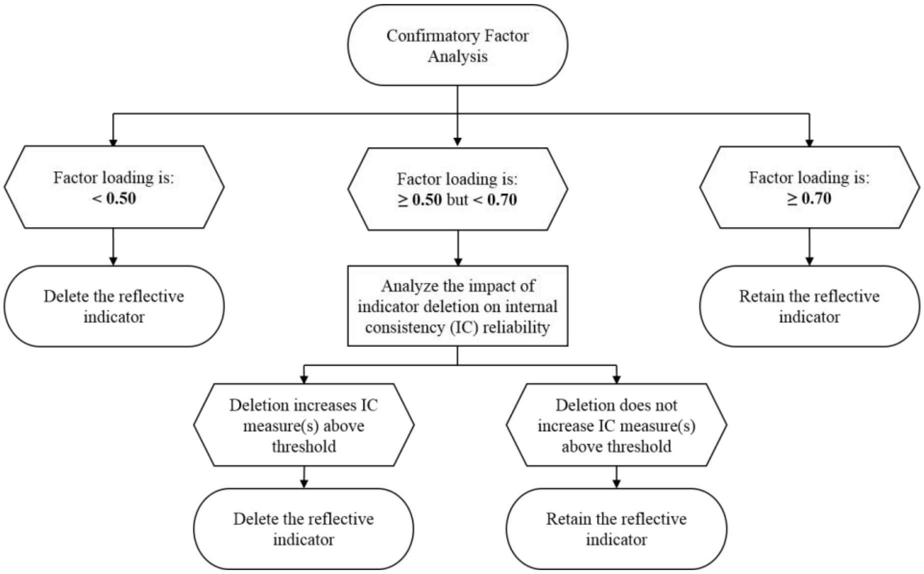


Figure 4.1 CFA-Based Variable Selection Process

(Adapted from Hair et al., 2016)

After the reliability of 33 out of 60 initial measurement variables has been guaranteed, it is necessary to evaluate the internal reliability, convergent validity, and discriminant validity of the LVs to ensure that there are no additional consistency issues. Those tests were implemented by using IBM SPSS Statistics 23.0 and SmartPLS 3.2.8 application software.

The Cronbach alpha test was conducted for each LV to confirm the internal reliability of the extracted variables. Similarly, composite reliability (CR) was also used to check the reliability of the LVs. Cronbach's alpha and CR values should be greater than 0.7 (Nunnally et al., 1967). In this study, the minimum Cronbach's alpha was 0.774, and the CR systematically exceeded 0.865. In addition, the results provided evidence of the convergence validity of the LVs, since their average variance extracted (AVE) ranged from 0.650 to 0.833. The cutoff point for AVE must be greater than 0.5 (Bagozzi et al., 1988; Fornell et al., 1981). Last, the discriminant validity of LVs was established because the Heterotrait-Monotrait Ratio of Correlations (HTMT) between LVs was systematically less than 0.9 (Hair et al., 2017). Equations (5) and (6) were used to compute the LVs' CR and AVE values, respectively.

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum(1 - \lambda_i^2)} \tag{5}$$

$$AVE = \frac{1}{n}\sum(\lambda_i^2) \tag{6}$$

where n is the number of indicators used to measure the LV, and λ_i is the factor loading of the i^{th} measurement variable (Raymond & Bergeron, 2008).

4.2.2 Structural Model

After confirming the robustness of the measurement model, the reliability of the structural model was evaluated. The structural model includes 28 causal relationships between the eight aforementioned LVs. However, contrary to covariance-based SEM, consensual goodness-of-fit metrics are still missing when the PLS-SEM method is used (Aibinu & Al-Lawati, 2010; Raymond & Bergeron, 2008).

Therefore, PLS-SEM practitioners prefer to test the research hypotheses by analyzing the reliability of the measurement model (c.f. section 4.2.1) and the squared multiple correlations (R^2) of endogenous constructs (Breiman & Friedman, 1985; Raymond & Bergeron, 2008). As reported by Hair et al. (2016), PLS-SEM aims at maximizing the R^2 values of the endogenous LVs; while the correct interpretation of the R^2 values depends on the particularities of the model and the research discipline, the R^2 values of 0.75, 0.50, and 0.25 generally explain substantial, moderate, and weak constructions, respectively. Also, it is essential to consider the statistical significance (i.e., p-value), value, and signs of the paths coefficients when analyzing the structural model (Raymond & Bergeron, 2008).

In this paper, the high percentage of variance explained for each endogenous LV (R^2), which varied from 70.6% for Environmental Sustainability to 91.2% for Economic Competitiveness, was indicative of a good fit by the model. Moreover, the hypothesized relationships were considered supported based on the significance level of 0.10 that is generally recommended for exploratory research (Garson, 2016).

Figure 4.2 shows the results, and they are justified mathematically in Table 4.4; 15 of the 28 hypothesized paths were confirmed statistically. For instance, according to the mathematical model (Figure 4.2), the Economic Competitiveness in smart cities is significantly enhanced by Open Governance (β_{H8} = +0.318), Intelligent Community (β_{H12} = +0.513), and Innovative Economy (β_{H16} = +0.447); it is noteworthy that the higher the path coefficient (indexed as β in this paper) becomes, the stronger the direct effect becomes on the endogenous construct. Notably, the structural model emphasizes the large internal effects of Technological Infrastructure on Intelligent Community (β_{H18} = +0.896) and of Intelligent Community on Innovative Economy (β_{H22} = +0.836). As emphasized by Zygiaris (2013), a city's innovation power depends significantly on the creativity and intelligence of the citizens.

All significant paths are positive except the one that connects Innovative Economy to Urban Livability (β_{H15} = -0.588); this negative influence is due to the drawbacks and threats of the fourth industrial revolution. The quantified effects derived from the 28 relations are discussed in the next section.

Table 4.4 Results of Hypothesis Testing

Hypothesized Relationship		Path Coefficient (β)	Standard Error	Critical Ratio (≥ 1.6)	P-value	Interpretation
External Effects Enabler Cluster → Performance Objective						
H1:	TI → E	+0.192	0.238	0.809	0.419	Not Supported
H2:	TI → S	+0.219	0.224	0.837	0.403	Not Supported
H3:	TI → L	+0.280	0.175	1.600	0.091	**Supported**
H4:	TI → C	-0.204	0.155	1.314	0.189	Not Supported
H5:	OG → E	-0.175	0.211	0.832	0.406	Not Supported
H6:	OG → S	+0.277	0.217	1.277	0.202	Not Supported
H7:	OG → L	+0.307	0.152	2.023	0.043	**Supported**
H8:	OG → C	+0.318	0.141	2.257	0.024	**Supported**
H9:	IC → E	+0.397	0.292	1.359	0.174	Not Supported
H10:	IC → S	-0.000	0.248	0.001	0.999	Not Supported
H11:	IC → L	+0.495	0.272	1.824	0.005	**Supported**
H12:	IC → C	+0.513	0.198	2.588	0.010	**Supported**
H13:	IE → E	+0.449	0.189	2.372	0.018	**Supported**
H14:	IE → S	+0.151	0.179	0.842	0.400	Not Supported
H15:	IE → L	-0.588	0.211	2.786	0.005	**Supported**
H16:	IE → C	+0.447	0.137	3.273	0.001	**Supported**
Internal Effects Enabler Cluster → Enabler Cluster						
H17:	TI → OG	+0.556	0.118	4.728	***	**Supported**
H18:	TI → IC	+0.896	0.020	44.162	***	**Supported**
H19:	TI → IE	-0.047	0.224	0.210	0.834	Not Supported
H20:	OG → IE	+0.107	0.156	0.689	0.491	Not Supported
H21:	IC → OG	+0.376	0.124	3.019	0.003	**Supported**
H22:	IC → IE	+0.836	0.168	4.979	***	**Supported**
Internal Effects Performance Objective → Performance Objective						
H23:	E → S	+0.248	0.153	1.628	0.098	**Supported**
H24:	E → L	+0.240	0.146	1.645	0.100	**Supported**
H25:	E → C	-0.191	0.121	1.581	0.114	Not Supported
H26:	S → L	+0.294	0.112	2.624	0.009	**Supported**
H27:	S → C	+0.079	0.081	0.974	0.330	Not Supported
H28:	C → L	-0.096	0.160	0.599	0.549	Not Supported

N.B. *** p-value < 0.001

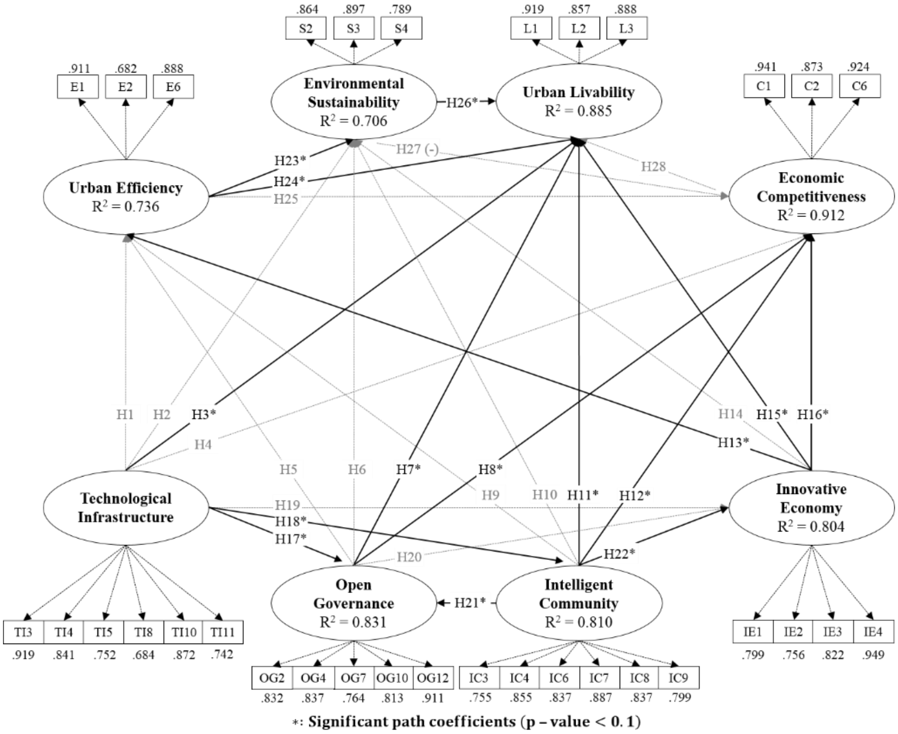


Figure 4.2 Results of the Best Fitting Developed SEM

4.3 Results and Discussions

The proposed model was validated with acceptable performance criteria (c.f. R^2 in Figure 4.2) to quantify how enabler clusters (i.e., Technological Infrastructure (TI), Open Governance (OG), Intelligent Community (IC), and Innovative Economy (IE)) structurally influence the four performance objectives of smart cities, i.e., Urban Efficiency (E), Environmental Sustainability (S), Urban Livability (L), and Economic Competitiveness (C).

4.3.1 Findings from the Measurement Model

The results derived from the measurement model indicated that the developed framework was capable of extracting the priority of smart city sub-enablers for practical applications (i.e., strategic smart city planning and development).

More specifically, the measurement model can explain how the potential of enabler clusters can be improved strategically. To this end, Table 4.5 summarizes the CFA standardized weights, labeled as ω, of selected sub-enablers. The distributed weights show the relative importance of sub-enablers for each enabler cluster. In detail, all measurement variables within an enabler cluster must be considered, but special attention should be paid to the critical ones (i.e., above average) that are marked with an asterisk in Table 4.5. For example, the impact of TI in smart cities is influenced mostly by technology sophistication (e.g., Internet of Things, cloud computing, and ubiquitous sensor network) (ω_{TI3} = 0.207) and followed by ICT adoption (ω_{TI10} = 0.186). As mentioned by Braun et al. (2018), if citizens are reluctant to use the technological infrastructure, the smart city becomes obsolete. Therefore, to make investments in technology smart and sustainable, it is important to build socio-technical complementarities using the following results. An appropriate OG in smart cities is developed primarily by promoting the transformational impacts of ICT integration (ω_{OG12} = 0.220) to deliver better service to citizens. It can be achieved through the enactment of a legal framework that facilitates ICT pervasiveness. In contrast, poorly designed ICT related-regulations can create inequalities and widen the digital divide. The transparency (ω_{OG2} = 0.209) (e.g., through open data) and efficiency (ω_{OG4} = 0.205) of government activities also influence the potential of OG. Next, IC is established mainly via the development of digital competences (ω_{IC8} = 0.188), creative abilities (ω_{IC6} = 0.172 and ω_{IC7} = 0.180), and lifelong learning skills (ω_{IC4}=0.170) of the population. Last, the integration of the latest computing innovations in the industry (ω_{IE4} = 0.297) controlled with proper regulations (ω_{IE2} = 0.253) is very important to foster innovation capacities and lay the groundwork for an IE.

As a result, based on those findings, urban strategists can formulate a new policy agenda to prioritize their investments and enhance preparedness for smart city transition.

Table 4.5 Sub-Enablers Ranked by CFA Weights

Technological Infrastructure (TI)			Intelligent Community (IC)		
Code	**Sub-Enabler**	**Weight (%)**	**Code**	**Sub-Enabler**	**Weight (%)**
TI3*	ICT Sophistication	**20.7**	**IC8***	Digital Skills	**18.8**
TI10*	Internet Usage	**18.6**	**IC7***	Scientific Creativity	**18.0**
TI8	Internet Security	15.9	**IC6***	Creative Ideas	**17.2**
TI4	Broadband Latency	15.8	**IC4***	Affinity for Studies	**17.0**
TI11	Smartphone Penetration	15.4	IC9	Cyber Vigilance	14.9
TI5	Broadband Speed	13.7	IC3	Energy Savings	14.2

Open Governance (OG)			Innovative Economy (IE)		
Code	**Sub-Enabler**	**Weight (%)**	**Code**	**Sub-Enabler**	**Weight (%)**
OG12*	ICT Regulations	**22.0**	**IE4***	Smart Factories	**29.7**
OG2*	Government Stability	**20.9**	**IE2***	Regulatory Environment.	**25.3**
OG4*	Urban Policies	**20.5**	IE1	Public R&D Investment	22.9
OG10	E-Participation	19.0	IE3	Start-up Ecosystem	22.1
OG7	Green Policies	17.5			

N.B. * Critical Smart City Sub-Enablers

4.3.2 Findings from the Structural Model

The structural model identified the direct and indirect effects of enabler clusters on performances objectives. Then, the integration of these paths (i.e., total effects) was used to provide public decision-makers with practical indications, including counterintuitive findings to reach each performance objective individually.

The results demonstrated the statistical significance and decisive contributions of both direct and indirect effects. Figure 4.2 shows the significant direct effects of the enabler clusters on urban performances (e.g., H3, H7, and H8), and it also enables the visualization of complex indirect paths (e.g., H17 - H7). Quantitatively, it was confirmed that the use of technology (e.g., Internet of Things) directly improves citizens' quality of life (e.g., public safety, health) (β_{H3} = +0.280) in line with the findings of previous studies (Braun et al., 2018; Jain et al., 2017). Next, in a strong OG-oriented city, the voice of citizens is listened to attentively by policy-makers in a non-confrontational manner. Therefore, OG directly influences the attainment of three performance objectives (i.e., S, L, and C) since citizens generally expect to live in sustainable, livable, and competitive environments. Furthermore, IC (through H11 and H12) and IE (through H13, H15, and H16) also contribute directly to the performances of smart city programs. A city with highly educated, intelligent, and aware citizens (i.e., IC) and strong IE is more likely to satisfy its performance objectives.

In addition to the direct effects, it was also possible to highlight the important participation of enabler clusters' indirect effects on smart city performances. The internal effects among enabler clusters, including, but not limited to, H17, H18, H21, and H22, are the starting points for those indirect effects. For instance, as stated by Chourabi et al. (2012), TI can be characterized as a meta-enabler since it also directly influences other enabler clusters (i.e., internal effects) like OG (β_{H17} = +0.556) and IC (β_{H18} = +0.896). As a result, through sequential paths involving mediator variables, such as OG ($\beta_{TI \rightarrow OG} \rightarrow L$ = +0.171) and IC ($\beta_{TI \rightarrow IC} \rightarrow L$ = +0.443), TI indirectly influences L. In the scenario TI→L, the indirect effects supported by Kitchin (2014) explain 67.3% of total influence. Table 4.6 shows that the results demonstrated the substantial impacts of indirect effects, especially for TI and IC, in the attainment of smart city performances. The decompositions of direct, indirect, and total effects are shown in Table 4.6. The main contribution of this study is the integration of direct and indirect effects, which provides opportunities to gain a comprehensive understanding of the development dynamics of a smart city.

Table 4.6 Direct, Indirect, and Total Effects of Enabler Clusters

	Technological Infrastructure (TI)			**Open Governance (OG)**			**Intelligent Community (IC)**			**Innovative Economy (IE)**		
	Dir.	**Ind.**	**Tot.**	**Dir.**	**Ind.**	**Tot.**	**Dir.**	**Ind.**	**Tot.**	**Dir.**	**Ind.**	**Tot.**
E	+0.19	+0.56*	**+0.75****	-0.18	+0.05	**-0.13**	+0.40	+0.33*	**+0.73****	+0.45*	-	**+0.45***
	25.6%	*74.4%*		*78.5%*	*21.5%*		*54.8%*	*45.2%*		*100.0%*	*0.0%*	
S	+0.22	+0.55*	**+0.77****	+0.28	-0.02	**+0.26**	-0.00	+0.42**	**+0.42***	+0.15	+0.11	**+0.26***
	28.4%	*71.6%*		*94.9%*	*5.1%*		*0.0%*	*100%*		*57.6%*	*42.4%*	
L	+0.28*	+0.58**	**+0.86****	+0.31*	-0.06	**+0.25**	+0.50*	-0.192	**+0.30***	-0.59**	+0.15	**-0.44***
	32.7%	*67.3%*		*84.6%*	*15.4%*		*72.1%*	*27.9%*		*79.9%*	*20.1%*	
C	-0.20	+1.02**	**+0.81****	+0.32*	+0.09	**+0.41****	+0.51**	+0.41**	**+0.92****	+0.45**	-0.07	**+0.38****
	16.7%	*83.3%*		*77.4%*	*22.6%*		*55.9%*	*44.1%*		*87.3%*	*12.7%*	

N.B. The percentages indicate the proportion of a total given effect explained by direct and indirect effects respectively.
* p-value < 0.1 ; ** p-value < 0.01

Based on the integration of direct and indirect effects (i.e., total effects), it was also possible to extract appropriate synergies to improve urban performances individually. For example, Table 4.6 and Figure 4.3 indicate that TI exhibits the strongest total effects for each performance objective except for C, where IC slightly predominates over TI.

However, even though TI is obviously fundamental in smart city development, the results confirmed the insufficient necessity of technological development for the future success of smart city initiatives (Aina, 2017; Nam & Pardo, 2011b). The authors believe that synergetic dynamics involving OG, IC, and IE collectively, can best exploit the potential of TI in order to enhance the attainment of smart city performance objectives. Such quantitative results and analyses can help urban leaders make project-control decisions such as consistent policy management to enhance smart city performances.

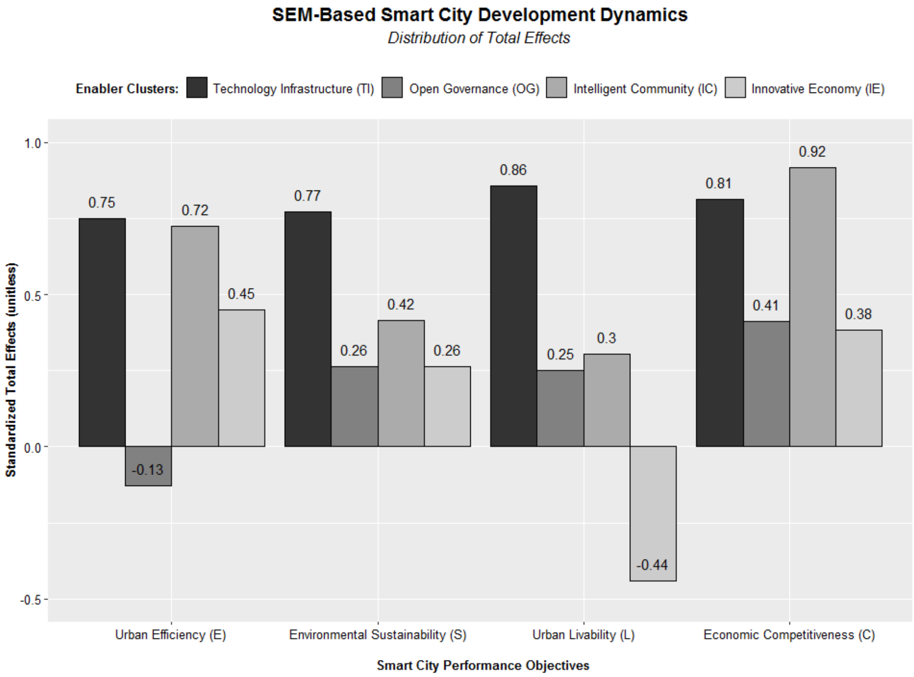


Figure 4.3 Integration of Direct and Indirect Effects

However, several challenges remain to be addressed to appropriately manage the development of smart cities (Figure 4.3).

First, the research team observed that the total effect of OG on E is negative ($\beta_{\text{Total: OG}\rightarrow\text{E}}$ = -0.127). The efforts of central and local governments to invigorate public participation (OG) can have undesirable effects. Through the consideration of citizens' demands and related possible conflicting interests, urban leaders encounter difficulties (e.g., socio-spatial inclusion) in managing and planning efficiently urban operations (e.g., public transportation) (E). Also, unplanned mass urbanization can deteriorate the efficiency of urban structures. Today, 55% of the world's population lives in metropolitan areas, and, by 2050, 68% of the global population is projected to be urban; the urbanization pace is expected to intensify especially in developing countries (United Nations, 2016). Therefore future research in urban sciences should investigate how smart city planning can deal with the resulting effects of rapid urbanization (Zeng et al., 2018)

In addition, the negative influence of IE on L ($\beta_{\text{Total: IE}\rightarrow\text{L}}$ = -0.440) is inconsistent with common sense that the fourth industrial revolution (i.e., industry 4.0) and related technological innovation (e.g., cognitive computing) could foster positive changes in society. For example, the introduction of artificial intelligence (e.g., robotics) in industries can enhance working conditions. However, the sudden introduction of pervasive computing in the economy, in addition to drastically redesigning every aspect of urban life, is threatening the workers' quality of life. With computer vision techniques for instance, video surveillance intrusively can track and monitor workers. Additional research opportunities include the security and privacy challenges in smart cities to increase the quality of life in a secure manner (Braun et al., 2018). Also, common labors in smart cities are being replaced progressively by computers, especially in smart factories, which are very important for IE (ω_{IE4} = 0.297). Even though they are designed to improve productivity, those innovative solutions can deteriorate the well-being of citizens (ω_{L2} = 0.343) by disrupting jobs, skills, and privacy. There is growing concern that this reliance on cutting-edge technology could create a smart dystopia. Therefore, urban strategists should keep in mind that just focusing on innovation when developing smart city projects can have a negative impact on citizens in the long term.

Future research should investigate how smart cities can control the pace of innovation to restore a human-centric perspective.

Chapter 5. Model Applications

5.1 Smart City Maturity Assessment

The SEM developed in this research shows how the performances of smart cities are affected by various enablers and sub-enablers. Specifically, the model can be utilized to systematically assess the maturity of smart city development enablers. With all weights derived for each detailed sub-enabler, the results of this research can be analyzed in depth to formulate strategic recommendations and practical guidelines. Furthermore, the SEM model can be used to estimate and compare the impact of alternative strategies on the attainment of performance objectives.

To show potential use cases, three case studies (i.e., Boston, Helsinki, and Seoul) were examined and analyzed through the lens of the SEM model. In practice, Boston has been acknowledged as an international center for higher education, Helsinki as a model in terms of citizen empowerment (Mora, Deakin, & Reid, 2019), and Seoul as a global ICT leader (PwC, 2016). The SEM-based results reported in Figure 5.1 tend to confirm these facts. The model can be further utilized to identify the strengths and weaknesses in smart city development.

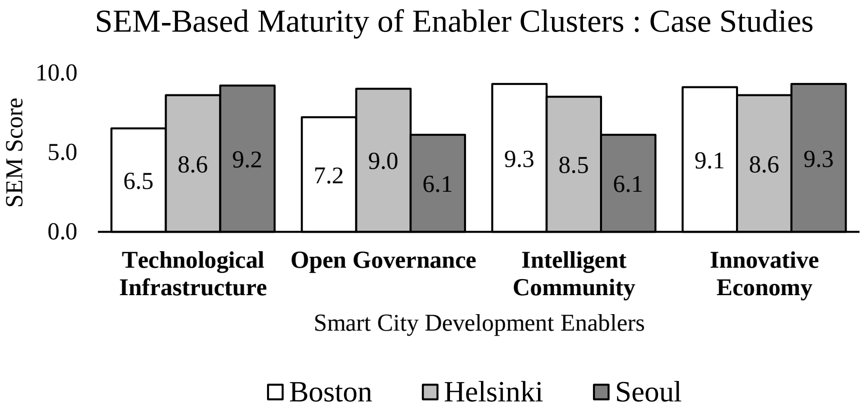
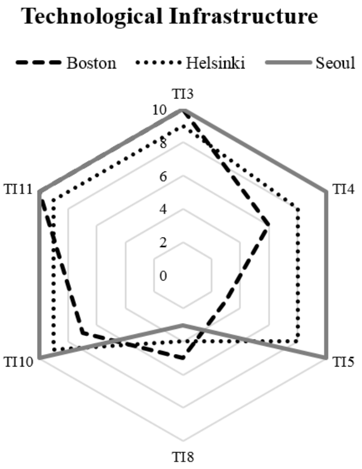


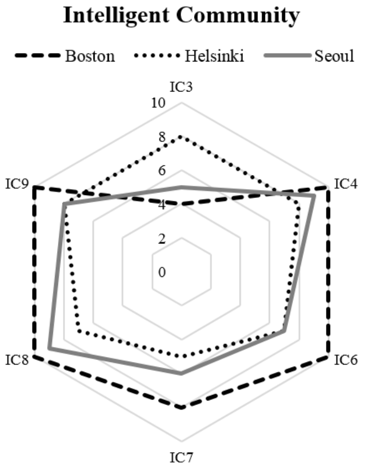
Figure 5.1 Smart City Maturity Assessment: Case Studies

For example, when evaluating the maturity of Technological Infrastructure in Figure 5.1, Boston appears to be relatively lagging compared to Helsinki and Seoul. A detailed investigation can be conducted to identify the causes of this gap. Through the spider map of Technological Infrastructure in Figure 5.2, urban leaders can inspect the conditions of critical technological sub-enablers (i.e., TI3 and TI10). While the score of TI3 (*ICT sophistication*) in Boston is comparable with advanced cities, TI10 (*ICT usage*) is neatly lagging. Therefore, the digital divide in Boston needs to be better filled to enhance the potential of Technological Infrastructure for successful smart city development. The developed model can aid policy-makers in designing coherent metropolitan policies.

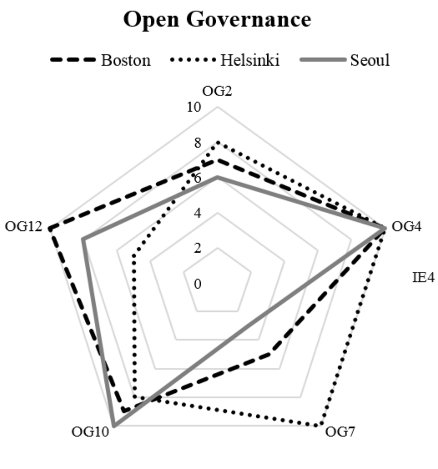
Consequently, urban leaders are able to evaluate and operate management strategies to significantly enhance the dynamics of smart city growth.



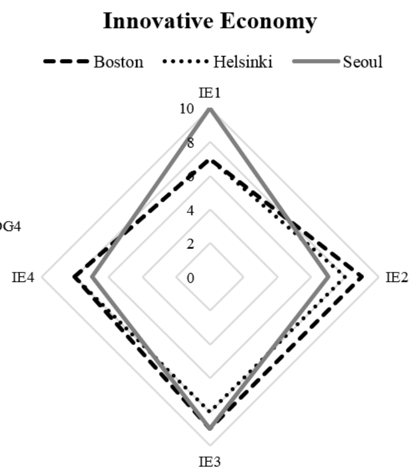
TI3	**ICT Sophistication**
TI10	**ICT Usage**
TI8	Internet Security
TI4	Broadband Latency
TI11	Smartphone Penetration
TI5	Broadband Speed



IC8	**Digital Skills**
IC7	**Scientific Creativity**
IC6	**Creative Ideas**
IC4	**Affinity for Studies**
IC9	Cyber Vigilance
IC3	Eco-Consciousness



OG12	**ICT Regulations**
OG2	**Gov. Stability**
OG4	**Admin. Efficiency**
OG10	E-Participation
OG7	Green Policies



IE4	**Smart Factories**
IE2	**Regulatory Env.**
IE1	R&D Investment
IE3	Start-up Ecosystem

Figure 5.2 Smart City Development Conditions: Spider Maps

5.2 Smart City Macro Trends Analysis

The developed assessment model can also be applied to extract the macro trends of smart city development, especially considering the influence of contextual factors. It is important to start understanding how contextual factors such as economic, geographic, and demographic factors can affect the maturation of smart city developments.

Based on the SEM model, the maturity of development enablers and the attainment of performance objectives in 50 smart cities have been contextually analyzed in Figure 5.3 and Figure 5.4 respectively. Specifically, the boxplot method was used to graphically display the respective influence of four context factors (i.e., economic development, geography, density, and size). Such efforts have been undertaken in order to extract general smart city development trends.

For instance, in Figure 5.3, it can be observed that smart city development scenarios are extremely different between developed and developing nations. Since developing nations have their financial commitments already aligned to achieve the basic entities (e.g., potable water supply, sanitation services), their smart city development perspectives are narrowed (Yadav et al., 2019). Also, denser cities tend to have more difficulties in developing performant technological infrastructure and achieving participatory governance structures.

Furthermore, regarding the attainment of performance objectives in smart cities (Figure 5.4), the efficiency of urban operations tend to be deteriorated in larger urban areas. However, larger cities also tend to have more economic power, since such cities can potentially contain a greater number of economic agents. The findings can be further developed for use when conducting smart city eligibility analysis.

Figure 5.3 Smart City Development Dynamics

Figure 5.4 Smart City Performance Dynamics

Chapter 6. Conclusion

6.1 Summary and Contributions

Smart city practitioners often encounter difficulties in formulating proper policies for successful planning and development due to the lack of comprehensive quantification of enablers' effects.

To address such challenges, this paper proposed an assessment model of enablers' direct and indirect effects on smart city performance objectives. To achieve this, the authors first classified 17 smart city enablers into four enabler clusters and extracted four decisive performance objectives through extensive literature review. Next, the structural research model was developed by identifying the meaningful relationships between the eight aforementioned LVs. Then, the SEM analysis was conducted using the bootstrapped data of 50 smart cities worldwide.

The findings validated the crucial contributions of indirect effects and also confirmed the importance of a synergistic approach, involving collectively Technological Infrastructure, Open Governance, Intelligent Communities, and Innovative Economies to build successful smart cities. Based on the quantitative results, it was inferred statistically that, for successful smart city development, it is important to build socio-technical complementarities upon (1) efficient and transparent city administration that promotes the digital transformation of public spaces, (2) educated, creative, and digitally-proficient population, and (3) properly-regulated, digital transformation of the economy.

In conclusion, the developed assessment model has the potential to provide useful guidelines to policymakers and metropolitan leaders for enhancing the growth of smart cities. Urban strategists can capitalize on the integration of quantified effects to build socio-technical complementarities in order to attain optimum urban performances.

6.2 Limitations and Future Study

This research starts bridging some theoretical and practical gaps for a holistic research approach to smart cities, especially in quantifying and understanding the development dynamics.

However, limitations can primarily arise from the insufficiency of observed data; this research analyzed the actual data of 50 pioneering smart city projects. The findings are highly influenced by the specificities of these cases. For model performance improvements, further achievements are expected to benefit from the maturation and expansion of the smart city phenomenon. The number of smart cities worldwide will continue to increase at a fast pace: for example, the Korean government announced in 2015 that 21 smart city initiatives were partially completed, 12 under construction, and 31 at the design stage (Yigitcanlar, 2015). More case studies would reinforce our understanding of smart city development dynamics and help researchers to share best practices on how to develop an effective smart city.

Secondly, this research identified the enablers of smart city development and quantified their effects on urban performances. The recognized sub-enablers might need to be evaluated further to know their causal interrelations and implications in smart city initiatives; alternative techniques such as Decision-Making Trial and Evaluation Laboratory (DEMATEL) might be applied.

Thirdly, further empirical and statistical analyses could be conducted to quantify the influence of contextual factors in smart city development.

Specifically, works mentioned in chapter 5.2 could be further developed to understand how contextual factors such as economic, geographic, and demographic factors can quantitatively affect the maturation of smart city development.

Lastly, this study positively explores why the smart city concept holds so much promise for cities worldwide. However, less is said in this paper about the negative aspects of smart cities that can be technical, social, and ethical. For instance, the potential for social polarization, the vulnerability to cyber-attacks, the educational and financial demands made on citizens in order to participate in urban life, technocratic and autocratic governance, and excessive surveillance in smart cities have not really been addressed in this paper (Söderström, Paasche, & Klauser, 2014).

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Appendix A

Appendix A Data Collection – Open Data Portal (Enablers)

No.	Enabler	Code	Sub-Enabler Description	Open Data Source
Technological Infrastructure (TI)				
1	ICT Availability	TI1	Number of Wi-Fi Hotspots Adjusted to the City Area	Easy Park[1]
		TI2	Fiber-Optic Route Density (km/km^2)	ITU[2]
		TI3	ICT Infrastructure Level of Development	WEF[3]
2	ICT Performance	TI4	Average Broadband Latency from Urban Networks (ms)	OpenSignal
		TI5	Average Bandwidth from Operators Networks (Mbps)	OpenSignal
3	ICT Affordability	TI6	Cost of 1 min of Prepaid Mobile Card (US $)	Numbeo
		TI7	Monthly Cost of the Internet (US $)	Numbeo
4	ICT Security	TI8	Secure Internet Servers (Per 1 Million People)	World Bank
		TI9	Dedicated Cybersecurity Teams	EIU[4]
5	ICT Adoption	TI10	Percentage of Individuals Using the Internet (%)	ITU[2]
		TI11	Smartphone Penetration in Society	Easy Park[1]
Open Governance (OG)				
6	Government Transparency	OG1	Corruption Perception Index (Scale [0:100))	TI[5]
		OG2	Likelihood of Political Instability (Scale [-2.5: 2.5])	WGI[6]
7	Admin. Efficiency	OG3	Perceptions of the Quality of Civil Services	WGI[6]
		OG4	Regulatory Environment for Operating a Local Company	World Bank
		OG5	Number of Government Services Provided Online	WEF[3]
8	Environment Interests	OG6	PM10 Concentration Reduction 2008-2013 (ug/m^3)	WHO[7]
		OG7	Green Area (% of public green area, parks, and garden)	Easy Park[1]
9	Participatory Governance	OG8	Number of Petitions (Per 100 000 inhabitants)	Change.org
		OG9	Local Elections Participation Rate	IDEA[8]
		OG10	Measures the Level of E-Participation of Citizens	WEF[3]
10	Digital Interests	OG11	Data Protection Policy (Scale [0:100])	EIU[4]
		OG12	Promotion of ICT penetration	WEF[3]
Intelligent Community (IC)				
11	Eco Conscious.	IC1	Water Withdrawn per Capita (m3/inhabitant/year)	FAO[9]
		IC2	Electricity Consumption per Capita (MWh/Capita)	IEA[10]
		IC3	Penetration of Energy Management Systems in 2018	Statista
12	Education	IC4	Mean Years of Schooling	UN
		IC5	PISA Score in Mathematics, Reading, and Sciences	Teleport
13	Creativity	IC6	Number of Start-ups Adjusted to Population	Angel.co
		IC7	Scientific Journal Articles (Per 100 000 inhabitants)	World Bank
14	Digital Proficiency	IC8	Ability of a Society to Make an Effective Use of ICT	WEF[3]
		IC9	Citizens Awareness of Digital Threats (Scale [0:100])	EIU[4]
15	Social Cohesion	IC10	GINI Coefficient (Scale [0:100])	CIA
		IC11	Foreign-Born Population (% of Population)	WCC[11]
		IC12	Part of Population Aged 65 And Over (%)	Teleport
Innovative Economy (IE)				
16	Innovation Ecosystem	IE1	Gross Domestic Expenditure on R&D (As Part of GDP)	UNESCO
		IE2	Existing Conditions for Innovation to Flourish	WEF[3]
		IE3	Attractiveness of Environment for Start-ups	Nestpick
17	4th Industrial Revolution	IE4	Innovation and Sophistication Factors	WEF[3]
		IE5	Integration of ICT to Generate Competitiveness Gains	WEF[3]

N.B. [1]Easy Park Smart City Index 2017. [2]ITU: International Telecommunication Union. [3]WEF: World Economic Forum. [4]EIU: The Economist Intelligence Unit (The Global Livability Index 2018). [5]TI: Transparency International. [6]WGI: Worldwide Governance Indicators. [7]WHO: World Health Organization. [8]IDEA: Institute for Democracy and Electoral Assistance. [9]FAO: Food and Agriculture Organization. [10]IEA: International Energy Agency. [11]WCC: World Cities Culture.

Appendix B

Appendix B Data Collection – Open Data Portal (Performance Objectives)

Code	Sub-Objective	Sub-Objective Description	Open Data Source
Urban Efficiency (E)			
E1	Smart Parking	Number of Parking Spaces in City Centre per km^2	Easy Park[1]
E2	Car Sharing Services	Car Sharing Industry Fleet in the City	Easy Park[1]
E3	Public Transport Reliability	Public Transport Satisfaction Percentage	Easy Park[1]
E4	Public Transport Use	Average Public Transport Journeys per Capita	Arcadis[2]
E5	Traffic Flow	Congestion Problems (Scale [0:100])	Easy Park[1]
E6	Traffic Safety	Road Traffic Fatalities (Per 100 000 people)	Arcadis[2]
Environmental Sustainability (S)			
S1	Renewable Energy	Percentage of Electricity From Renewable Sources	Easy Park[1]
S2	Energy-Efficiency	Efficiency of Buildings (GDP per Unit of Energy Use)	Easy Park[1]
S3	Waste Recycling	Percentage of Waste that is Recycled	Easy Park[1]
S4	Clean Air	Pollution Index Rate 2018	Numbeo
Urban Livability (L)			
L1	Social Services	Dvpt of Social Infrastructure (e.g., Healthcare)	EIU[3]
L2	Happiness	Quality of Life Index	Numbeo
L3	Feeling of Security	Perceived Criminality in Society	VoH[4]
L4	Public Safety	Global Peace Index (Scale [1:5])	VoH[4]
Economic Competitiveness (C)			
C1	Business Competition	Global Competitiveness Index	WEF[5]
C2	Urban Wealth	GDP Per Capita (US $)	Brookings
C3	Employment	Employment as the Share of the Labour Force (%)	OECD
C4	Attractiveness	Price to Buy Apartment in City Centre (US $ per m^2)	Numbeo
C5	Diplomatic Power	Number of Foreign Representations (e.g., Embassies)	EmbassyPages
C6	Average Salary	Average Net Salary Adjusted to the GDP per Capita	Easy Park[1]

N.B. [1]Easy Park Smart City Index 2017. [2]Arcadis Sustainable Cities Mobility Index 2017. [3]EIU: The Economist Intelligence Unit (The Global Livability Index 2018). [4]VoH: Vision of Humanity. [5]WEF: World Economic Forum.

초 록

최근 몇 년 동안, 스마트 시티 프로젝트는 도시개발과 재생을 강화시키는 계획들로 상당한 관심을 끌어왔다. 또한 스마트시티 진도관리와 계획, 설계를 더 잘 통제하기 위한 기술적 그리고 비기술적 인자들이 많은 연구들에 포함되어왔다. 그러나 상당한 효과들과 성과들에도 불구하고, 성과면에서 스마트시티의 직간접적 효과들은 포괄적으로 정량화 되지 못한 것이 사실이다. 즉, 스마트시티의 적절한 전략과 성공적인 개발정책을 세우는데 있어서 불충분한 정량화 및 이해부족과 도시 지도자들이 맞닥뜨리는 어려움들 때문이다. 이러한 문제를 다루기 위해서 이 연구는 스마트 시티의 중요한 요소들을 규명하고 이들의 다양한 효과들을 정량화하기 위해서 (즉, 직간접적인효과) 구조방정식모형(Structural Equation Modeling, SEM)을 사용했다. 보다 구체적으로, 저자들은 SEM을 네가지 요소클러스터(즉, 기술적 인프라, 열린 정부, 지적 공동체, 혁신적 경제)의 관계와 네가지 성능목표(즉, 효율성, 지속가능성, 거주적합성, 경쟁력)를 평가 및 추정하기 위해 50개의 스마트 시티들의 실제 데이터를 이용하여 적용했다. 이 통계 결과를 통해 기술적 인자들(즉, 기술적인프라) 뿐만 아니라 비기술적 인자

클러스터(즉, 열린 정부, 지적 공동체, 혁신적경제)가 고도로 밀접하고 다양한 시너지와 함께 스마트시티의 성과에 상당한 영향을 미친다고 입증되었다. 이 수학적 결과들을 바탕으로, 도시 지도자들은 더 나은 정책 관리를 통한 스마트 시티 이행의 전략적인 계획을 강화시킬 수 있다.

주요어: 스마트 시티, 프로젝트 관리, 도시개발, 도시재생, 개발인자, 성과목표, 구조방정식모형

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