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Determinant Factors of Smart Cities: The Case of MENA[a] Countries

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Abstract: This study seeks to explore determinant factors in smart cities using a sample of 13 countries from the Middle East and North Africa region (MENA) during the period from 2012 to 2018. The study suggests five determinant factors in smart cities namely, infrastructure; macroeconomic environment; health and education; technological readiness and innovation. These factors are measured using data collected from the Global Competitiveness Report over seven years from 2012 to 2018. To examine significant effects and causal relations between the five factors in smart cities, the study has conducted the path analysis. Two models with different paths are employed. The first has three paths among them one is not significant at the common levels of significance. The second model has four paths which all are statistically significant. Findings of the study reveal that the infrastructure and economy based on smart technology positively affect other factors (the education & health and innovation). In addition, the results demonstrate a high effect of technology readiness and macroeconomic environment as determinant factors in smart cities on other factors namely, health and education and innovation. To the best of the authors knowledge, this is the first study on smart cities conducted in MENA countries to employ path analysis as a unique technique.

Keywords: Infrastructure, Health and Education, Technological Readiness, Innovation, Macroeconomic Environment, MENA Countries and Smart Citi

1. Introduction

The concept of smart and sustainable cities is a comprehensive term for developing, supporting and managing cities through facilitating new technology, protection of the environment, well social and economic conditions and innovations. A smart city is a modern concept that refers mainly to a civil area in which digital and engineering techniques are used to improve the economic and social conditions of its inhabitants by providing them with easy access to various services. On the other hand, Caird and Hallett (2019), argued that smart city development is essentially a multi-disciplinary endeavor rather than only offering a technological fix for urban challenges. Serbanica and Constantin (2017, p. 60) argued that "countries and regions should identify and select a limited set of priority areas for knowledge-based investments, focusing on their strengths and competitive advantages".

In smart cities, different types of sensors and electronic monitoring are used to collect data which is analyzed, processed and converted into information used to manage assets and other resources efficiently and effectively. Smart cities provide a decent life for citizens via meeting their basic infrastructure needs and via implementing smart solutions that ensure a clean and sustainable environment as an integral part of any future urban project. They create optimistic solutions for some of serious problems such as the use of conventional energy. For instance, they are using solar energy, which is clean, less in cost and protect the environment. Nowadays many countries have initiatives to

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establish smart cities. For example, the GCC countries seek to diversify their economic resources instead of depending on oil as a major economic source and to accelerate the implementation of renewable energy projects which comes in the forefront of solar energy. Moreover, establishing smart cities could assist the GCC region to deal with the existing challenge such as the delivery of potable water. In a study accomplished in the GCC, Saxena and Al-Tamimi (2018, p. 237) point out that "GCC are keen on building upon their infrastructure to push their "smart city" agenda which would go a long way in furthering the economic diversification objective of their region besides improving the quality of public services". Although several studies on this area of research have focused on the concept of smart cities, there is no consensus on such a concept. The current study provides a unique contribution to smart cities' literature. Instead of focusing on the concept smart cities, it seeks to explore determinant factors in smart cities; as well as it examines the significant effects and causal relations between these factors using path analysis as a new technique. Using a sample of 13 MENA countries covering a 7-year period from 2012 to 2018 is considered another contribution in this study due to the scarcity of such studies in MENA region.

The study is structured as follows: Section 2 provides the related literature on smart cities. Section 3 presents determinant factors in smart cities. Section 4 shows the applied research methods. Section 5 and 6 provide discussion on the results of the current study. Finally, section 7 underlines conclusions.

2. Literature review on smart cities' framework

There is a growing research trend to address the topic of smart cities in many different aspects (e.g.: Rana et al., 2019; Myeong et al. 2018; Saxena and Al-Tamimi, 2018; Yeh, 2017 and Rossi, 2016). For example, Saxena and Al-Tamimi (2018) used a qualitative approach to investigate initiatives across the six GCC countries to establish smart cities through conducting 13 interviewees from public and private sectors. They concluded that GCC countries are more interested in building smart cities and providing a high level of quality of life for their societies. Moreover, Rossi (2016) conducted a research using a case study approach to investigate the smart city initiatives of an Italian city, Turin. In Germany, another case study focusing on Dutch railway station areas was conducted by de Wijs et al. (2016) who applied in depth interviews to investigate smart cities' objectives. In Taiwan, Yeh (2017) used a questionnaire to investigate 1,091 citizens about their perceptions on smart cities and initiatives around these cities. Yeh (2017) reported the desire of citizens in the existence of smart cities with the availability of innovative services, privacy and high quality of life.

Furthermore, in India, Rana et al. (2018) employed an Analytic Hierarchy Process (AHP) technique to prioritise 31 barriers of smart cities development which divided over 6 categories. They reported 'Governance' as the most important category of barriers for smart city development, followed by 'Economic, 'Technology', 'Social', 'Environmental' and 'Legal and Ethical' category respectively. Besides, Myeong et al. (2018) used the analytic hierarchy analysis to investigate determinants of smart cities. The authors found that citizen involvement, leadership, and infrastructure are internal factors in smart cities while political system, stakeholders, and the fourth Industrial Revolution are external factors.

Fernandez-Guell et al. (2016, p. 46) defined smart cities as "those innovative urban systems that strategically invest in new technologies and human capital, seeking to improve services effectiveness, quality of life, economic competetiveness, environmental sustainability, and participatory governance". Furthermore, Saxena and Al-Tamimi (2018, p.238) identified four components of smart city which are "technology (to collect and manage new data sources, conduct analyses and use networked tools and technologies to manage cities), sustainability (adoption of a diversity of urban growth management policies), human and social capital (knowledge exchange, creativity and innovation) and governance (institutional preparation and community governance)". Concerning factors of smart cities, Chourabi et al. (2012, p.2289) identified 8 core factors which are "management and organization, technology, governance, policy context, people and communities, economy, built infrastructure, and natural environment".

Furthermore, Giffinger et al. (2007, p.12) suggested six components of smart city namely: "smart economy, smart people, smart governance, smart mobility, smart environment, and smart living". On the other hand, Bélissent (2010, p.1) identified 8 features for smart city as "transportation, healthcare, education, public safety and security, building management, city administration, waste management". The European Parliament of the European Union (EU) (2014) discussed components of smart cities and proposed a map within the EU countries and summarizes features of smart cities including governance, economy, mobility, environment, people, living. Based on the above discussions, it is clear that the concept and components of smart cities differ between researchers and among different bodies. Accordingly, the current study suggests five determinant factors of smart cities including: technological readiness (TECH); infrastructure (INFR); health and education (HHED); macroeconomic environment (MCEN) and innovation (INNV).

3. DETERMINANT FACTORS IN SMART CITIES

A. Technological readiness (TECH) factor

TECH is considered as one of the most important factors affecting smart cities. It is the key driver of smart city initiatives. According to Bifulco et al. (2016, p. 136), TECH is a fundamental feature with specific qualities as it is an across-the-board driver, specifically “a key enabler for cities to address these challenges in a ‘smart’ manner”. In this regard, Caragliu et al. (2011, p. 50) concluded that “we believe a city to be smart when investments in human and social capital and traditional (transport), TECH and communication, infrastructures fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance”. Schaffers et al. (2011) reported that Internet technologies and sustainability are the key interest in smart cities. Caragliu et al. (2011) argue that without advanced TECH there is no smart city that provides a high quality of life, with a sustainability for natural resources and environment, through a wise governance.

It can be argued that TECH is the lifeblood of smart cities and in the absence of modern technologies it is inconceivable, the presence of smart cities that offers smart solutions, quality level of citizens and protect the environment. Consequently, the current study expects TECH is the vial factor in smart cities while other factors should be built on advanced TECH such as INFR and MCEN.

B. Infrastructure (INFR) factor

The literature on smart cities indicates that INFR is one of the main dimensions in these cities (Myeong et al. 2018; Buntak et al. 2019). Bhattacharyay (2009) classified INFR into two categories, namely, hard and soft INFR. Concerning hard INFR, it consists of physical structures or facilities that support the society and economy; while soft INFR contains nontangible, social networks, and transparency and accountability. Hollands (2008) defines a smart city in terms of INFR network which improves economic and political efficiency and helps in furthering social, cultural and urban development. Further, Cavada et al. (2017) stated that it is recognized in smart cities that INFR is an essential prerequisite for sustainability, urbanization, digitization, innovation and a green environment. This confirmed also by several researchers such as Chourabi et al. (2012) and Saxena and Al-Tamimi (2018).

In Zimbabwe, Chakacha et al. (2014) used the qualitative approach to test the importance and effect of INFR on the quality and efficiency of the educational process. They indicated that the quality of INFR in primary schools is closely related to the quality of education in the higher stages in the future. Besides, Myeong et al. (2018) argued that INFR in smart cities should relate to advanced technology such as wireless communication, sensor, digital devices and the Internet of Things. Consequently, the current study expects INFR as one of the determinant factors in smart cities and should be built on a high level of technology.

C. Health and education (HHED) factor

HHED factor is a key element of smart cities initiatives. Education is one of the main factors in increasing the quality of people's lives and is helping to increase the efficiency and skills of individuals. In fact, education can play an essential role in achieving people's economic prosperity. It creates a positive impact on people's lives and provides them with employment opportunities and higher income. Therefore, its presence in smart cities is crucial (Aditya, 2016). As well, smart cities seek to provide high quality health services, a clean environment and green spaces (Sophie, 2018). In the same line, Bélissent (2010) indicated that HHED factor is essential for smart cities.

HHED factor is a key element of smart city initiatives (Bélissent, 2010). Education is a main factor in increasing the quality of people's lives and is a mean to increase the efficiency and skills of individuals. In fact, education can play an essential role in achieving people's economic prosperity. It creates a positive impact on people's lives and provides them with employment opportunities and higher income. Therefore, its presence in the smart cities is crucial (Aditya, 2016). As well, smart cities seek to provide high quality health services by providing a wide range of TECH, a clean environment and green spaces (Sophie, 2018).

D. Macroeconomic environment (MCEN) factor

Economy is a main nerve for the establishment of smart cities and is one of the most important characteristics of such cities which gives a strong competitive advantage for the continuation of these cities (Giffinger et al., 2007; Chourabi et al., 2012). On the other hand, the basic idea and purpose behind the establishment of smart cities is the best use of environmental resources and conservation of the environment and achieve sustainable development through the increase of green areas and the preservation of watercourses clean and rational use of smart energy (Bronstein, 2009; Hall, 2000). Several studies suggested the environment and sustainable development as features of smart cities (Giffinger et al., 2007; Chourabi et al., 2012). Besides, Buntak et al. (2019) argued that the economy is the main driver of all smart cities’ initiatives.

E. Innovation (INNV) factor

Large cities should make greater usage of innovation for improving the sustainability and efficiency of services provided. Nam and Pardo (2011, p. 185) pointed out that “A smart city is one with a comprehensive commitment to innovation in technology, management and policy. INNV for a smart city entails opportunities and risks at the same time”. Buntak et al. (2019) indicated that a smart city represents a spatial area that brings together TECH and people to improve INNV, learning, knowledge, and problem solving. Similar argument is provided by Myeong et al. (2018, p. 2) who indicated that "INNV in technology has always been at the heart of the implementation of new cities, including smart cities". Examples for INNV in a smart city can be seen in smart technologies as instrumentation with intelligent sensors, mobile technologies, virtual technologies, cloud computing, and digital networks (Yovanof and Hazapis, 2009).

Based on the previous discussion, the current study expects a positive relationship among the five determinant factors of smart cities through specific paths. Therefore, the following research hypothesis (H_1) is suggested:

H_1: The infrastructure and economy based on smart technology positively affect education & health and innovation factors.

4. Research Method

A. Sample and data collection

In the light of determinant factors in smart cities that are suggested in the above section, smart cities include five main factors which are TECH, INFR, HHED, MCEN and INNV. To evaluate these five factors in 13 MENA countries (Algeria, Cyprus, Egypt, Jordan, Kingdom of Bahrain, Kingdom of Saudi Arabia, Kuwait, Libya, Qatar, Sultanate of Oman, United Arab Emirates, Tunisia and Turkey), the current study gathered the required data through using the Global Competitiveness Report which issued by the World Economic Forum as the International Organization for Public-Private Cooperation. This organization was established in 1971 as a not-for-profit organization and is headquartered in Geneva, Switzerland. According to the Global Competitiveness Report (2017-2018, p.12), "The World Economic Forum has used the Global Competitiveness Index (GCI) combines 114 indicators. These indicators are grouped into 12 pillars. The current study employed the R-software to analyze the gathered data over a 7-year period, 2012-2018.

B. The path analysis

The path analysis was first introduced by Sewell Wright in 1920 (Kelloway, 1995; Hox 9). It is a method that can be used to build a model for the explanatory associations among observed variables. These variables are assumed to have no measurement error while the dependent variables should contain residuals errors that are an unexplained variation by the explanatory variables. In other words, the path analysis aims to estimate the size and significant hypothetical causal relations between group of variables (Bentler and Speckart, 1981; Byrne, 2013; Gana and Broc, 2019). In the current study, we applied the path analysis to examine the significant effects and causal relations between the determinant factors in smart cities (TECH, INFR, HHED, MCEN and INNV), consequently we designed our model as shown in Figure 1 below.

C. Design the hypothesized model

Based on the objective of current study, the design of the hypothesized model consists of five variables. The path analysis in Figure 1 illustrates H1 which is "INFR and MCEN based on TECH positively affect both HHED and INNV factors". In Figure 1, there are three paths where the variables MCEN, INFR, HHED and INNV depends on TECH in path. While, INFR, HHED and INNV depends on TECH in another path. Finally, INNV depends on TECH in last path.

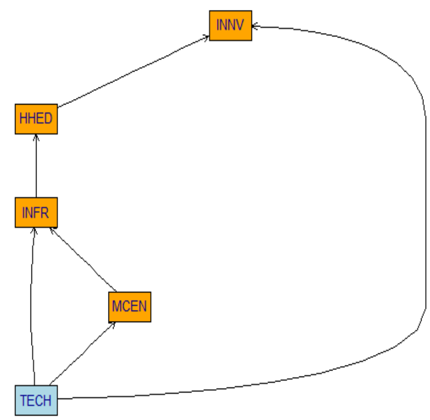

Figure 1. The hypothesized model of determinant factors of smart cities

Moreover, the hypothesized model can be written in system of equations as

$$MCEN = \beta_1 TECH + E_1$$
$$INFR = \beta_2 TECH + \beta_3 MCEN + E_2$$
$$HHED = \beta_4 INFR + E_3$$
$$INVV = \beta_5 HHED + \beta_6 TECH + E_4$$

Where $\beta_1, \ldots, \beta_6$ are coefficients and $E_1, \ldots, E_6$ are the residuals of the model.

5. Empirical Analysis and Discussion

A. Descriptive statistics and correlation

The descriptive analysis provides a picture of variables used in the current study. Further, correlation analysis helps to investigate the association among these variables. Table 1 shows the mean, variance and correlation for the five variables (TECH, INFR, MCEN, HHED and INNV) which reflect determinants of smart cities.

TABLE 1. CORRELATION MATRIX AND DESCRIPTIVE STATISTICS OF THE DETERMINANT FACTORS IN SMART CITIES

Variable	TECH	INFR	HHED	MCEN	INNV
TECH	1				
INFR	0.891	1			
HHED	0.719	0.769	1		
MCEN	0.342	0.461	0.324	1	
INNV	0.812	0.285	0.611	0.285	1
Mean	3.892	4.305	5.551	5.143	3.312
Variance	0.796	0.912	0.433	1.323	0.415

It can be noted that all the correlations for the five variables which represent determinant factors in smart cities are positive. The lowest correlation is 0.285 between MCEN and INFR. Also, the same correlation is revealed between INNV and INFR. The strongest revealed correlation is 0.891 between TECH and INFR. It is worth
mentioning that the ratio of largest variance to smallest variance is 1.323/0.415= 3.19. This indicates that the From Table 2, it can be noted that the standardized coefficients of the direct effects of TECH on MCEN, INFR and INNV are about 0.34, 0.83 and 0.77 respectively. For the level of INFR, one standard deviation above the mean is associated with HHED level about 0.77 standard deviation above the mean. A level of HHED one standard deviation above the mean is associated with INNV level about 0.06 standard deviation above the mean. Likewise, a level of MCEN one standard deviation above the mean is associated with INFR level about 0.18 standard deviation above the mean. Note that, the size of standardized direct effect of TECH on INFR is about 2.5
times of MCEN.

The minimum size of standardized direct effect is about 0.06 between HHED and INNV, while the maximum size of standardized direct effect is about 0.83 between TECH and INFR. In Table 2, the value of R^2 reflects percentage of explained variation for variables by its causes. This means that the proportion of explained variance for HHED by INFR is 59.4%. Similarly, the proportion of explained variance for MCEN by TECH is 12.3%, INFR by INFR and MCEN is 82.4% and INNV by TECH and HHED is 66.3%. Figure 2 below shows path analysis of the standardized estimates and disturbance variances of determinant factors in smart cities.

variation ratio among the variables are not too large and the correlation matrix is suitable for the path analysis (Kline, 1998).

B. The estimation of hypothesized model (Model 1)

The R-software was used to estimate Model 1 using the maximum likelihood method (Team, 2013; Holst et al., 2013). The results of unstandardized and standardized estimates of β, disturbance variances and p-values for the path model of determinant factors in smart cities are given in Table 2. It can be noted that the p-values of all paths are 0 except for HHED→INNV. This indicates that all paths are statistically significant at 0.01, 0.05 and 0.10 levels except for HHED→INNV path which is not statistically significant at all levels where 0.42 > 0.10.

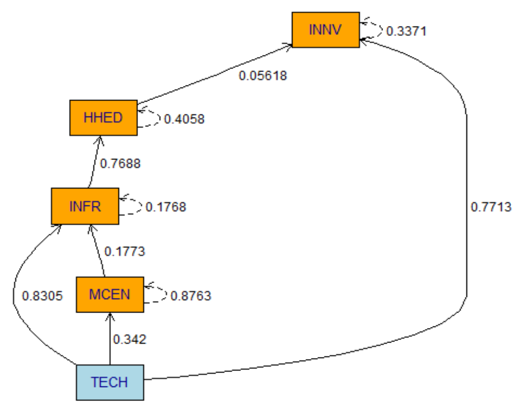

Figure 2. The standardized estimates and disturbance variances of determinant factors in smart cities using path analysis

C. The total effects of the variables in Model 1

The Total effects are the sum of all direct and indirect effects of one variable on another. The total effects of variables in Model 1 are shown in Table 3 and Table 4. Table 3 shows the total effects of TECH on MCEN, INFR, HHED and INNV. It can be noted that all effects of TECH on MCEN, INFR, HHED and INNV are statistically significant at 0.05 and 0.10 levels except for TECH→INVV is not significant at 0.05 or 0.10.

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TABLE 2. THE PATH ANALYSIS OF MODEL 1 FOR THE DETERMINANT FACTORS IN SMART CITIES

Parameter	UnStd β estimate	p-value	Std β estimate		Model fit Index	Value	p-value
TECH →MCEN	0.441	0	0.342		χ^2_M	5.93	0.204
TECH→INFR	0.889	0	0.831		df_M	4	
MCEN→INFR	0.147	0	0.177		RMSEA (90% CI)	0.061(0, 0.15)	0.348
INFR→HHED	0.529	0	0.769		GFI	0.997	
TECH→INNV	0.557	0	0.771		CFI	0.996	
HHED→INNV	0.055	0.42	0.056		SRMR	0.015	
	UnStd Dist. var	p-value	Std Dist. Var	R^2	AIC	796.05	
MCEN	1.159	0	0.876	0.123	BIC	824.72	
INFR	0.161	0	0.177	0.823	BIC(Adjusted)	793.10	
HHED	0.176	0	0.406	0.594			
INNV	0.140	0	0.337	0.663			

(*) Unstandardized (UnStd); standardized (Std) direct effect estimates of $\boldsymbol{\beta}$; disturbances; (Dist), variances (Var.).

TABLE 3. TOTAL EFFECTS OF TECH ON MCEN, INFR, HHED AND INNV VARIABLES

Variables	Estimate	Causal TECH Std err.	p-value
MCEN			
Direct	0.441	0.106	0
Indirect T.	-	-	-
Total	0.441	0.106	0
INFR			
Direct	0.889	0.042	0
Indirect T.	0.065	0.021	0.002
Variables	Estimate	Std err.	p-value
Total	0.954	0.043	0
HHED			
Direct	-	-	-
Indirect T.	0.505	0.043	0
Total	0.505	0.043	0
INNV			
Direct	0.557	0.037	0
Indirect T.	0.027	0.035	0.424
Total	0.585	0.037	0

(*) Standard errors (Std err) & Total: (T.).

TABLE 4. TOTAL EFFECTS OF MCEN, INFR AND HHED ON INFR, HHED AND INNV VARIABLES

					Causal				
		MCEN			INFR			HHED	
Variables	Est.	Std err	pValue	Est.	Std err	p-value	Est.	Std err	p-value
INFR									
Direct	0.147	0.033	0	-	-	-	-	-	-

E-mail:author's email

Indirect T.	-	-	-	-	-	-	-	-	-
Total	0.147	0.033	0	-	-	-	-	-	-
HHED									
Direct	-	-	-	0.529	0.038	0	-	-	-
Indirect T.	0.078	0.018	0	-	-	-	-	-	-
Total	0.078	0.018	0	0.529	0.038	0	-	-	-
INNV									
Direct	0.004	0.005	0.43	-	-	-	0.055	0.069	0.423
Indirect T.	-	-	-	0.029	0.036	0.424	-	-	-
Total	0.004	0.005	0.43	0.029	0.036	0.424	0.055	0.069	0.423

(*) Standard errors (Std err); Estimate (Est.) & Total (T.).

Moreover, Table 4 above shows the total effects of MCEN, INFR and HHED on INFR, HHED and INNV. There is a direct effect of TECH on INNV (0.557) and two indirect effect via INFR-HHED (0.026). The path (MCEN-INFR-HHED) (0.002) that gives total effect equals 0.585. Also, there is no direct effect between TECH and HHED, but there are two indirect effects via INFR (0.470) and MCEN-INFR (0.035) that gives total effect is 0.505. All effects of MCEN, INFR and HHED on INFR, HHED and INNV are statistically significant at 0.05 except for MCEN→INNV, INFR→INNV and HHED→INNV are significant only at 0.10 level.

D. The goodness of fit for Model 1

Values of fit statistics of Model 1 are presented in Table 2. Note that, a good model fit would provide insignificant results at pre-specified level of significant for chi-square test (χ^2_M), the value of root mean square error of approximation (RMSEA) should be ≤ 0.08, goodness of fit index (GFI) is ≥ 0.95 and comparative fit index (CFI) is ≥ 0.95 (Hu and Bentler, 1999). For Model 1, the p-value is 0.204 more than 0.01, 0.05 and 0.10 levels, the value of the RMSEA is 0.06 with p-value of 0.348, GFI of 99.7% and CFI of 99.6%. Consequently, the goodness of fit Model 1 confirms that H1 in our study cannot be rejected. Moreover, RMSEA reflects how well the model would fit the population covariance, GFI reflects the proportion of variance that is accounted for the estimated population covariance and CFI compares the sample covariance structure with null model (see for example, Bentler and Speckart, 1981; Bollen and Long, 1993; Joreskog, 1993 and MacCallum et al. 1996).

6. Modified model (Model 2)

Because Model 1 has the path HHED→INNV which is not significant, we look for an alternative path that can be statistically significant. After several trails, the modified model (Model 2) gives better fit over Model 1 with significant paths. The system of equations for Model 2 can be written as follows:

$$MCEN = \beta_{11} TECH + E_{11}$$
$$INFR = \beta_{22} TECH + \beta_{33} MCEN + E_{22}$$
$$HHED = \beta_{44} INFR + E_{33}$$
$$INVV = \beta_{55} INFR + \beta_{66} TECH + E_{44}$$

Where $\beta_{11}, \ldots, \beta_{66}$ are coefficients and $E_{11}, \ldots, E_{66}$ are the residuals of Model 2.

It can be noted that the path HHED→INNV is replaced by the path INFR→INNV.

A. The estimation of Model 2

The results of unstandardized and standardized estimates of β, disturbance variances, p-values and model fit for Model 2 of determinant factors in smart cities are given in Figure 3 and Table 5. It can be noted that the p-values of all paths are less than 0.05 in Table 5. This indicates that all paths are statistically significant at 0.05 and 0.10 levels.

In Table 5, the values of R^2 reflects percentage of explained variation for variables by its causes. This means that the proportion of explained variance for HHED by INFR is about 59%. Similarly, the proportion of explained variance for MCEN by TECH is about 12%, INFR by TECH and MCEN is about 82% and INNV by TECH and INFR is about 67%.

For a level of INFR, one standard deviation above the mean is associated with HHED level about 0.77 standard deviation above its mean. Also, an increase one standard deviation above the mean in the level of INFR is associated with INNV level about 0.23 standard deviation above its mean. Likewise, an increase one standard deviation above the mean in the level of level MCEN above the mean is associated with INFR level about 0.18 standard deviation above the mean.

From Figure 3, it can be noted that the size of standardized direct effect of TECH on INFR is about 1.5 times that of INNV. The minimum size of standardized direct effect is about 0.18 between MCEN and INFR while the maximum size of standardized direct effect is about 0.83 between TECH and INFR.

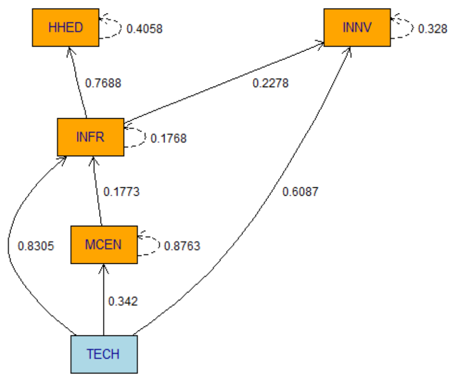

Figure 3 The standardized estimates and disturbance variances of determinant factors in smart cities for path analysis of Model 2.

Furthermore, from Figure 3, the standardized coefficients for the direct effects of TECH on MCEN, INFR and INNV are about 0.34, 0.83 and 0.61 respectively. These coefficients have the same meaning as discussed in a previous section (See: 5.2 above).

Table 5 The statistical analysis of Model 2 for determinant factors in smart cities

Parameter	UnStd β estimate	P-value	Std β estimate		Model fit Index	Value	p-value
TECH →MCEN	0.441	0	0.342		χ^2_M	2.37	0.498
TECH→INFR	0.889	0	0.830		df_M	3	
MCEN→INFR	0.147	0	0.177		RMSEA (90% CI)	0(0, 0.13)	0.625
INFR→HHED	0.529	0	0.769		GFI	1	
TECH→INNV	0.440	0	0.609		CFI	1	
INFR→INNV	0.154	0.04	0.228		SRMR	0.015	
	UnStd Dist. var	p-value	Std Dist. Var	R^2	AIC	794.5	
MCEN	1.160	0	0.876	0.121	BIC	826.03	
INFR	0.161	0	0.177	0.822	BIC(Adjusted)	791.24	
HHED	0.176	0	0.406	0.591			
INNV	0.136	0	0.328	0.670			

(*) Unstandardized (UnStd); standardized (Std) direct effect estimates of $\boldsymbol{\beta}$; disturbances; (Dist), variances (Var.).

B. Total effects of the variables in Model 2

Table 6 shows the total effects of TECH variable on other variables (MCEN, INFR, HHED and INNV). For example, the effect of TECH on INFR is direct with a coefficient of 0.889 and it has also an indirect effect with a coefficient of 0.065 which gives the total effect of TECH on INFR is 0.954. It can be noted that all effects of TECH on MCEN, INFR, HHED and INNV are statistically significant at 0.05 and 0.10 levels.

TABLE 6. TOTAL EFFECTS OF TECH ON MCEN, INFR, HHED AND INNV VARIABLES

variables	Causal TECH estimate	Std error*	p-value
MCEN			
Direct	0.441	0.106	0
Indirect T*.	-	-	-
Total	0.441	0.106	0
INFR			
Direct	0.889	0.042	0
Indirect T.	0.065	0.021	0.002
Total	0.954	0.043	0
HHED			
Direct	-	-	-
Indirect T.	0.505	0.043	0
Total	0.505	0.043	0
INNV			
Direct	0.440	0.080	0
Indirect T.	0.147	0.072	0.041
Total	0.587	0.037	0

(*) Standard errors (Std err), and T: Total

Concerning effects of MCEN and INFR on INFR, HHED and INNV, Table 7 shows that these effects are statistically significant at 0.05 except for MCEN→INNV which is significance only at 0.10 level. Furthermore, Table 7 shows that there is no direct effect between MCEN and INNV while there is an indirect effect of 0.022.

TABLE 7. TOTAL EFFECTS OF MCEN AND INFR ON INFR, HHED AND INNV VARIABLES

				Causal		
				MCEN		
variable	Est.	Std err	p-value	Est.	Std err	p-value
INFR						
Direct	0.147	0.033	0	-	-	-
Indirect T.	-	-	-	-	-	-
Total	0.147	0.033	0	-	-	-
HHED						
Direct	-	-	-	0.529	0.038	0
Indirect T.	0.078	0.018	0	-	-	-
Total	0.078	0.018	0	0.529	0.038	0
INNV						
Direct	-	-	-	0.154	0.075	0.04
Indirect T.	0.022	0.012	0.06	-	-	-
Total	0.022	0.012	0.06	0.154	0.075	0.04

(*) Standard errors (Std err), Estimate (Est.) and Total (T.)

C. The goodness of fit for Model 2

Values of fit statistics for Model 2 was reported in Table 5. For Model 2, it shows that the p-value is 0.498 (more than 0.01, 0.05 and 0.10 levels), the value of the RMSEA is 0 with p-value 0.625, GFI is 100% and CFI is 100%. Based on the above figures, the goodness of fit for Model 2 confirmed that H1 cannot be rejected. The two models are doing well but in terms of χ^2_M, RMSEA, GFI and CFI, Model 2 gives better results than Model 1. To distinguish and compare between the two models, we used the values of Akiake information criteria (AIC), Bayesian information criterial and Bayesian criteria adjusted by sample size (BIC-adjusted) reported in Table 2 and Table 5. Consequently, the model which has less AIC, BIC and BIC-adjusted should be preferred than the other one (Kline, 1998; Hu and Bentler, 1999). From Table 2 and Table 5 above, it can be noted that AIC and BIC-adjusted for Model 2 is less than AIC and BIC-adjusted for the original model while BIC for Model 1 is less than BIC for Model 2. There are two criteria in favour of Model 2, consequently, Model 2 is preferred to Model 1. In addition, in Model 2, chi-square value (2.37) is less than that value (5.93) in Model 1. Some studies argues that the exact fit for the model is obtained when the value of model chi square is 0 (Bollen and Long, 1993; Bentler, 2007).

7. Conclusions

Due to rapid changes and developments in our life, there is no general agreement on the definition of smart cities or their components. Our study examined determinant factors in smart cities using a sample of 13 countries from MENA region during a period of 7 years, 2012-2018. The study suggested five determinant factors in smart cities which are TECH; INFR; HHED; MCEN and INNV. Our study ran two models with different paths. The first model has three paths; however, one of the three paths is not significant at the common levels of significance. The second model has four paths and all of them are statistically significant at 0.05 level. The main finding of the study is that the INNV and MMCEN based on TECH positively affect HHED and INNV factors. The current study is subject to a number of limitations. First, it was conducted in a sample of MENA countries, consequently generalizing its results needs a careful action. The sample size of this study might be expanded by including all countries on MENA area. This could enable researcher to compare the results among a wide range of MENA countries. Second, although the current study may contribute to understanding determinant factors in smart cities using five factors, other determinant factors need to be considered in a future research.

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