Conceptual Smart City KPI Model: A System Dynamics Modelling Approach

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***Abstract*—Smart City is becoming increasingly popular all over the word, gaining the status of paradigm for steering urban and regional strategies oriented to improve the citizens' quality of life through IT-led solutions. Despite of its international relevance, still consensus on its most significant components and their reciprocal influence does not exist. Building on a wide scholarship on Key Performance Indicators (KPI) for Smart Cities, this paper suggests that System Dynamics could provide an appropriate conceptual model for interpreting the dynamic interconnections among the core components of a Smart City -i.e., Smart Infrastructures, Smart Institutions and Smart People-. At this goal, this paper offers a novel application of System Dynamic, which is used to analyze a robust set of new data, collected in three different cities. The model allows modelling and interpreting the role played by each component in implementing the Smart City paradigm and offers a new perspective on how to diversify the concept of Smart City according to site-specific conditions. Findings show that whilst a Smart City in a mature stage is highly influenced by the people and the infrastructure, for a Smart City in a developing country it is mainly the smart infrastructure component that shall be emphasized.**

Keywords—Smart City Innovation, Sustainable Urban Development, System Dynamics, Smart Infrastructure, Smart Institution, Smart People

I. INTRODUCTION

Global demographic projections show an increase of urban residents, due to natural growth combined with rural population moving to cities. This trend posites a challenge but also represents an opportunity to address sustainable urban development with greater impact on the wider environment. Having an efficient organisation of cities in place is therefore imperative. By adopting the Smart City concept, there is a widespread aspiration that chances to make cities more capable to meet people needs and to pursue sustainable development goals will be increased. This should be achieved by adopting innovative technologies enabling stakeholders to re-cast the concept of urbanization and development through Smart and Sustainable City evolution. Batty [1] in using the systems' theory to explain the paradigm shift in the evolution of cities, described cities as complex systems organically growing through a bottom up dynamic, in contrast to the top down approach [3]. In this context, cities are regarded as different kinds of features knotted together in sets of interactions.

Whereas the adoption of Smart City concept has gained traction all over the world, there is currently no reliable existing framework model of indicators to measure the impacts of smartness or how intelligent cities have become; neither has any research effort addressed the summarisation of existing models [4]. The development of framework models that consider the dynamic and interrelated impacts of the core components of Smart Cities to support timely decision-making among stakeholders is still an open research subject.

In this paper, we build on the novel framework for Key Performance Indicators (KPIs) for measuring the impacts of Smart Cities in Emerging Economies [2] utilising the core factors and indicators established from the sequential methodologies adopted for the investigation. The purpose of this work is to explain the causal relationships among the core components of Smart Cities through System Dynamics' modelling and simulation. The remaining part of this paper is organised into four main sections. Section II provides background information and state of the art in the Smart City and System Dynamics' modelling approaches. Section III discusses methods, data and the models. Section IV presents case study results and the model equations from the simulations. Finally, Section V summarises the conclusion and presents the direction for future research work.

II. BACKGROUND

A. Smart City Definition

Smart City is an important area of research that has elicited significant interest among researchers. There have been several definitions of the term 'Smart City'. A well-known definition is the one proposed by Forrester, according to which a Smart City can be defined through 'the use of smart computing technologies to make the critical infrastructure components and services of a city – which include city administration, education, healthcare, public safety, real estate, transportation, and utilities – more intelligent, interconnected, and efficient' [5]. Another leading definition is the one proposed by IBM [6], which reflects the industry perspective: 'a Smarter City uses technology to transform its core systems and optimize resources. Smarter Cities are knowledge-based systems that provide real-time insights to stakeholders, as well as enabling decision makers to proactively manage the city's sub-systems. This is a definition that has been made at the highest levels of maturity. Effective information management is critical to this this capability, and key enablers include integration and analytics' [7].

Lee et al. [8] cited a Gartner definition which states that 'a Smart City is based on an intelligent exchange of information that flows between its many different subsystems. This flow of information is analysed and translated into citizen and commercial services. The city will act on this information flow to make its wider ecosystem more resource-efficient and sustainable. The information exchange is based on a smart governance operating framework designed for sustainable cities'. According to the authors, the concept of Smart City derives its definition from a variety of terms such as: ubiquitous city, knowledge city, information city, intelligent city, digital city, and information city. After a critical review of the different attributes of the Smart City concept, the authors concluded that 'Smart Cities are envisioned as creating a better, more sustainable city, in which people's quality of life is higher, their environment more livable and their economic prospects stronger'.

According to Chourabi et al. [9] the Smart City concept connects a variety of different infrastructures in the wider meaning of the term (from business to the physical, from the social to the IT), to exploit the potential of the collective intelligence of the city. Batty et al. [10] noted that Smart Cities are simply 'instruments for improving competitiveness in such a way that community and quality of life are enhanced'. The International Telecommunications Union (ITU) also sought to achieve a shared definition of Smart and Sustainable Cities and at this aim it analysed over 100 publications [7] through a ITU's focused group analysis, thus discovering that Smart City definitions kept revolving around 50 keywords like ICT, quality of life, systems, management, technology, intelligent, integrate, innovations, etc.

In summary, a major aim for Smart Cities is to ensure improved services and quality of life, hence the concept of the Smart City is clearly related to the objective to improve the quality of life in today's densely populated cities around the globe, and to overcome exclusion in the access to the basic services. In this context, it is crucial for Smart Cities to leverage on social innovation and emerging technologies such as the Internet of Things (IoTs), Cloud Computing, Open Data, Big Data analytics, and the Cloud of Things as platforms for pursuing integrated solutions and achieving sustainable urban development.

B. Assessing Smart City Standards: a Framework

There is a growing interest and debate about standardizing the metrics for monitoring cities' development, from which different perspectives have emerged. As an example, City Protocol has developed a hierarchical model for city governance, evaluation, and transformation [11]. This model combined the original City Anatomy CPA-I 001 body of knowledge, Anatomy Indicators CPA-PR 002, Anatomy Ontology CPAPR 003, and Livable District CPC 004, etc. As expected, cities in different regions of the world are unique and present different developmental challenges based on their experience and history. For instance, some deal with challenges of congestion, insecurity, and energy while others deal with challenges such as environmental pollution [12]. The issue of measuring and monitoring the smartness of the cities has been resolved by releasing standards, which now include the ISO-37101 Sustainable Development and Resilience Communities – Management Systems; ISO-37120 standard for the Sustainable Development and Resilience of Communities - Global City Indicators for Service and Quality of Life; NIST – Internet of Things (IoT) Enabled Smart City Framework; ITU Smart Sustainable Cities; Spanish Standards (AENOR) – UNE 178301 on Open Data; and UNE 178303 Requirements for Municipal's Asset Management, etc. A comprehensive discussion on Smart City standards and frameworks for impact assessment has been developed in previous studies, leading to propose a novel KPIs framework enabling to measure impacts of Smart Cities in Emerging Economies [2].

C. Smart City Initiative as Complex Systems in Need of a System Dynamics' Approach

As planners and environmental evaluators, Lombardi et al. [13] in their work on modelling Smart Cities' performance, argued that a city is a complex system and the complexity is a result of some unpredictable interactions. According to these authors, the complex systems of cities exhibit unpredictable behaviours from which, when certain actions are taken, it is possible to generate feedback. Complexity, according to Dodgson and Gann [14], increases with diversity and these authors feel that approaches are required that are adaptive and collaborative in nature. In addition, the complex system of a city is a valuable image when related to the evolution of information systems [15]. Assessing the performance of Smart Cities, therefore, requires a complex model that can address the core components of cities for effective decision-making.

Exploring the systems' approach as described in different bodies of work (for example in the works of Harrison and Donnelly [15] and Dodgson and Gann [14]) and assessing the performance of cities can be achieved effectively through the modelling of the core sub-systems of a city in order to simplify the complex systems of the Smart City innovation. Interestingly, systems' science scholars such as Sterman [16] recommend modelling as a means of simplifying the complex processes and the ways of making responses quicker and more effective. Sterman suggested modelling as complement to other tools and not to be used as a substitute.

Because cities are organic in the way they evolve over time, a systems' dynamic approach is suitable for assessing the innovation ecosystems of cities in order to provide guidance for planners, policy makers and innovators on the appropriate course of actions in all their efforts to make cities more liveable and sustainable.

D. *The Need for a System Dynamics Approach in Smart Cities*

System Dynamics relates to research on system information feedback and an approach to solving problems inherent in systems. The complexity of cities as systems in this scenario relates to the issue of clarity of the level of interaction among the city sub-systems over time. System Dynamics, according to Vafa-Arani et al. [17], is one the best tools for modelling socio-economic problems with complex characteristics. Thus System Dynamics is a methodology and a mathematical modelling approach to discover the behaviour of complex systems over time. In system dynamics therefore, the structure of a system is about the relationships that exist among the system components which, in this case, has direct implications for the causal relationships among the core components of Smart Cities which is the major concern of this study.

As emphasised in the previous section, cities and the current wave of Smart City innovation is very complex and dynamic in nature. As Chao and Zishan[18] argued, in their system dynamics model for passenger transportation structure evolution for Shanghai city, relying solely on qualitative and quantitative research methods for analysing or solving problems comes with certain limitations. Thus, there is a need for a system dynamics' approach built on a good combination of both quantitative and qualitative methods.

In addition, one of the key objectives of Smart City innovation is to de-risk investments [19]. Thus, a system dynamics' approach seeks to simplify reality requiring effective solutions with clear-cut baselines for creating transparency and quantifying metrics of all actions suitable for studying the dynamism of the core factors of Smart Cities.

E. *System Dynamics and its Applications*

In recent years, system dynamic methods have found applications in different fields for policy analysis and design. A System Dynamics' approach has been widely applied in different fields to gain better understandings of systems with dynamic, complex, and interacting with nonlinear variables [20]. The System Dynamics' methodology, according to Xu and Coors [20], has been applied in telecommunications, software engineering, energy and power production systems, performance evaluation, policy analysis, etc. System Dynamics are growing at an exponential rate spreading to many areas as people appreciate their ability to represent the real-world (Forrester [21]). The system dynamics' methodology, according to Sterman [16], was originally developed in the 1950s to assist industry leaders in improving their understanding of the behaviour of complex social systems especially in the industrial context. As noted by Forrester [21], System Dynamics have developed from systems' thinking as a modelling method and it is an aspect of systems' theory that deals with a method for understanding the dynamism of complex systems.

System Dynamics, according to Sterman [16], can be applied to any dynamic system. This author cited use cases in corporate strategy formulation, healthcare related policies, and the automobile industry where the approach has been applied successfully. According to Fiksel [22], in developing strategies for economic growth, environmental sustainability, and a host of other challenges, the system dynamics' approach has been adopted by researchers to comprehend a holistic view of policies and development.

In the built environment, urban dynamics was the first modelling work produced by the earliest system scientists at MIT that generated strong emotional reactions (Forrester [23]). In addressing environmental problems, the system dynamics' method is being applied to ecological problems. For instance, in the work of Park and Kim [24], using the System Dynamics' approach in modelling the management policy implementation of a water supply system, the authors analysed the effects of investment on water quality improvements for a city region in Busam, South Korea and concluded that the System Dynamics' model helped to quantify the benefits of the investment in the efficient waste-water treatment in the upstream sector for the city. In this study, the System Dynamics' principle is adopted to assess and interpret the causal relationships that exist among the core components of Smart Cities.

F. *Application of a System Dynamics Approach in Smart Cities*

The application of a System Dynamics' methodology in addressing the complex problems of cities is no longer new. For instance, Tsolakis and Anthopoulos [25], in their integrated framework for an "eco-city", adopted a System Dynamics' methodology to assess the sustainability of an eco-city in order to assist policy makers and urban planners on effective policies for monitoring and assessing the sustainability performance of eco-cities. The holistic System Dynamics' methodological framework used case study data generated from a multi-method approach in Hsmichu city, Taiwan and in Tiamjin city in China. Similarly Chao and Zishan [18], in proposing the Shanghai passenger transportation structure evolution model, applied the System Dynamics' approach based on transportation survey data to validate their proposed model for a passenger transportation structure.

In environmental sustainability, which is at the core of Smart City innovation, Saysel et al. [26] employed the System Dynamics' methodology for an experimental analysis of a long-term environmental sustainability in policy making. The authors addressed a range of issues related to regional agricultural projects and water resource development but the analysis was focused on the totality of the environmental, social, and economic-related issues. In addition, Chen et al. [27] applied the concept of System Dynamics to analyse the causal relationships of air pollution problems resulting from transportation and the complex system of urban development. Their proposed sustainable urban development model for assessing air purification policies for Taipei city was based on System Dynamics' modelling.

The previous sections suggest that the main focus of System Dynamics is to understand how system components interact, how the changes in one component impact on the other components, and how such changes affect the entire system [28]. The interactions in System Dynamics are based on the three building blocks (modes) of positive feedback (reinforcing loops), negative feedback (balancing loops) and delay (negative feedback with delay). Other more complex patterns of behaviour, according to Sterman [16], arise due to the nonlinear interaction among these structures. System

Dynamics' models can be qualitative (conceptualisation) or quantitative. System scientists have argued that a quantified simulation model is always superior to a qualitative model [29]. While a qualitative model is mainly utilised for creating cause-effects diagrams, quantitative models are devoted to simulation. The qualitative and quantitative data collection for System Dynamics can also incorporate interviews, surveys, focus groups, experiments, and observation [30]. In this study, a variety of these data collection approaches was employed during the field investigation.

III. Methods, Data and the Model

This study uses a multi-case study approach within the three cities of Boston, Abuja and Manchester to establish the core components of Smart Cities and the associated factors and indicators for assessing the impacts of smartness. After analyzing the feedback from the pilot study with stakeholders in Federal Capital Territory (FCT) Abuja, a 3-component factor was established (see Table 1). The general structure of the model is based on the outcomes from the empirical data from the case study analysis and the correlation analysis of the survey components conducted in Abuja to validate the core factors/indicators of Smart City KPIs extracted from the literature and experts' interviews.

TABLE 1: STRUCTURE COEFFICIENT OF EXTRACTED COMPONENTS

Item	Component		
	1	2	3
SCOMP5	0.955		
SCOMP8	0.955		
SCOMP3	0.949		
SCOMP13	0.933		
SCOMP18	0.927		
SCOMP19	0.923		
SCOMP17	0.922		
SCOMP10	0.884		
SCOMP9	0.71		
SCOMP14	0.651		
SCOMP7	0.394	0.907	
SCOMP6	0.336	0.905	
SCOMP4	0.397	0.903	
SCOMP12	0.395	0.901	
SCOMP15	0.375	0.868	
SCOMP1	0.449	0.864	
SCOMP11			0.994
SCOMP16			0.993
SCOMP2			0.991

The case study analysis and the survey covered the core Smart City stakeholders in the ICT Industry, Urban Planning and in academia (see Table 2).

TABLE 2: SUMMARY OF PRIMARY DATA COLLECTION: NUMBER OF RESPONDENTS

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	ICT Industry	37	35.2	35.2	35.2
	City Admin	36	34.3	34.3	69.5
	Academia	32	30.5	30.5	100
	Total	105	100	100	

For the modelling and simulations, the System Dynamics' software application Vensim PLE was employed in this study. Vensim is an interactive software/simulation environment that allows for the exploration, development, analysis and optimisation of the simulation models [31]. Vensim was developed to help system scientists in improving the quality and understanding of models. It was introduced to assist in solving problems from a systems' perspective. The modelling environment utilising Vensim includes provisions for defining qualitative and quantitative tests, as well as the automatic execution of a test on a simulation model called a reality check [32]. It also includes a method for the interactive tracing of behaviour in a model structure through causal links [32]. The reality check allows users to automatically perform validity tests. The test in this case takes the form: "if test input A is imposed on a valid model, then behaviour B will result". However, this only refers to the behaviour and not the structure. Further information on using Vensim for System Dynamics modelling can be found in the work of Eberlein and Peterson [31].

A. *Causal Loop Diagram and Stock and Flow Maps*

A systems scientist, Sterman [16], argued that model boundary charts and sub-system diagrams show the boundaries and the architecture of a model, however they do not show how the variables are related. Thus, causal loop diagrams are flexible and useful tools for diagrammatically representing the feedback structure of systems in any given domain. They are simply maps indicating the causal links that exist among the variables. The arrows of the causal links point from a cause point to an effect. Fig. 1 depicts the feedback flow map for a typical Smart City initiative.

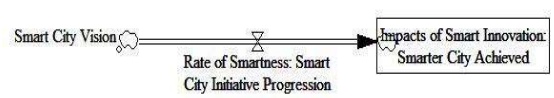

Fig. 1: Feedback Flow Map for Smart City Initiative

B. *Designing the Model Structure and Stating the Assumptions*

Models can be classified in different ways and according to different criteria which includes physical or symbolic, dynamic or static, deterministic or stochastic factors and so on [33]. With respect to validity, [33] Barlas emphasised that a choice must be made between "causal-descriptive" models that are purely theory-like ("White-Box") and correlational models that are purely data-driven ("Black-Box"). On the one hand, the concern of the correlation model is the aggregate output behaviour and the model is assessed for validity based on the matches between its output and the "real" output within some specified range of accuracy, in which case there is no recourse to the validity of the individual relationships that exist in the model. A good example of this type of model is the regression model. A causal-descriptive model, on the other hand, refers to statements on how the real system actually operates in some aspects.

As emphasised by Sterman [34], most of the critical assumptions in any model, whether mental or formal, are the implicit ones buried deeply in the system. These assumptions are usually not known to the modelers and they are not in the model equation or its documentation. In any case, it is important to make clear assumptions about the variables in order to clearly define their boundaries and to provide the required information on them. Fig. 2 represents some simplified assumptions as follows:

- The smartness of a city as a result of innovation depends on the rate of smart initiatives.

- A smart City vision flows to rate of smartness initiatives.
- A smart City (a final smarter city) improves by the rate of smartness, and
- The rate of smartness is a function of a Smart City vision or goal and a final smarter city achieved.

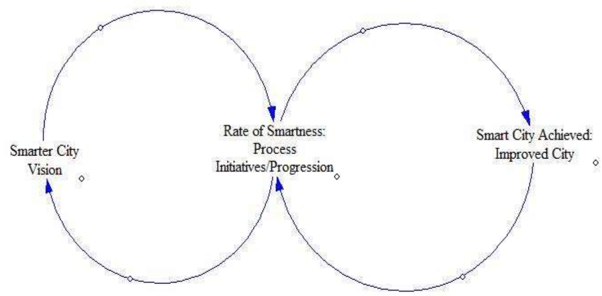

Fig. 2: Causal Loop Diagram for the Smart City Initiative

As captured in the model boundary, the first and most important assumption is the model's scope and the focus. Thus, it places more emphasis and the research focus on the working mechanism of the core components - Infrastructure, Institution and People - within the Smart City innovation. An enabling environment for Smart City innovation is another key important boundary assumption. The third important assumption are the units described as factors and the indicators in the model. In order to explain the causal relationships amongst the components, the hypothetical model developed for the simulation was continually revised to examine the effects.

C. *Model Testing and Validation*

In order to establish confidence in the accuracy, soundness and usefulness of a model, it is imperative to conduct model validation and testing. The techniques commonly used for model testing and validation include tests of model structure and tests of model behaviour. The tests, according to Senge and Forrester [35], can be further classified into a model structure verification test, a model parameter verification test, a model extreme-condition test, a model adequacy test, a model dimensional consistency test, a model behaviour prediction test, etc. Model testing is considered an essential part of the modelling process in System Dynamics to enable validation mainly to uncover errors and to improve on the model, and to understand the limitation of the model in order to assist in decision making [16]. The tests conducted in this study using Vensim are summarised as follows:

1) Model Structure Verification Test: The model structure verification test must not contradict the knowledge about the structure of the real system. The verification may include comparisons of the model assumptions with descriptions of decision-making and relationships found in relevant literature [35]. It is important to note here that the Vensim application used for the model and simulation in this study has in-built mechanisms for model testing and validation. Thus, all the models were properly checked and verified "ok" showing the causal relationships between, and the influence of, the variables on one another as shown in the diagrams. The relationships were guided by the results from the correlation analysis conducted for the variables which eliminated a number of factors with weak correlation (relationship) in the models. The tests for the model's structure were confirmed "ok" in all the diagrams as shown in Fig. 3a. In addition, the model's dimensional consistency was also checked.

2) Model Parameter Verification Test: In System Dynamics, parameter verification is mainly concerned with determining whether or not the parameters of the model correspond conceptually with real life by comparing the model parameters to the knowledge of the real system [35]. Parameter verification and structure verification tests are interrelated. As a systems' scientist [16] has suggested, a wide range of methods (such as the use of statistical methods) are available for System Dynamics' parameter verification. The other methods include judgemental (based on interviews), focus groups' experience, retrieval, experts' opinion amongst other methods. In this study, a number of these methods were employed to establish the core factors and indicators for Smart City assessment metrics starting from literature evidence established by renowned Smart Cities' scholars and Smart City standards, outcome of a pilot study, and experts' interviews with key Smart City stakeholders in Boston, FCT Abuja (with the survey component) and Manchester respectively. The outcomes of the field investigation were properly analysed using appropriate statistical tools and techniques.

3) Model Extreme-Condition Verification Test: As noted by Senge and Forrester [35], structures in System Dynamics' models should permit consistency in performance even in unusual extreme cases. Sterman [16] suggested the need to test if the model responds plausibly to extreme policies, shocks and parameters. Following established procedures, the model equations and the simulations in this study were tested at extremely low at "0" level and high at "100" level. Based on the outcomes, the models performed very well.

D. *The Stock and Flow Diagram for the Smart City KPI Model*

This section discusses the stock and flow diagram for the proposed Smart City KPI model. The discussion covers the model diagrams for the Smart Infrastructure, the Smart Institution, and the Smart People components respectively. The two fundamental concepts within the System Dynamics' theory are the stocks and flows and the feedback [16]. The causal relationships among the elements of the System Dynamics' models are represented in a stock and flow diagram with algebraic representation for simulation in order to enhance the analysis of the relationships among the elements of the model.

The core factors and indicators of Smart City KPIs were established through correlation analysis using SPSS and the outcome of the content analysis. Thus, to simulate the relationships among the core factors and indicators, the stock and flow diagram for the Smart City was developed using Vensim software as a modelling tool (see Fig. 3a). It is important to note here that the variables included in the stock and flow diagram for the System Dynamics' model are variables established from the correlation analysis with strong correlation coefficients and these variables were also confirmed by the experts' interviews. The factors and indicators with weak correlation coefficients and those not mentioned or apparent from the experts' interviews were not included in the stock and flow diagrams. To assess the impacts of one variable on the other parts of the model, simulations were run to determine the criticality of a particular variable over another and the entire model.

Based on the individual models, Smart Infrastructure was established as having four critical factors, namely Availability of ICT Infrastructure, Environmental Sustainability, Constant Power Supply, and Secured and Innovative Transport Systems, with each of the factors further established with measures of the core indicators. Similarly, Smart Institution was established as having three critical factors namely Transparent Governance, Entrepreneurship and Sustainable Development, and Productivity; also with measures of the core indicators. Lastly, Smart People was established as having four critical factors namely Quality of Life, Productivity, Quality Education, and An Environment that Supports Productivity together with their respective measures of indicators. The individual component factors were modeled and tested "ok" prior to the general model described in Fig. 3a. All the different factors from the three distinct components and their corresponding variables (indicators) were used to model the dynamic KPI model for assessing Smart Cities. The overall model was also tested "OK" as depicted in Fig. 3a.

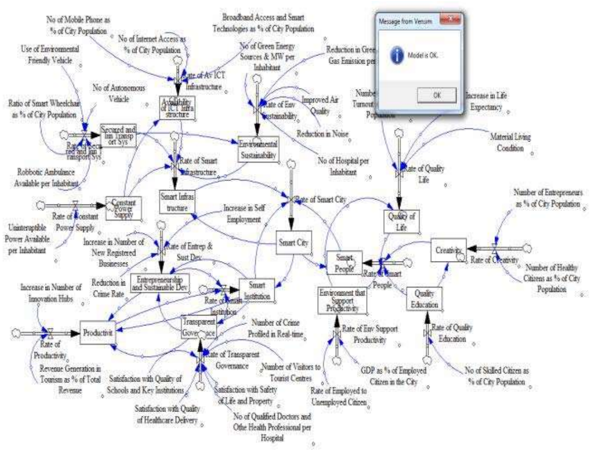

Fig. 3a: Dynamic KPI Model for Assessing Smart Cities

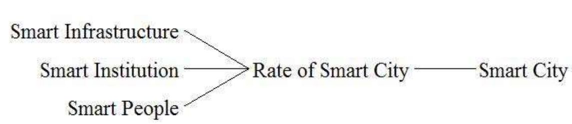

Fig. 3b: Tree Diagram of the Dynamics' Model for Smart Cities

The Tree Diagram in Fig. 3b above shows the variables that drive the performance of the rate of Smart City from the causal loop diagram of the stock and flow in Fig. 3a. The equation for the model is given by:

Smart City = INTEG (Smart City^0.5+Rate of Smart City).
The unit is given by:
Units: "percent" [0, 100].

The equation of dynamic KPI is shown as follows.

$$SC_{grow} = \int \left(SC_0^{\frac{1}{2}} + SC_{rate} \right) dt \tag{1}$$

$$SC_{rate} = \sum_i^n (SINF + SINS + SPEO) \tag{2}$$

$$SINF = \int \left(SINF_0^{\frac{1}{2}} + SC_{grow}^{\frac{1}{2}} + SINF_{rate} \right) dt \tag{3}$$

$$SINF_{rate} = \sum_i^n \left(ICT_{inf} + CP_{sup} + ENV_{sus} + INT_{sys} \right) \tag{4}$$

$$SINS = \int \left(SINS_0^{\frac{1}{2}} + SC_{grow}^{\frac{1}{2}} + SINS_{rate} \right) dt \tag{5}$$

$$SINS_{rate} = \sum_i^n (ES_{dev} + Pro + TG) \tag{6}$$

$$SPEO = \int \left(SPEO_0^{\frac{1}{2}} + SC_{grow}^{\frac{1}{2}} + SPEO_{rate} \right) dt \tag{7}$$

$$SPEO_{rate} = \sum_i^n \left(CR_{tvy} + ESP_{ro} + QE_{du} + QL_{ve} \right) \tag{8}$$

Where, SC_{grow} is the Smart City growth. SC_{rate} is the growth rate of Smart City. SINF is the Smart Infrastructure component. $SINF_{rate}$ is the growth rate of Smart Infrastructure component. SINS is the Smart Institution component. $SINS_{rate}$ is the growth rate of the Smart Institution. SPEO represent the Smart People component while $SPEO_{rate}$ is the growth rate of the Smart People.

Before deploying the system for the simulation and evaluation of the causal influences, the dynamic KPI model was tested at the extremely low value of 0% and the extremely high value of 100% level to observe the consistency of the performance when subjected to unusual conditions.

IV. A Conceptual Case Study – Simulation Results and Discussion

In order to establish the model equation for the three core components established in this study and the overall performance of the Smart City model, the correlation coefficients of the core indicators were loaded onto the model for simulation. Following the successful loading of the model with all the values of the indicators, the model simulation was tested at the two extreme scenarios of 0% and the 100% level respectively. In doing so, the performances of the individual components were compared across the system by adjusting the values for each variable of a particular component while keeping others unchanged. For instance, to check the influence of Smart Infrastructure on the model, all the variables of Smart Infrastructure components were stepped down to 0% while others were kept at 100% and the results compared and vice versa.

The same process was repeated for Smart Institution and Smart People to compare the dynamic impacts of the individual components on the overall performance of the model. The results of the simulations in different scenarios are presented in Figs. 4 to 7.

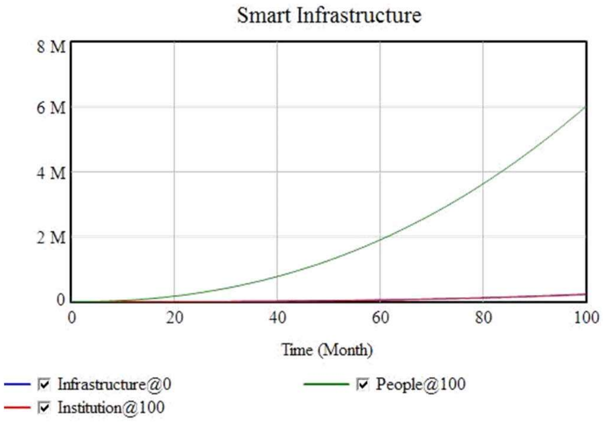

Figure 4: Graph of the Dynamic Impact of Smart Infrastructure at 0%, Smart Institution at 100%, and Smart People at 100%.

Fig. 4 shows the simulation results comparing the performance of components with the Smart Infrastructure component stepped down at 0% while keeping the Smart Institution and the Smart People components at 100%. Based on the dynamic interrelationship, the result indicates the strong influence of Smart Infrastructure on the institution component. The performance of the institution component is worst at Smart Infrastructure@0. This suggests that when city infrastructure is poor, it invariably has an adverse effect on the performance of institutions. However, the people component still performs optimally well indicating that the performance of the people is not necessarily tied to the smarter infrastructure of the city. The blue line represents infrastructure@0, the red line represents institution@100 while the green line represents people@100 respectively. Visual inspection of Fig. 4 shows that, as Infrastructure goes down, it affects the institution component negatively. Using the examples of initiatives cited in the experts' interviews, forward-thinking (smart) institutions seeking to deliver smarter services in cities naturally influence the need for infrastructure to deliver such services. For instance, the Air Quality Monitoring initiative by CityVerve in Manchester can be seen as a typical example of forward-thinking institutions seeking to deliver smart services which definitely need infrastructure (e.g. sensors) for the delivery of such services. Thus, it holds that the deployment of Smart Infrastructure is a pre-requisite for institutions to deliver smarter services which explains the negative impact of infrastructure@0 on the institution component.

The simulation process was repeated for the Smart Institution@0. The result is shown in Fig. 5.

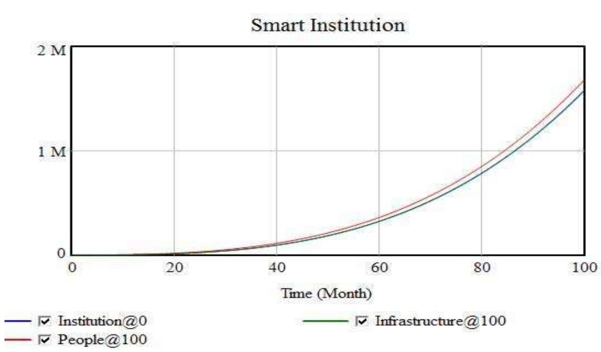

Fig. 5: Graph of the Dynamic Impact of Smart Institution at 0%, Smart Infrastructure at 100%, and Smart People at 100%.

Fig. 5 shows the simulation results comparing the performance of Smart Institution stepped down at 0% while keeping the infrastructure and the people components at 100%. This indicates an interesting result, namely that the development of the infrastructure component strongly influences the performance of the institution component. Here, the blue line represents institution@0, the green line represents infrastructure@100, while the red line represents people@100. It can be seen clearly that the blue line and the red line are tied together resulting from the strong influence of the infrastructure component. The dynamic influence simply explains the need for building Smart Institutions alongside deploying Smart Infrastructure for delivering smart services.

The simulation process was repeated for the Smart People@0. The result is shown in Fig. 6.

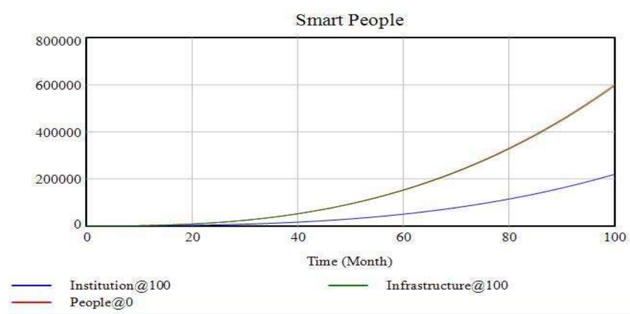

Fig. 6: Graph of the Dynamic Impact of Smart People at 0%, Smart Infrastructure at 100%, and Smart Institution at 100%.

Fig. 6 shows the simulation results comparing the performance of Smart People stepped down at 0% while keeping the infrastructure and the institution components at 100%. Here, the performance of people@0 is strongly influenced by the infrastructure@100 while impacting negatively on the performance of the institution component. Again, the blue line represents institution@100, the green line represents infrastructure@100 and the red line represents people@0. This suggests that the development of the Smart Institution component requires an adequate human capacity to sustain it. Thus, under-performance by the people component can be an impediment to the institution component. An example would be building institutions for developing skilled human capacity (such as universities) without adequate or expertise to deliver the content. The result also demonstrates that Smart Infrastructure has great potential for impacting positively on cities with many unskilled citizens; For instance, the ongoing innovation for deploying intelligent devices (Smart Infrastructure) such as drones by forward-looking organisations like Amazon to deliver services (parcels). In this instance, the delivery of parcels by un-manned drone to individuals does not require the recipient to be "smart" to enjoy such services.

Overall, to assess the influence of all the components of Smart City, the simulation process was repeated for the Smart City with all the components @100. The result is shown in Fig 7.

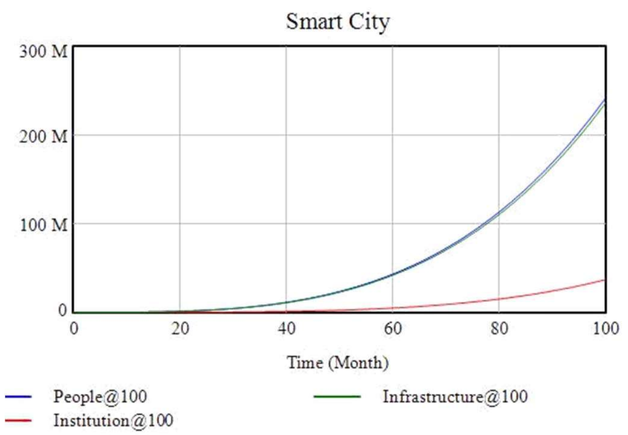

Fig. 7: Graph of the Dynamic Impact of Smart Infrastructure at 100%, and Smart Institution at 100%, and Smart People at 100%.

Fig. 7 shows the overall performance of the Smart City initiatives at the extreme level of 100% for all the components. The influence of the individual components at 100% shows that each of the KPI components has impacts on the level of smartness of a city. The result suggests that the dynamic influence of the institution component reduces significantly as the development infrastructure for Smart Cities improves. This result demonstrates that a smarter city environment at a maturity level with Smart Infrastructure and Smart People performing well at optimum level does not necessarily require much influence from the institution component. This finding also tends to agree with the views expressed in the existing literature regarding how the envisioned Smart Cities of being technocratic in nature and risk of catering for smaller stakeholders--skilled citizen.

It is important to note here that the proposed model is based on a strong scientific basis and tested methods. This study therefore provided an opportunity for using tested and priority factors/indicators as building blocks to develop a novel framework model as a guide for Smart City stakeholders especially in developing countries and cities with a similar history and experience in advanced region.

V. CONCLUSION AND FUTURE WORK

In this paper we modelled and analysed the causal influence of the core components of Smart Cities. The resulting system confirmed the criticality of the Smart Infrastructure components based on their influence on the performance of city institutions and how they influence the population (see Figs. 4 and 6). Based on the model, a Smarter City at a mature stage is highly influenced by people and infrastructure with very minimal influence by the institutional components.

The proposed framework model introduces the dimension of Smart Infrastructure which, prior to this study, has not been well emphasised. The emphasis on Smart Infrastructure is unique as it focuses on the importance of addressing the foundational issues for Smart and Sustainable City development especially in cities where infrastructure provision is still a major challenge.

This work is an ongoing research, thus the results are preliminary. Nevertheless, the tests provide promising evidence that using the proposed model can help in summarizing the metrics for assessing the impacts of smartness on cities especially in developing countries. However, for an in-depth analysis, further validation efforts are required to improve some aspects of the model and its credibility. In the future, therefore, we intend to validate the model through qualitative data/experts' opinions as well as extending the scope of the model's applicability.

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