4-1-2019

Identifying the Components and Interrelationships of Smart Cities in Indonesia: Supporting Policymaking via Fuzzy Cognitive Systems

Hendra Sandhi Firmansyah
Institute of Technology Bandung

Suhono Harso Supangkat
Institute of Technology Bandung

Arry A. Arman
Institute of Technology Bandung

Phillipe J. Giabbanelli
Furman University

Recommended Citation

H. S. Firmansyah, S. H. Supangkat, A. A. Arman and P. J. Giabbanelli, "Identifying the Components and Interrelationships of Smart Cities in Indonesia: Supporting Policymaking via Fuzzy Cognitive Systems," in *IEEE Access*, vol. 7, pp. 46136-46151, 2019. https://doi.org/10.1109/ACCESS.2019.2908622

Identifying the Components and Interrelationships of Smart Cities in Indonesia: Supporting Policymaking via Fuzzy Cognitive Systems

HENDRA SANDHI FIRMANSYAH[1], **SUHONO H. SUPANGKAT**[1],
ARRY A. ARMAN[1], **AND PHILIPPE J. GIABBANELLI**[2]

[1]School of Electrical and Informatics Engineering, Institute of Technology Bandung, Bandung 40132, Indonesia
[2]Computer Science Department, Furman University, Greenville, SC 29613, USA

Corresponding author: Philippe J. Giabbanelli (giabbanelli@gmail.com)

ABSTRACT Multiple Indonesian cities currently aim to qualify as "smart cities." Previous research on defining smart cities (e.g., the implementation-oriented maturity model) tends to focus on components over interrelationships, is challenging to apply to a specific context such as Indonesia, and offers limited support for policy-relevant questions. In this paper, we propose to address these shortcomings to support policymakers in identifying concrete action plans in Indonesia specifically. Our approach clarifies interrelationships for the context of use and supports structural (e.g., what aspects of a "smart city" are impacted by an intervention?) as well as what-if policy questions. We started with a systems' science approach to developing a cognitive map of the components and their interrelationships, as is increasingly done in participatory modeling and particularly in socio-ecological management. We transformed semi-structured interviews of 10 Indonesian experts into maps and assembled them to create the first comprehensive smart cities cognitive map for Indonesia, totaling 52 concepts and 98 relationships. While a cognitive map already provides support for decision-making (e.g., by identifying loops in the system), it is only conceptual and thus cannot form predictions. Consequently, we extended our cognitive map into a fuzzy cognitive map (FCM), whose inference abilities allow to examine the dynamic response of an indicator (e.g., "smart city") in response to different interventions. As fuzzy cognitive maps include the strengths of interrelationships but not the notion of time, future research may refine our model using system dynamics. This refinement would support policymakers in investigating *when* to conduct and/or evaluate an intervention.

INDEX TERMS Cognitive computing, participatory modeling, public policy, systems for smart cities.

I. INTRODUCTION

The population is increasing not only around the world but also in Indonesia [1], [2]. This is paralleled with a tendency for people to cluster in cities, which are already central to Indonesia and are due to play an even more important role. According to Parasati, about 59.35% of people live in urban areas [3]. The share of the Indonesian population living in

cities is predicted to reach 67.66% by 2025, and 82% by 2045. These dynamics have many consequences on economical and societal factors in cities [4]. In particular, the challenges that cities face will become even more pressing, calling for new infrastructures [5]. Challenges include waste management, traffic, and quality of life [6], [7]. Additional challenges come from changes in the age pyramid as the population gets older. Cities thus need new strategies [8], calling for innovative scenarios and solutions [9]. The concept of 'smart city' is one of the solutions.

The associate editor coordinating the review of this manuscript and approving it for publication was Anna Visvizi.

The definition of a 'smart city' often takes place at a high level of abstraction, by listing generic domains [10]–[12]. This proves challenging for policymaking for at least three reasons. First, policymaking takes place in a specific *context* rather than in an abstract form. A definition should thus clearly identify what is relevant to selecting and implementing a smart city agenda in a context of use, such as one particular town. This is echoed by the work of Angelidou, who moved from abstract strategic planning for smart cities to more concrete strategies, for instance by starting with an assessment of what exists in a city and then setting goals accordingly on domains such as the soft (e.g., knowledge and innovation economy) and hard aspects of infrastructure (e.g., transportation, energy) [13], [14]. Second, domains and the components within them are *interrelated*: a modern city is a system of systems [15], [16]. For instance, Albino *et al.* point out that connections exist between people, technology, and governance [9]. Several approaches have relied on a list of independent rather than interconnected domains, as can be seen in [17] for Brazilian cities, and in [18] for Indonesia. This oversimplification leads, for instance, to assuming that investments in Information and Communication Technology (ICT) infrastructures automatically trigger sustainable growth and a better quality of life, without unintended side effects. Third, a definition is rarely *operationalized* in a quantitative sense. For example, it might include indicators such as 'creativity', or a relatively vague 'people' domain. This presents a dilemma for policymakers: either they do not try to quantify the effects of a policy (which limits planning and evaluation efforts) or they struggle in putting an exact number on 'creativity' or 'people'.

In this paper, we aim to address all three shortcomings for the specific context of a 'smart city' in Indonesia. First, rather than listing generic domains, we identify indicators relevant to Indonesia. Second, instead of listing isolated indicators, we take a systems science approach to focus on their interrelationships [19]. That is, we develop a *systems map* that provides stakeholders of smart cities with both a comprehensive evaluation framework and a tool to address structural questions (e.g., what are the rippling consequences of an intervention?). Finally, to avoid the issue of either avoiding quantification or struggling with conducting it, we extend our systems map into a simulation model as a Fuzzy Cognitive Map (FCM). A FCM yields quantitative results by simulating dynamics: policymakers can quantify how much an indicator changes based on an intervention. While outputs are quantitative, inputs have the flexibility of being either quantitative (when data is available and/or policymakers are confident on the value) or qualitative (e.g., setting an indicator as being initially 'high' or 'medium'), which allows policymakers to deal with uncertainty in measurement.

The remainder of this paper is structured as follows. In section II, we provide a succinct overview of the three areas of research involved in this paper (i.e., smart cities, systems thinking, and simulation). We structured this overview along four topical questions selected to make the paper self-contained while allowing the reader to use our references for a more in-depth introduction to the material. In section III, we detail the methods used to construct a cognitive map and then transform it into a Fuzzy Cognitive Map. These methods are applied in section IV, which includes the results of the quality control procedures for model building. Section V is devoted to using the model, either to address structural questions (via the cognitive map) or simulate scenarios (via the fuzzy cognitive map). The final section contextualizes the practical implications of our work and concludes with suggestions for potential extensions.

II. BACKGROUND

A. HOW ARE SMART CITIES DEFINED?

There has been a growing interest in smart cities. The concept was born in 1994, and has gained a lot of popularity in the last two decades [9] with many scholars working on defining it [12]. Numerous projects in Asia and America have focused on the development of smart cities [20], and detailed examples are now available for cities such as Amsterdam, Seoul, San Francisco, and New York [20], [21].

Many scholars have explored the meanings and the (implicit) components of smart cities [22]. The developing of the concept started with cyber-, digital-, intelligent- and then smart-cities [7]. Dameri, quoting Carugliu and Qi, explained that the different terms cover similar concepts [23], which all lead to the notion of a 'smart city' [10], the *de facto* term in the field. In the 1990s, smart cities had a focus on Information and Communication Technology (ICT). Years later, the concept started to include citizens and city governance [9]. This widening definition resulted in incorporating multiple domains within smart cities, such as ICT, human resources, economics, and governance [24].

According to [7], there is at least 100 definitions for a smart city. In addition to the definitions aforementioned, other definitions (Table 1) include designating a city as 'smart' when human and social assets interact with the infrastructure and technology to create economic growth while enjoying a livable environment. Alternatively, a smart city has been identified as combining a variety of technologies to create a friendly environment, while providing the community with a more equitable life [7].

B. WHY DO WE MAP SYSTEMS?

Cases as diverse as a smart city, population health, or social unrest are often seen as complex or 'messy' [33], [34]. In such cases, the outcome of interest is shaped by, and contributes to, a multiplicity of factors which are also interdependent. This stands in contrast with *simple* problems where an optimal solution may be found by isolating a set of root causes, fixing them, and seeing the result straightforwardly propagate onto a final outcome through chains of causes-and-effects. Consequently, complex problems are often situated in a *system*.

Systems thinking typically starts with creating a map, either because there is value in the mapping process and/or

TABLE 1. Definitions for smart cities from 14 articles.

Definition	Reference
Smart city is a synthesis of hard infrastructure (or physical capital) with the availability and quality of knowledge communication and social infrastructure.	[11]
A smart city is a well-defined geographical area, in which high technologies such as ICT, logistic, energy production, and so on, cooperate to create benefits for citizens in terms of wellbeing, inclusion, and participation, environmental quality, intelligent development.	[23]
A city well performing in a forward-looking way in economy, people, governance, mobility, environment, and living, built on the smart combination of endowments and activities of self-decisive, independent and aware citizens. Smart city generally refers to the search and identification of intelligent solutions which allow modern cities to enhance the quality of the services provided to citizens.	[15]
Smart cities defined as attaining sustainability of a city with help of modern technologies while the environmental sustainability is an essential target.	[1]
Smart cities are now including qualities of people and communities as well as ICTs.	[9]
Smart City is a city built on the human being. The smartness of a city refers to its ability to promote a lifestyle in which the needs of the individual citizen match those of the community.	[25]
The application of information and communications technology (ICT) with their effects on human capital/education, social and relational capital and environmental issues is often indicated by the notion of smart city.	[26]
A Smart City consists of not only components but also people. Securing the participation of citizens and relevant stakeholders in the Smart City is, therefore, another success factor. There is a difference if the participation follows a top-down or a bottom-up approach. A top-down approach promotes a high degree of coordination, whereas a bottom-up approach allows more opportunity for people to participate directly.	[10]
A smarter city is one that uses technology to transform its core systems and optimize the return from largely finite resources. By using resources in a smarter way, it will also boost innovation, a key factor underpinning competitiveness and economic growth.	[27]
The smart city contains a wish list of infrastructure and services that describes his or her level of aspiration. To provide for the aspirations and needs of the citizens, urban planners ideally aim at developing the entire urban eco-system, which is represented by the four pillars of comprehensive development-institutional, physical, social and economic infrastructure.	[28]
A developed urban area that creates sustainable economic development and high quality of life by excelling in multiple key areas; economy, nobility, environment, people, living, and government. Excelling in these key areas can be done so through strong human capital, social capital and/or ICT infrastructure.	[29]
The Council defines a smart city as one that has digital technology embedded across all city functions.	[30]
The smart city works to raise the efficiency and the effectiveness of its services and activities. The resources it harnesses to achieve this can be highly varied but are often digital technologies (information and communication technologies or ICT).	[31]
A technology-intensive city, with sensors everywhere and highly efficient public services, thanks to information that is gathered in real time by thousands of interconnected devices. A city that cultivates a better relationship between citizens and governments - leveraged by available technology. They rely on feedback from citizens to help improve service delivery and creating mechanisms to gather this information.	[32]

because the map will support additional activities. While a comprehensive list of reasons for creating a map has been provided elsewhere [34]–[36], three reasons are of particular importance in the present paper. First, "effective participation by stakeholders in [creating a map] increases the legitimacy of decisions" [34]. In our context, a transparent process for co-creating a map with Indonesian experts on smart cities will contribute to building trust in the result, thus increasing the potential use of the map for decision-making in Indonesia. Second, creating a map is a step toward the development of an operational solution to a problem. Indeed, a map identifies the relevant factors (within the boundary of the problem) and their interactions. Translated to our application, a map tells us what we need to consider when deciding whether or how an Indonesian city can qualify as a smart city. Third, a map may support analytical tasks and policy-oriented questions, particularly when it is developed as a network. Note that we specifically refer to *structural questions* because the answer is obtained only by investigating the structure of a map, which is different from 'what-if' questions or scenarios which involve the use of computational experiments in simulation models.

Using a map for structural questions is one of the key tasks in this paper. These questions are relatively common in policymaking [37]–[40] and include:

- In which way(s) will an intervention *impact my evaluation outcome*? Structurally, this means finding the paths from the intervention factors to the outcome [37], [40].

- Will an intervention have *impacts beyond the evaluation outcome*? This common question about 'rippling effects' can be satisfied by searching for factors that are directly impacted by the intervention set, and following the chains as far as possible (i.e. performing a breadth-first search) [37], [40].

- What are the *leverage points* to alter the dynamics of the system? This question, most common for policymakers trained in systems thinking or System Dynamics, involves an inventory of higher-level structures involving several interdependent concepts [37], [39], [41], such as loops.

- What are the *core components* of the system? As systems are usually entirely connected, the classic network definition of 'strong' and 'weak' components may not apply. Instead, policymakers are particularly interested in identifying communities and seeing how the system can be reduced to interactions between communities of factors [38].

C. HOW DO WE MAP SYSTEMS?

The many approaches to create maps of systems can be broadly divided into two categories. They can be data-driven, for instance by using Machine Learning (ML) and Natural Language Processing (NLP) to derive maps from a text corpus [36], [42]. In a data-driven approach, researchers typically *collect* the data produced by individuals (e.g., reports, longitudinal data, social media excerpts) and transform it with

sophisticated methods. In contrast, researchers taking a Participatory Modeling (PM) approach facilitate the *production* of data by individuals, and ensure that a participant's input is processed in a transparent manner [34], [43]. For example, a participant may be asked 'what do you think contributes to this problem?', and all entities mentioned in the answer will then be connected to the problem of interest within a network diagram [35]. As mentioned in the previous section, transparency in creating the model with experts is important in our work to develop trust and support the model's uptake. Consequently, we focus on the PM approach.

Maps are routinely used in participatory modeling projects to examine socio-environmental dynamics [44], although their use also extends to societal [45] and public health issues [46]. The two most common participatory modeling methods to map systems are *rich pictures* and (variations of) *causal loop diagrams* (CLD). Both are highly transparent and result in artifacts that are easy to modify (see Table 1 in [43]). A rich picture is an unconstrained drawing of the issues, structure, process, and outcomes related to a problem of interest [47]. Rich pictures often serve as a "starting point to surface the different *factors* influencing a problem situation" [34] (emphasis added). Thus they may not include any *interdependency* between factors, or if they do, the exact nature of the interdependency may not be provided.

A CLD and its variations use a more structured process to create a map as a network in which factors are represented as nodes (e.g., governance, infrastructure) and connected via directed edges. The constraints ensure that edges are identified, thus resulting in a network rather than a collection of isolated factors. Edges may have no labels (in an Interrelationship Digraph [34]), qualitative labels (Mind Map, Causal Map [43]), or categorical labels. In a CLD, the categorical labels serve to specify the causality. Consider for instance a causal edge from *A* to *B*, meaning that a change in *A* will have an impact on *B*. The causality is categorized either as positive (labeled '+') when an increase in *A* triggers an increase in *B*, or negative (labeled '-') when an increase in *A* promotes a decrease in *B*. Categorical labels are commonplace when the system map is a step toward the development of a simulation model. Due to historical differences between fields, a model using System Dynamics (SD) calls an intermediate system map a CLD whereas a model using Fuzzy Cognitive Maps (FCMs) may present it as a 'causal map' or 'cognitive map' [48]. In this paper, we create a systems map of Smart Cities as a step toward the development of a FCM. From here on, we will refer to the map as a 'cognitive map', that is, a directed network with categorized causal edges (positive '+', negative '−').

D. HOW CAN WE MEASURE THE CONSEQUENCES OF AN ACTION?

Structural questions are useful for policymaking (section II.B) but they are limited to *identifying* components. Policymakers also often ask 'what-if' questions, or scenarios, such as: how much do we need to improve the infrastructure

such that we shift toward a smart city? Conversely, if we have to make cuts, in which area can we decrease investments while minimally impacting the rest of the system? A systems map (section II.C) cannot support such quantitative what-if questions because it is a diagram. That is, what-if questions require a *simulation model* to predict the dynamical effect of an intervention [49]. There are several ways to extend a systems map into a simulation model [43]. Two particularly common approaches in a participatory context are System Dynamics (SD) and Fuzzy Cognitive Maps (FCMs).

As explained by Lavin *et al.* [50], cognitive maps only capture the existence of a causal relation from a factor *A* to another factor *B*. Helping experts to detail the nature of these relations remains an active field of research in participatory modeling [51]. For instance, relations can be characterized through parameters including intensity of the change (how much does *B* change when *A* changes?), timing (is the impact constant per time unit? are there delays?), and previous history (does the change depend on previous values of *A* and/or *B*?). System Dynamics can handle all three parameters and has been used to model smart or 'eco-cities' [52], with a prominent example being the 'Systems Dynamics for Smarter Cities' app developed by IBM and applied to Portland, OR (c.f., chapters 8-9 in [53]). However, building SD models in a participatory context faces many challenges: "individuals may not be readily able to provide a clear number or to precisely estimate the duration of a time lag" [54], and the process may take many months with extensive logistics to facilitate groups or perform in depth interviews. Fuzzy Cognitive Mapping provides an alternative: it is less detailed, as neither time nor history are represented, but the sole focus on capturing the intensity of the change is significantly simpler for participants. The simple process to develop an FCM is a key asset emphasized in several books and reviews [55]–[60].

As summarized by Dickerson and Kosko, an FCM is a nonlinear dynamical system akin to a neural network. Its structure is a fuzzy signed digraph with feedback, where nodes are fuzzy sets and edges are fuzzy rules [61]. An FCM has been formalized in several ways, using a 4-tuple [62] or a 6-tuple [63]. Others have defined an FCM not only by its structure but also by how nonlinear dynamics are performed, thus creating FCMs that behave differently [64]. In line with our previous work, we formalize an FCM through a compact notation with three tuples [48], [50], [65]. A Fuzzy Cognitive Map $F^t = (V^t, E, f)$ at step t is formed of a set V^t of n nodes taking values in [0, 1] (0 indicating the absence and 1 the presence of a concept), which interact through a set E of edges with a causal weight in [−1, 1]. The last tuple f is a clipping function which forces a node's value to remain in its operating range. The updated FCM F^{t+1} is computed from F^t by transforming the values of nodes through Equation 1.

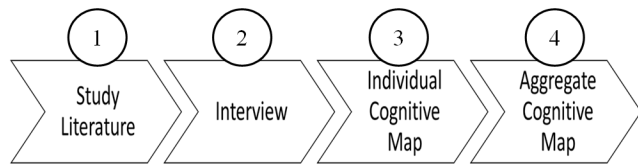$$V_i^{t+1} = f\left(V_i^t + \sum_{j=1, j \neq i}^{j=n} V_j^t \times e_{j,i}\right) \quad (1)$$

FIGURE 1. Overview of our the four steps to develop a cognitive map.

The equation is performed repeatedly until the nodes chosen as outputs either (*i*) stabilize when they change by less than a given threshold from one update to the next; or (*ii*) more than τ steps of updates have been done, suggesting that stabilization with the desired threshold cannot be achieved. While a comprehensive introduction to the theories and tools of FCM is beyond the scope of this paper, a few technical aspects should be mentioned to support the replication of our results. First, the choice of the clipping function f noticeably impacts the results of an FCM and whether stabilization will occur. Indeed, a discrete f forces the FCM into a fixed point or a limit whereas a continuous f enables a chaotic attractor [66], [67]. In this work, we use a hyperbolic tangent like many previous works [50], [68]–[70], which means that we need to watch for the presence of a chaotic attractor. Second, machine learning can be used to create [58], or improve [71] an FCM (e.g., ensuring that it converges faster without significantly changing the results [72]). As we take a participatory modeling approach (section II.B) rather than a data-driven approach, we build the FCM with experts rather than optimizing the weights based on data. We also do not re-engineer the FCM so that it converges faster: the small computational footprint of our experiments does not call for an improvement in convergence speed, and modifying the FCM would detract from the essential goal of keeping a transparent process in participatory modeling.

III. METHODS
A. DEVELOPMENT OF A COGNITIVE MAP
There are four steps to create a comprehensive cognitive map of the factors and interrelations at work in a complex system (Figure 1). The first step is to set the boundaries for the map: what does it seek to represent, and what lies outside its scope? For emerging problems, facilitated sessions with stakeholders often serve to identify boundaries. In a well-studied domain such as smart cities, we extensively analyzed the literature to identify suitable boundaries. That is, we searched Google Scholar for articles published in English since 2016 that included one of the following sets of keywords: ''smart city'', ''smart cities'' and ''sustainable city''. We read the abstracts to identify relevant articles, which were then examined to identify the components commonly included in 'smart cities' and group them into themes.

The second step starts the participatory approach by identifying experts and helping them to externalize their knowledge. Experts are selected given the domains identified in the first step. Three criteria are essential to select experts in participatory modeling. First, experts have to be collectively *representative* of the range of stakeholders involved in a smart city: that is, they must be from the 'triple helix' [73] consisting of government representatives, industry members, and individuals from educational institutions. Second, to qualify as expert, each person needs at least 3 years of *experience* in implementing a given domain to smart cities. A same person may qualify as expert in several domains. Third, there must be a *sufficient number* of experts: each domain must be covered by multiple experts, and their conclusions should not vary in ways that create significant uncertainty in the model. Saturation is checked upon completion of the interviews and uncertainty is checked at a later stage (section IV-E). Having selected experts, semi-structured interviews take place to identify which concepts compose a relevant domain, and account for connections within as well as across domains [74].

The third step transforms the recorded interviews into individual maps. When an expert mentions that one factor causes another, we record it as a directed, labeled ('+', '−') edge in the map. At this stage, we also check the structure of each map given the expectations of participatory modeling. In particular, having too many nodes may be symptomatic of a lack of focus, which may jeopardize the model's boundaries.

The last step is to create a comprehensive map by combining the individual maps. This is a common practice in participatory modeling, where an aggregate map represents the ''mental model help by a group of stakeholders'' [50]. If experts are limited to using a pre-defined list of concepts, then aggregating their individual maps is straightforward: if two experts use a concept with the same name, then it represents the exact same idea and the aggregated map shows it as a single concept [75]. In semi-structured interviews, however, each expert freely decides how to name each concept. This approach causes two challenges [76], [77]: a single idea may be referred to under different names, and a single name may actually cover two ideas depending on the context at a particular moment of the interview. The challenges are resolved manually, by identifying whether two concept names refer to the same idea based on context, and if so, gathering them under a single name in the aggregate map [76]. Similarly to the third step, we analyze the structure of the aggregate map and also compare it with the individual maps (e.g., to identify whether the synthesis represents a general agreement). This final map is under particular scrutiny, thus the analysis also includes higher-order metrics such as the number of loops or density of connections, to assess whether experts were selective.

B. ADDING FUZZY VALUES AND INFERENCE CAPABILITIES
As detailed studies show how to extend a cognitive map into an FCM [33], [46], [68], we provide a succinct overview. Note that the FCM assigns a weight to the edges and can update (via Equation 1) the value of nodes, but node values are not set
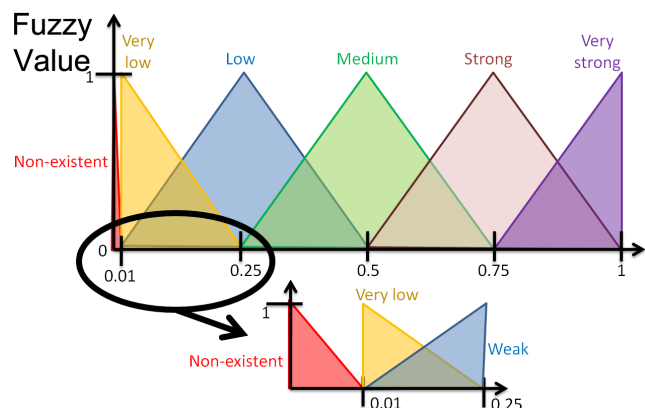
FIGURE 2. Fuzzy memberships functions account for the vagueness and uncertainty in linguistic terms.

when *creating* the model: they are provided when *using* the model on a specific case (as in section V-B). This is similar to the machine learning process, in which we create a model (e.g., a classifier) and later provide it with cases to classify. We use a classical three steps process to assign a weight to each edge [33], [46], [68]:

(1) Create a questionnaire, distributed to each participating expert. For each relationship, the questionnaire asks to categorize the causal strength using a linguistic term chosen from 'non-existent', 'very low', 'low', 'medium', 'strong', 'very strong', and 'unsure'.

(2) A triangular Fuzzy Membership Function is associated to all linguistic terms (Figure 2) but 'unsure', which is discarded as an expert does not feel confident to answer.

(3) For each edge, we transform the experts' answers into a number using Fuzzy Logic with Mamdani rules and the centroid method for defuzzification.

Similarly to the previous section in which we controlled the structural soundness of the maps, we examined the linguistic terms chosen by the experts. We cannot presume that a specific expert is 'right' or 'wrong' in choosing a term: we use participatory modeling as we do not know what the right value would be. Therefore, quality control in an FCM is not exerted by looking at correctness in individual respondents but rather by looking at cohesion in the group. If experts are equally likely to choose any of the terms for a relationship, then there is low cohesion, which translates to more uncertainty in the model's weights, thus suggesting an insufficient number of experts (see step 3 in section III-A). Conversely, if all experts agree on the term for a relationship, then cohesion is maximal. As in our previous work, we used *entropy* to measure cohesion in the experts' answers [46]. The entropy $E(R)$ for a relationship R is given by

$$E(R) = -\sum_{i=1}^{7} p_i \times log_2(p_i) \qquad (2)$$

where p_i represent the proportion of answers to each of the seven linguistic variables.

IV. CREATING THE MODEL

A. STEP 1: MODEL BOUNDARIES

We found a total of 150 references which, after manual examination, were narrowed to 29. Fourteen of the articles, often in the form of institutional statements rather than peer-reviewed articles, proposed definitions for smart cities that *implicitly* touched on the core components. These fourteen broad interpretations of a 'smart city' are listed in Table 1. The remaining fifteen peer-reviewed articles either provided explicit models for smart cities or examined the specific components required for a smart city (Table 2). These fifteen articles provided the foundations to set model boundaries.

As expected, we observe that different articles emphasize different components when discussing the concept of a smart city. One articled looked for an innovative economy and infrastructure combined with a specific form of governance [7] while another identified six major components (each being made in turn of several indicators): economy, people, governance, mobility, environment, and living [15]. Technology was common to many definitions, with many referencing Information and Communications Technology (ICT) specifically [1] or technology in general [12]. The common theme across articles is that a smart city is first and foremost a comfortable city with easy access to a wide range of services, while performing well on social and environmental metrics.

We grouped the themes from the literature into nine domains (Table 3) to guide the identification of experts. We avoided the use of 'niche' domains by requiring that a domain appeared in at least three articles.

B. STEP 2: SEMI-STRUCTURED INTERVIEWS

The objective of this step is to transform the nine domains into concepts (or 'indicators') and interrelationships. In other words, we want to see precisely which concepts compose a domain, and account for connections within as well as across domains. We identified 10 experts, who all accepted to participate in phone interviews held from November 20 to November 30, 2017. All participants provided informed consent and were recorded for later analyses. A sample interview is provided as Appendix. The semi-structured interviews share the same goal and methodology, which is to tease out interrelationships by following on the experts' suggestions. Since the experts make different suggestions and are familiar with different domains, the specific questions vary across interviews. Interviews lasted between 40 and 60 minutes and were all conducted in Indonesian.

C. STEP 3: FROM INTERVIEWS TO MAPS

Each individual interview from step 2 resulted in a recorded conversation mentioning specific concepts and interrelationships. As performed in previous research [74] we represented the outcome of each interview as a causal map. For instance, consider an expert who stated:

> "The increasing use of technology makes the city even smarter in solving their problem."

TABLE 2. Components in fifteen articles on smart cities.

No.	Reference	Domain/component
1	[1]	Built environment, Economy, Education, culture, science Energy Governance and citizen engagement ICT Natural environment Transport Water and water management Well-being and health
2	[2]	Smart economy, environment, governance, living, mobility, and people
3	[78]	Economy Energy Environment Living
4	[79]	Energy Governance Mobility Smart economy Smart environment
5	[80]	Environment Governance Living Mobility People
6	[12]	Citizen Governance Land/geographical area Technology
7	[81]	Citizen Education Governance Infrastructure and technology Innovations in economy
8	[18]	Citizen Environment Governance Industry Infrastructure Innovation economy
9	[82]	Economic features Environmental features Institutional features Physical features Social features
10	[83]	People Institutions Technology
11	[26]	Smart economy, environment, governance, human capital, and living
12	[15]	Smart economy, environment, governance, living, mobility, and people
13	[6]	Communities Economy Governance Infrastructure Natural environment
14	[7]	Governance Infrastructure and utilities Innovative economy
15	[16]	Business Communication Environment Human capital Public service

TABLE 3. Domains and specific indicators based on the literature.

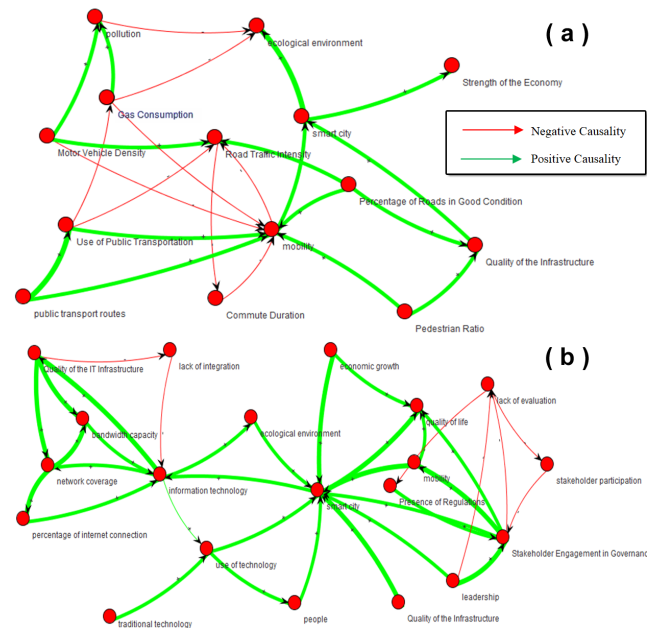| Domain	Sample indicators	No. from Table 2
Economy	Poverty rate, Unemployment rate, Innovation in economy	1, 2, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14
People	Educational attainments, Sustainability, Creativity	2, 5, 7, 8, 10, 12, 13, 13
Environment	Air pollution, Water pollution, Waste management	1, 2, 3, 5, 7, 8
Governance	Leadership, Organization, Strategy	1, 2, 4, 5, 6, 8, 11, 12, 13, 14
Mobility	Pedestrian areas, Facilities for mass transportation, Access to public transportation	2, 4, 5, 12
Energy	Use of gas, electricity, water, Renewable energy by GDP	1, 3, 4
Living	Crime rate, Access to education/health facilities, Population density for housing	2, 3, 5, 11, 12
Government	Public administration, Access, Transparency	7, 9, 11,15
Information Technology	E-services / e-government, Bandwidth, Network connectivity	1, 6, 7, 10

FIGURE 3. Individual maps produced from two semi-structured interviews.

This is shown in Figure 3-B as an edge going from "use of technology" to "smart city" with a positive causality (+). In another interview, an expert stated:

"As more people use public transportation, it will decrease gas consumption in the city, and it will automatically increase the quality of the ecological environment through decreasing the pollution caused by gas consumption."

This statement is represented via several edges in Figure 3-A: "Use of Public transportation" connects with negative causality (-) to "Gas consumption", which in turn connects with negative causality to "ecological environment".
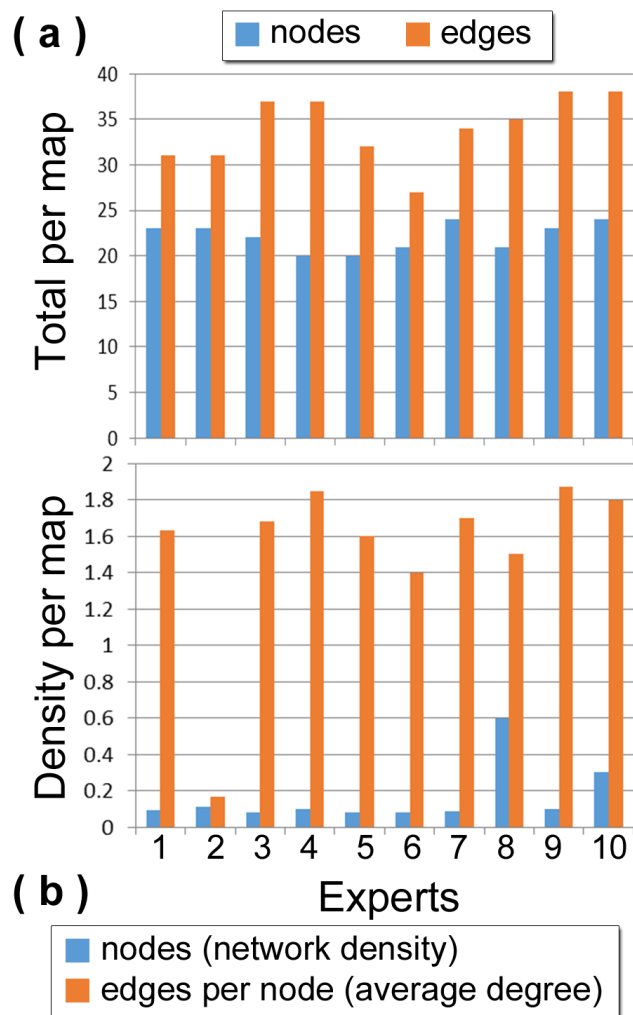
FIGURE 4. Total (a) and density (b) of nodes and edges for each of the 10 experts. Experts are numbered, but not ordered.

Upon completion of this step, we obtained 10 individual maps, whose structural properties are summarized in Figure 4, while sample maps are shown in Figure 3. Our results indicate that the experts used from 20 to 24 nodes, and from 27 to 38 edges. These results are in line with previous participatory studies that produced maps of socio-ecological systems: a study of environmental management with 20 participants had an average of 24 nodes and 27 edges [84], while an article on ecosystem conservation with 51 participants reported 24 nodes and 43 edges on average [85], and research on coastal management with 59 participants resulted in 18 nodes and 28 edges on average [86].

D. STEP 4: AGGREGATING MAPS

The 10 individual maps were aggregated into one (Figure 5) that synthesizes the expertise of all participants. Note that large maps of complex systems are notoriously problematic when used as decision-support systems [87]. As will be detailed in section VI, we note that our map is meant to be used either through interactive tools for participatory

modeling, or reduced to sub-structures of interest for policymakers. Instead of analyzing a picture, readers wishing to examine our map can access it on a third-party repository (https://osf.io/z543j/) as a list of weighted edges.

This aggregate map has $n = 52$ nodes and $m = 98$ edges of which 26 expressed negative causation and the remaining 72 expressed positive causation. The network density, given by $\frac{m}{n(n-1)}$, is 0.037. A very low density is typical for maps produced by experts, as they are highly selective in the causal connections that they form between concepts [50]. On average, there are 1.94 edges per node, which further highlights that experts were very selective in linking concepts.

The concepts were further categorized [75] into driver concepts (i.e. where a node or concept influences, but is not influenced by, the system; in other words, nodes that only have outgoing edges), ordinary concepts (i.e. nodes with both incoming and outgoing edges), and receiver concepts (i.e. nodes with only incoming edges). Table 4 reports how many, and which, concepts fell under each category. The table also reports on the two categories of feedback loops [88]: reinforcing (when a part of the system that may grow or amplify) and balancing (a stabilizing or goal-seeking process). Loops were automatically extracted and categorized using the `ActionableSystems` software [37].

Finally, we compared the characteristics of our aggregate map with the individual maps used to create it (Table 5). If the experts often disagreed, then their maps would have very little in common, thus the number of nodes and edges in the aggregate map would be close to the sum of nodes and edges across the individual maps. Conversely, when experts report the same concept or connection, it is represented only once in the final map. A higher level of agreement is thus indicated by a lower number of elements in the final map. We find that the number of nodes and edges are respectively 2.5 and 3 times as numerous in the final map as in an average expert map, indicating general agreement.

E. EXTENSION INTO A FUZZY COGNITIVE MAP

All ten experts were given access to the online questionnaire in Indonesian, accessible at https://tinyurl.com/survey FCM2018. The questionnaire first prompted them to provide identifying information, and then to choose a linguistic term representing the causal weight for each relation. The ten experts completed the form from October 12th 2018 to October 25th 2018. Their anonymized answers can be accessed at https://osf.io/z543j/. Figure 6-a shows that, out of the 10 answers made by each expert, a relationship was on average most commonly seen as 'strong' (3.39), 'very strong' (3.38), or 'medium' (2.38). While we may expect experts to consider that relations from their own interviews are important, Figure 6-a suggests that experts found *most* relations to be important, even if they did not suggest them in the interview. Experts thus considered that relations included in the map were often important. This finding is reinforced by noting that there are very few cases when experts
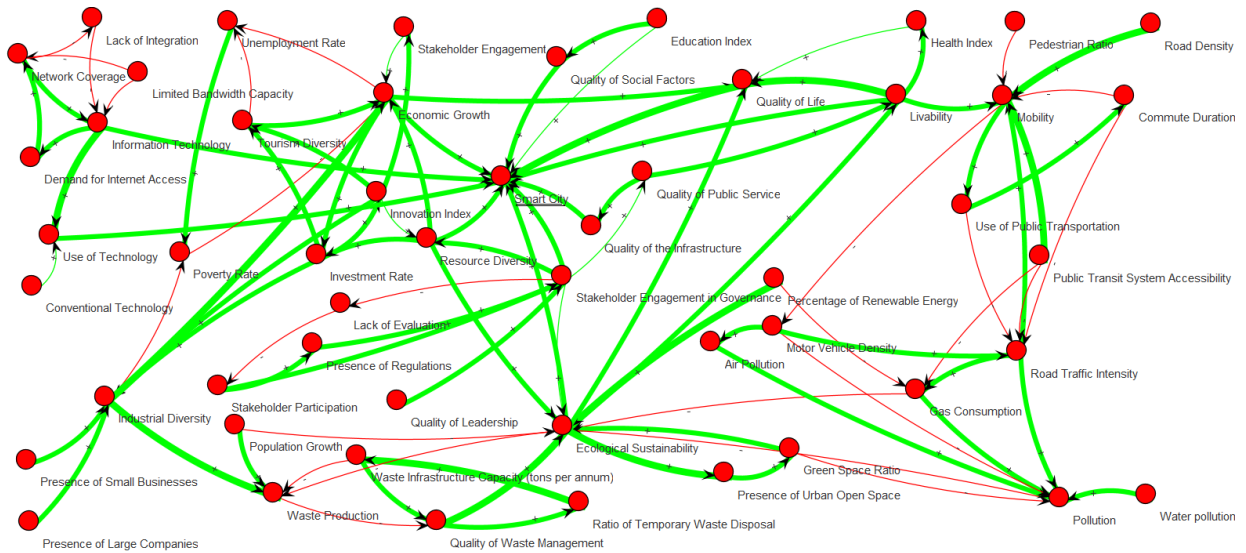
FIGURE 5. Our final aggregate map, built from the individual maps of the 10 contributing experts.

TABLE 4. Content of the aggregate map at the concept level (alphabetically ordered per category) and loop level.

Driver concepts (13)	Air Pollution, Conventional Technology, Education Index, Limited Bandwidth Capacity, Pedestrian Ratio, Percentage of Renewable Energy, Population Growth, Presence of Large Industry, Presence of Small Business, Public Transit System Accessibility, Quality of Leadership, Road Density, Water Pollution.
Ordinary concepts (38)	Commute Duration, Demand for Internet Access, Ecological Sustainability, Economic Growth, Gas Consumption, Green Space Ratio, Health Index, Innovation Index, Industrial Diversity, Information Technology, Investment Rate, Lack of Evaluation, Lack of Integration, Livability, Mobility, Motor Vehicle Density, Network Coverage, Pollution, Poverty Rate, Presence of Regulations, Presence of Urban Space, Quality of Infrastructure, Quality of Life, Quality of Public Services, Quality of Social Factors, Quality of Waste Management, Ratio of Temporary Waste Disposal, Resources Diversity, Road Traffic Intensity, Stakeholder Engagement, Stakeholder Engagement in Governance, Stakeholder Participation, Tourism Diversity, Unemployment Rate, Use of Public Transportation, Use of Technology, Waste Infrastructure Capacity, Waste Production.
Receiver concepts (1)	Smart City
Reinforcing loops	16
Balancing loops	6

considered that a relation may be candidate for deletion ('no causality' = 0.2).

We also used entropy to assess whether experts formed a cohesive group in their answers. The *least* cohesive group would choose the linguistic variables uniformly at random. If there were ten variables to choose from, then each of the ten experts would choose a different one. Since there are only seven variables to choose from, the most uniform distribution is obtained when three variables are chosen by two experts each, and the other four variables are each picked by one expert. This would lead to an entropy of $3 \times (-\frac{2}{10} \times log_2(\frac{2}{10})) + 4 \times (-\frac{1}{10} \times log_2(\frac{1}{10})) \approx 2.72$. Consequently, a relation with an entropy close to 2.7 indicates no cohesion among experts. We found the minimum (i.e. best) entropy to be 0.971, as experts often agreed on the relation from 'quality of social factor' to 'smart city', and the maximum (i.e. worst) entropy to be 2.32, as experts had different takes on how the 'percentage of renewable energy' would impact 'gas consumption'. The entropy for each question is shown as part of additional interactive visualizations provided as supplementary online material hosted on `Tableau Server` at

TABLE 5. Comparing individual maps with our final aggregate map.

	Individual maps	Final map
Number of maps	10	1
Number of nodes	21.50	52
Number of links	32.50	98
Density	0.09	0.037
Edges per node	1.39	1.94

https://tinyurl.com/analyzeFCMsurvey. As shown in Figure 6-b, there is strong agreement in the experts' choices: over 80% of the relationships had an entropy of 1.8 and under. The agreement is even stronger when it comes to relations that directly impact the key concept of 'smart city': their average entropy is 1.47.

After performing quality control on the group-level cohesion, we used their answers to create the FCM. This was accomplished through a Python script written in a Jupyter Notebook. The script starts by converting the experts' linguistic variables into numerical edge weights using the `skfuzzy` library. These weights and the network structure (stored via the `NetworkX` library) are then passed to a Python FCM
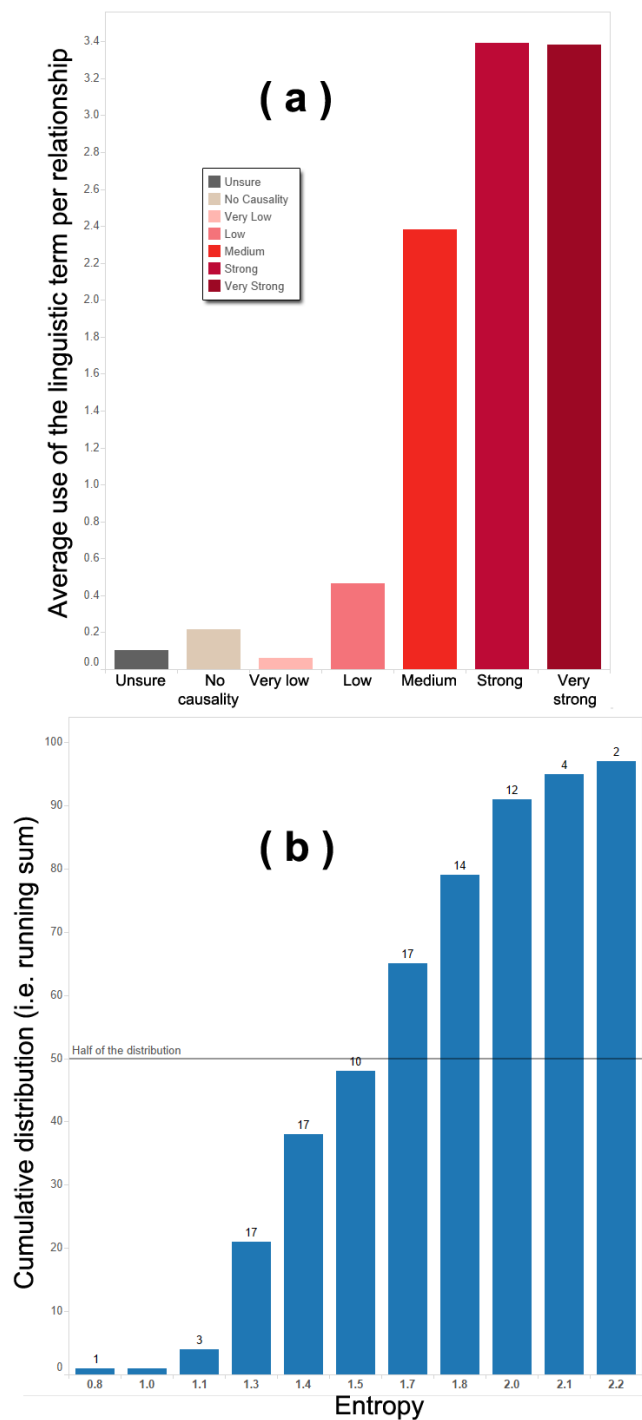
FIGURE 6. Average use of each linguistic term per question (a; top) and cumulative distribution of entropy across all questions (b; bottom).

library previously developed by our research group [48], [50] to create the FCM object. At that stage, the FCM can be provided with a case (i.e. an initial value of all nodes' weights) to predict their dynamics until stabilization of the output (i.e. smart city). Both the notebook and the FCM library are provided in a compressed archive in our repository at https://osf.io/z543j/. As we are not the authors of either `skfuzzy` or `NetworkX`, we note that readers

interested in replicating our work will need to install these two libraries.

V. USING THE MODEL
A. STRUCTURAL QUESTIONS
There is a common misunderstanding in systems science and policymaking that large systems maps can simply be looked at, as if they were images. For instance, a map created for obesity through a participatory modelling approach similar to ours was depicted as "brilliantly useful in demonstrating the complexity of factors [while] difficult to see how one might use it in any practical way to develop system approaches" [87]. Instead of appearing as a herald of complexity in smart cities, our map seeks to support policymakers in elucidating structural questions. Rather than an image, our map is first and foremost a *network*. Consequently, structural questions are addressed using network analysis software or, when policy-makers are the target audience, using a software for interactive network visualization and analysis (e.g., `ActionableSystems` [37], `Gephi`). In this section, we exemplify how the map can be decomposed based on specific policy tasks (Figure 7), rather than being used as one massive piece as shown in Figure 5.

As an example of structural policy question, consider that decision makers wish to directly promote a "smart city". They can use well-known levers such as ecological sustainability and the quality of the infrastructure (Figure 5). A systems approach reveals that increasing the engagement of stakeholders in governance may have both a small direct contribution to a smart city, and a stronger indirect contribution by promoting social factors. While the factors directly affecting a smart city can be seen as high-level, more distal and concrete drivers are represented, such as accessibility to the public transit system, the use of temporary waste disposal, or network coverage.

One important task is to understand the current state of the system, before trying to alter it through an intervention. Loops play an important role in the dynamics of a system, as do alternative paths between factors [89]. Using `ActionableSystems`, we decomposed the map into its 16 reinforcing and 6 balancing loops (Figure 7a-b), and we also navigated its many alternative paths (Figure 7-c).

Figure 8(a) shows a reinforcing loop by which a greater demand for internet access is met with increased network coverage, which eventually prompts higher demands. This loop is a useful lever to promote a smart city from an information technology standpoint. As reinforcing loops cannot grow forever, such loops implicitly call for decision makers to identify the resources or limits to growth, which may then be re-allocated. Figure 8(b) brings attention to a problem of smart cities, whereby an interest in increased mobility could be met with a higher motor vehicle density, thus reducing the ecological sustainability and quality of life that are important to a smart city. In short, identifying the virtuous cycles allows policymakers to benefit from naturally occurring dynamics
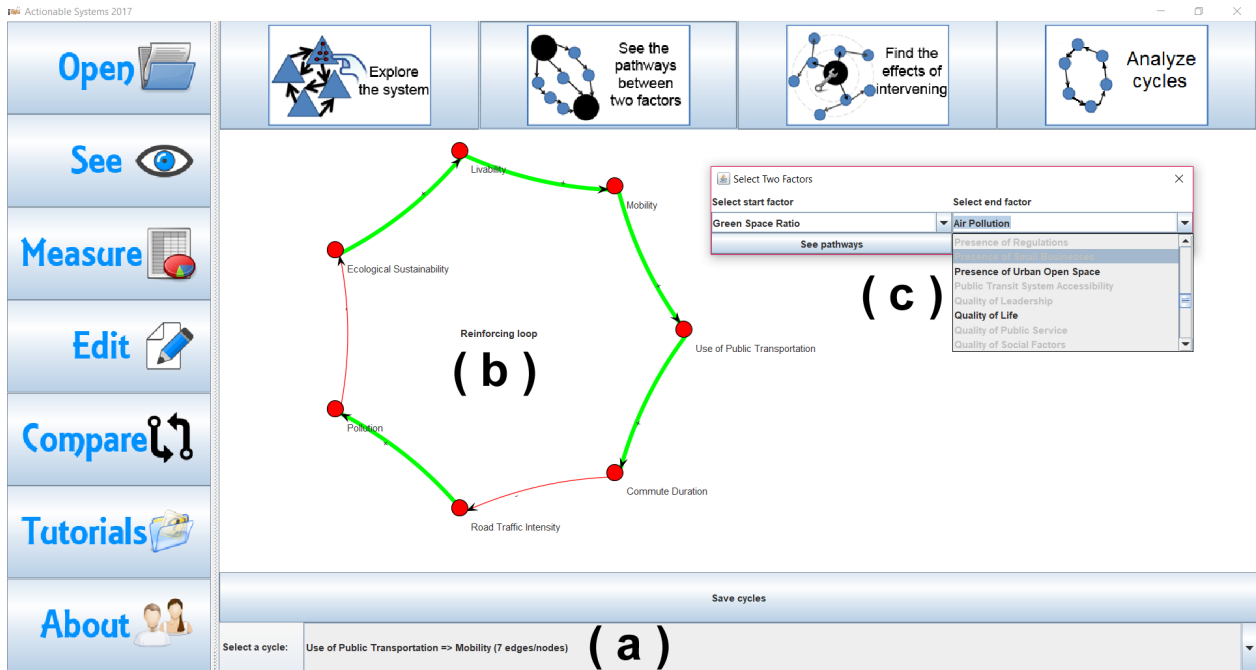
FIGURE 7. The map viewed through the open-source ActionableSystems (https://osf.io/7ztwu/) software. The software can decompose the map into loops (a), to display and categorize them once at a time (b). Starting from a given intervention factor, decision makers can see all factors eventually impacted (c) and click on one to visualize the route.

of the system for their intervention (e.g., through reallocation of resources to further fuel a loop), while identifying problematic loops prompts important questions about the balance of priorities, or how an action in the system may produce unintended consequences. Unintended rippling effects can also be explored by selecting a possible factor for intervention, and examining all affected factors from most proximal to distal. Figure 8(c) exemplifies how the smart city system would be affected when attempting to directly intervene on economic growth: there would be positive effects by reducing poverty and unemployment, and eventually more economic growth may be observed (bottom-right); however, waste production will also be increased and, without appropriate waste management, ecological sustainability may be negatively affected.

B. FUTURE SCENARIOS

As explained in section II-D, a Fuzzy Cognitive Map is a simulation model that can update the value of nodes based on the causation represented by edges. The value of the nodes must depict a specific *case*. For instance, when simulating ecosystems, the nodes can be initialized to represent a specific type of lake [50]. As our FCM was designed for smart cities in Indonesia, it is essential to follow its context of use and apply it to cases consistent of such cities. We use Bandung as a guiding example, since it has been previously been analyzed from a smart city perspective [90]. In our Jupyter Notebook (available at https://osf.io/z543j/), we assigned a value to each node based on the city of Bandung. For instance, we accounted for the high traffic density and use of technology

('Road Traffic Intensity'='Use of technology' $= 0.8$) but also noted a low share of renewable energy ('Percentage of Renewable Energy' $= 0.3$). Note that policymakers *may* similarly assign numerical values when they are certain and/or quantitative data is available for a case. However they are not limited to numerical values: a case may be described using linguistic terms which are mapped to numbers (Figure 2), thus allowing experts to deal with uncertain values in indicators.

We ran the FCM with this case of Bandung as a *baseline*. That is, given Bandung as it currently stands, we projected what it would become in the absence in an intervention. The FCM stopped updating the weights of nodes (Equation 1, section II-D) when 'smart city' changed by less than 0.001. Results suggest that Bandung may eventually be categorized as a 'smart city' with high economic growth and use of technology, but at the expense of significant pollution. To change these expected consequences of the current situation, policymakers may consider several interventions as possible scenarios. As documented elsewhere, possibilities include an increase in green space, a change in the energy mix, and an improvement in the waste infrastructure [12], [26], [83]. We thus considered two possible scenarios: (A) increasing the share of green space, and (B) increasing the share of green space while promoting renewable energy over gas consumption. Our results are shown in Figure 9 and can be entirely replicated by running our notebook from https://osf.io/z543j/. The baseline pollution of 0.91 decreases by only three percent points when promoting green spaces (0.88), but by 22 percent points when also promoting renewable energy (0.69).
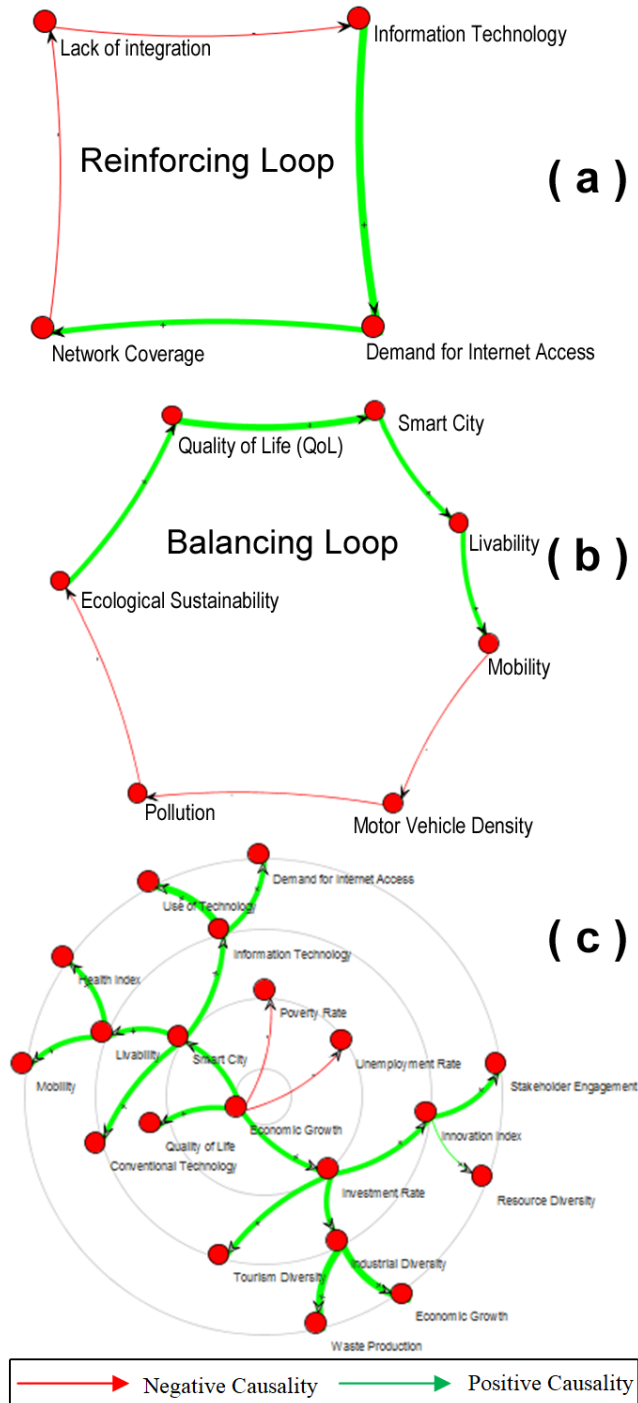
FIGURE 8. Loops (a-b) and rippling consequences (c), as seen from the `ActionableSystems` software [37].

FIGURE 9. Level of pollution in Bandung, Indonesia, from 0 (absent) to 1 (fully present) in the baseline case compared to two future scenarios.

FIGURE 10. Quality of social factors in Bandung, Indonesia as a result of cuts in the education index.

As discussed in section II-D, what-if questions can include identifying the right improvements in the pursuit of a higher outcome (as we examined with pollution), or estimating the effect of a cut when budgetary restrictions are considered. We provide an example of the latter case by focusing on cuts in education. Although this hypothetical example primarily serves to illustrate the capacity of our FCM to support decision-making, we note that education is an important topic
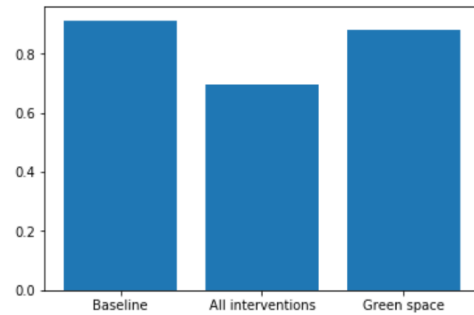
in Indonesia, and a contributor to the concept of a smart city in this setting (Figure 5). Kawamura recently reported that, although "the amended constitution provides at least 20% of budgetary allocations to the education sector [...], education spending has still been lower than the average of lower middle-income countries as well as neighboring countries in the region" [91]. In addition, shifting government educational priorities have occasionally resulted in cuts to higher education in favor of basic education. To examine the impact of cuts, we set the FCM to stabilize when both 'smart city' and the 'quality of social factors' (our evaluation outcome) changed by less than 0.001. We lowered the investment in education (captured by the Education Index) to reflect cuts of different amplitudes, from small (preserving an index of 0.7 close to its baseline) to large (lowering the index to 0.2). Our heatmap (Figure 7) shows the value for 'quality of social factors' as the FCM iterates until stabilization. Note that the number of iterations depends on initial conditions but remains very small, thus reiterating that our FCM does not need automatic simplifications to lower the number of iterations (section II-D). Results also demonstrate the presence of nonlinear effects, since a reduction in the education does not have a constant effect on the quality of social factors: going from 0.8 to 0.7 only causes a reduction of 0.019 whereas going from 0.3 to 0.2 has a difference of $0.2266 - 0.1596 = 0.067$ (i.e. the effect is 3.5 times larger).

VI. DISCUSSION

Many scholars have provided definitions for the concept of a 'smart city' (section II-A). However, the wide

range [10]–[12] and apparent widening of the definition proves problematic when decision makers seek to implement and/or evaluate implementations to make a city 'smarter'. Different cities or countries will examine different concepts and components, or pursue different approaches toward different objectives. Definitions can be made more precise when broken down into domains (Table 2), but the translation of these domains into practical objectives for decision making remains arduous. Most importantly, independently mapping each domain to metrics for interventions would ignore that domains are interrelated [9]. Implementing a smart city policy based on seemingly disconnected domains may thus lead to implicitly forming erroneous assumptions, such as thinking that investing in one domain may be sufficient to trigger a change without addressing limiting factors found in other domains. Conversely, the impact of a change may be underestimated, as rippling effects can permeate across domains and amplify a change through virtuous cycles.

In this paper, our overarching objective is to provide an operational definition of a smart city that is suitable for Indonesia, which experiences a significant growth of urban populations [3], thus creating a timely call for innovative scenarios [8], [9]. This objective was realized in two consecutive steps. First, we took a systems science approach to map the specific factors within each domain, and their interconnections within as well as across domains. We used a participatory modelling approach by creating maps with ten Indonesian experts, and combining these individual maps into one overall systems map ("the map") consisting of 52 factors (or concepts) connected by 98 directed, weighted causal links (or relationships). Second, we extended the map into a Fuzzy Cognitive Map by asking experts to characterize each causal link, and transforming intuitive characterizations into numbers through Fuzzy Logic.

The systems maps and the FCM can be used to address different policy-relevant questions. By leveraging the expertise of several contributors, the map provides a repository in which practical factors can be studied vis-a-vis their impact on the central goal of a smart city. In particular, it allows users to target one set of factors and identify the factors that those directly and indirectly impact, as well as giving the specific causal strength of those impacts. It also allows users to work backward from a target by identifying what levers can be used to impact it. In contrast with the purely structural use of the map, the FCM provides support for scenario-based or 'what-if' policy questions. We demonstrated for the city of Bandung that two hypothetical scenarios could be simulated, and their effects on pollution contrasted. We further illustrated that the FCM is a dynamical system (i.e. it updates values until stabilization) by simulating the consequences of budgetary reductions in the educational system. While the scenarios simulated were chosen as they are relevant interventions for smart cities and/or challenges specific to Bandung, our main takeaway is the ability of our system to simulate scenarios impacting Indonesian smart cities in general rather than these specific guiding examples.

There are several limitations to this work. First, it is grounded in the specific context of Indonesia. Comparative studies of smart cities have highlighted significant differences in implementation [20], [21], thus our map may not be immediately applicable to any other context. Future work may identify which parts of the map can be used as more generic 'building blocks', and which ones need alterations.

Second, there is no typical number of participants in a participatory modeling. On the one hand, maps have been built in participatory models with as few as 7 [46], 8 [92] or 12 participants [93]; on the other hand, studies have been conducted with as many as 51 [85], or even 59, participants [86]. Our study recruited ten experts to reach saturation on each of the nine domains that we identified from the literature (Table 3). Experts generally agreed on the causal strength between indicators (Figure 6), particularly for the indicators that directly drive the concept of 'smart city'. Nonetheless, having additional experts may contribute to capturing under-studied aspects of smart cities, thus creating new concepts or interrelationships, which in turn can create new loops. Our map may be changed as new evidence becomes available, or if additional experts wish to revise its structure.

Finally, the map was only built from the knowledge of experts, which is very sparse as they selected the relationships for which they think there is strong evidence. In contrast, groups of stakeholders with lower expertise in the system would be expected to generate more dense maps [50]. Obtaining and contrasting the maps of experts with those produced by other groups can have important implications for decision-making [94]. Indeed, the expert map may point to an intervention with high expected benefits, but constituents may expect lower or even negative consequences. Reconciling perspectives to assess which interventions are supported is an essential step to go from the identification to the realization of an intervention [95]. Future studies may thus extend our approach to compare and contrast perspectives between groups, either to bridge gaps or to identify interventions with a large support.

VII. CONCLUSION

Smart city is a broad concept, often based on a list of high-level domains or independent indicators. We created an operational definition of smart city, specific to the context of Indonesia. Our approach is rooted in participatory modeling, and involved 10 experts working on smart cities in Indonesia. Our definition includes a systems map of 52 indicators and 98 relationships, which can be used to understand the system surrounding smart cities. Our definition also provides a simulation model to quantify the consequences of possible interventions. Together, the map and simulation model support the identification and evaluation of specific interventions.

APPENDIX
SAMPLE INTERVIEW

This sample verbatim transcript was translated from Indonesian and edited for clarity as well as anonymity of the

interviewee (A). All interviews were conducted by the first author (H).

H: Hello, how are you, this is Hendra.

A: Hi, I'm fine. How are you doing today?

H: I'm fine. I'm calling for the interview about my research in identifying smart city components through an expert's perspective. And I'm here to interview you.

A: Ok, we can continue.

H: Prior to starting, your agreement is required on the consent that I already sent to you via email.

A: Ok. I have the consent.

H: Please read it.

A: *[Read the subject information and consent form.]*

H: So, before we begin, have you read and understood the subject information and consent form, and freely agree to participate?

A: Yes, I will.

H: So let's begin, basically there are two points that I seek in this interview. The first one that I want to touch on is about what it takes to make the city smarter in general, and the second one is to identify what are the components that can make a city smarter according to your expertise. Can we continue?

A: Ok, we can continue.

H: Based on your perspective, what are the components that can make cities smarter?

A: According to my views, human resource is important, technology, governance, and it is about regulations.

H: The regulations are about the government?

A: Yes, you're right.

H: Is there another one which will boost a smart city?

A: Yes, economic. With economic increase, the cities will become smarter.

H: How about the environment?

A: It's more of an impact. When the cities get smarter, the environment will be better.

H: Let's talk about the impact of these components on each other. For instance, what about the effect that human resources have on the concept of the smart city. As you said, the governance, technology and economy are smart city components.

A: Basically, the city will become smarter when it manages the human resource. And then the city has a good governance in manage the cities. Another component which makes cities smarter is when a government has good regulations. So basically there is the connection between government and governance.

[Continue to discuss this connection across components.]

H: Let's talk about economics. How do you think it relates with smart cities?

A: Well, the smartest of the cities will increase the economic growth. It's a normal relationship when the city has a lot of innovations starting, entrepreneurship. . . They will have a support to fuel the economic growth.

H: Can you mention the indicators of economic growth?

A: As I said before. Initiating innovations, entrepreneurship, co-creation, diversity of industries, and a good governance.

[Continue to tease out factors and relationships. Closing remarks.]

AUTHOR CONTRIBUTIONS

Conceived the study design: PJG. Conducted the experiments, performed the literature review, and wrote the first draft of this manuscript: HSF. Contributed to the writing of the manuscript: PJG. Revised the manuscript: PJG, HSF. All authors have read, and confirm that they meet, ICMJE criteria for authorship.

REFERENCES

[1] H. Ahvenniemi, A. Huovila, I. Pinto-Seppä, and M. Airaksinen, "What are the differences between sustainable and smart cities?" *Cities*, vol. 60, pp. 234–245, Feb. 2017.

[2] S. E. Bibri and J. Krogstie, "Smart sustainable cities of the future: An extensive interdisciplinary literature review," *Sustain. Cities Soc.*, vol. 31, pp. 183–212, May 2017.

[3] H. Parasati. (2013). National City Development Framework (Roadmap Pembangunan Perkotaan Nasional). [Online]. Available: https://www.unescap.org/sites/default/files/Session%202-%20Hayu%20Parasati%20-Indonesia.pdf

[4] D. Schuurman, B. Baccarne, L. De Marez, and P. Mechant, "Smart ideas for smart cities: Investigating crowdsourcing for generating and selecting ideas for ICT innovation in a city context," *J. Theor. Appl. Electron. Commerce Res.*, vol. 7, no. 3, pp. 49–62, 2012.

[5] "Smart cities: Background paper," Dept. Bus., Innov. Skills, London, U.K., Tech. Rep. BIS/13/1209, 2013. [Online]. Available: https://www.gov.uk/government/publications/smart-cities-background-paper

[6] H. Chourabi *et al.*, "Understanding smart cities: An integrative framework," in *Proc. 45th Hawaii Int. Conf. Syst. Sci. (HICSS)*, Jan. 2012, pp. 2289–2297.

[7] H. Schaffers *et al.*, "Smart cities and the future Internet: Towards cooperation frameworks for open innovation," in *The Future Internet Assembly*. New York, NY, USA: Springer, 2011, pp. 431–446.

[8] L. Aelenei, "Smart city: A systematic approach towards a sustainable urban transformation," *Energy Procedia*, vol. 91, pp. 970–979, Jun. 2016.

[9] V. Albino, U. Berardi, and R. M. Dangelico, "Smart cities: Definitions, dimensions, performance, and initiatives," *J. Urban Technol.*, vol. 22, no. 1, pp. 3–21, 2015.

[10] C. Manville *et al.*, "Mapping smart cities in the EU," European Parliament, Directorate-General for Internal Policies, Policy Department A: Economic and Scientific Policy, Brussels, Belgium, Tech. Rep. EP-50486, 2014.

[11] A. Caragliu, C. Del Bo, and P. Nijkamp, "Smart cities in Europe," in *Proc. 3rd Central Eur. Conf. Regional Sci.*, 2009, pp. 45–59.

[12] R. P. Dameri and A. Cocchia, "Smart city and digital city: Twenty years of terminology evolution," in *Proc. 10th Conf. Italian Chapter (AIS ITAIS)*, 2013, pp. 1–8.

[13] M. Angelidou, "Smart city policies: A spatial approach," *Cities*, vol. 41, pp. S3–S11, Jul. 2014.

[14] M. Angelidou, "Smart cities: A conjuncture of four forces," *Cities*, vol. 47, pp. 95–106, Sep. 2015.

[15] G. Rudolf and N. Pichler-Milanović, "Smart cities-ranking of European medium-sized cities," Rapport Techn., Vienna Centre Regional Sci., Vienna, Austria, Tech. Rep., 2007.

[16] D. Lu, Y. Tian, V. Liu, and Y. Zhang, "The performance of the smart cities in China—A comparative study by means of self-organizing maps and social networks analysis," *Sustainability*, vol. 7, no. 6, pp. 7604–7621, 2015.

[17] R. A. Afonso, K. dos Santos Brito, C. H. do Nascimento, V. C. Garcia, and A. Álvaro, "Brazilian smart cities: Using a maturity model to measure and compare inequality in cities," in *Proc. 16th Annu. Int. Conf. Digit. Government Res.*, 2015, pp. 230–238.

[18] R. Susanti, S. Soetomo, I. Buchori, and P. M. Brotosunaryo, "Smart growth, smart city and density: In search of the appropriate indicator for residential density in Indonesia," *Procedia-Social Behav. Sci.*, vol. 227, pp. 194–201, Jul. 2016.

[19] P. L. Mabry, D. H. Olster, G. D. Morgan, and D. B. Abrams, "Inter-disciplinarity and systems science to improve population health: A view from the NIH office of behavioral and social sciences research," *Amer. J. Preventive Med.*, vol. 35, no. 2, pp. S211–S224, 2008.

[20] J. H. Lee, M. G. Hancock, and M.-C. Hu, "Towards an effective framework for building smart cities: Lessons from Seoul and San Francisco," *Technol. Forecasting Social Change*, vol. 89, pp. 80–99, Nov. 2014.

[21] J.-S. Hwang and Y. H. Choe, "Smart cities Seoul: A case study," ITU-T Technol. Watch Rep., 2013. [Online]. Available: https://www.itu.int/dms_pub/itu-t/oth/23/01/T23010000190001PDFE.pdf

[22] R. K. R. Kummitha and N. Crutzen, "How do we understand smart cities? An evolutionary perspective," *Cities*, vol. 67, pp. 43–52, Jul. 2017.

[23] R. P. Dameri, "Searching for smart city definition: A comprehensive proposal," *Int. J. Comput. Technol.*, vol. 11, no. 5, pp. 2544–2551, 2013.

[24] A. Abdoullaev, "Keynote: A smart world: A development model for intelligent cities," in *Proc. 11th IEEE Int. Conf. Comput. Inf. Technol. (CIT)*, 2011, pp. 1–20.

[25] E. Bruni, A. Panza, L. Sarto, and F. Khayatian, "Evaluation of cities' smartness by means of indicators for small and medium cities and communities: A methodology for Northern Italy," *Sustain. Cities Soc.*, vol. 34, pp. 193–202, Oct. 2017.

[26] P. Lombardi, S. Giordano, H. Farouh, and W. Yousef, "Modelling the smart city performance," *Innov., Euro. J. Soc. Sci. Res.*, vol. 25, no. 2, pp. 137–149, 2012.

[27] S. Dirks and M. Keeling, "A vision of smarter cities: How cities can lead the way into a prosperous and sustainable future," IBM Inst. Bus. Value, Somers, NY, USA, Tech. Rep., 2009.

[28] Smart Cities Mission. (2017). *What is Smart City*. [Online]. Available: http://smartcities.gov.in/content/innerpage/what-is-smart-city.php

[29] Business Dictionary. (2018). *Smart City*. [Online]. Available: http://www.businessdictionary.com/definition/smart-city.html

[30] Smart Cities Council. (2018). *Definitions and Overviews*. [Online]. Available: https://smartcitiescouncil.com/smart-cities-information-center/definitions-and-overviews

[31] Brussels Smart City. (2017). *What is a Smart City?* [Online]. Available: https://smartcity.brussels/the-project-definition

[32] A. Muente-Kunigama and V. Mulas. (2015). *Smart Cities*. [Online]. Available: http://www.worldbank.org/en/topic/digitaldevelopment/brief/smart-cities

[33] P. J. Giabbanelli, "Modelling the spatial and social dynamics of insurgency," *Secur. Inform.*, vol. 3, no. 1, p. 2, 2014.

[34] H. de Pinho, "Generation of systems maps: Mapping complex systems of population health," in *Systems Science and Population Health*, A. M. El-Sayed and S. Galea, Eds. Oxford, U.K.: Oxford Univ. Press, 2017, pp. 61–76.

[35] T. Reddy, P. J. Giabbanelli, and V. K. Mago, "The artificial facilitator: Guiding participants in developing causal maps using voice-activated technologies," in *Proc. 13th Int. Conf. Augmented Cogn.*, 2019.

[36] M. Sandhu, P. J. Giabbanelli, and V. K. Mago, "From social media to expert reports: The impact of source selection on automatically validating complex conceptual models of obesity," in *Proc. 11th Int. Conf. Social Comput. Social Media*, 2019.

[37] P. J. Giabbanelli and M. Baniukiewicz, "Navigating complex systems for policymaking using simple software tools," in *Advanced Data Analytics in Health*. Cham, Switzerland: Springer, 2018, pp. 21–40.

[38] D. T. Finegood, T. D. Merth, and H. Rutter, "Implications of the foresight obesity system map for solutions to childhood obesity," *Obesity*, vol. 18, no. S1, pp. S13–S16, 2010.

[39] P. J. Giabbanelli and R. Crutzen, "Using agent-based models to develop public policy about food behaviours: Future directions and recommendations," *Comput. Math. Methods Med.*, vol. 2017, Mar. 2017, Art. no. 5742629.

[40] P. Giabbanelli *et al.*, "Developing technology to support policymakers in taking a systems science approach to obesity and well-being," *Obesity Rev.*, vol. 17, pp. 194–195, Apr. 2016.

[41] L. Malhi, Ö. Karanfil, T. Merth, M. Acheson, A. Palmer, and D. T. Finegood, "Places to intervene to make complex food systems more healthy, green, fair, and affordable," *J. Hunger Environ. Nutrition*, vol. 4, nos. 3–4, pp. 466–476, 2009.

[42] V. S. Pillutla and P. J. Giabbanelli, "Iterative generation of insight from text collections through mutually reinforcing visualizations and fuzzy cognitive maps," *Appl. Soft Comput.*, vol. 76, pp. 459–472, Mar. 2019.

[43] A. Voinov *et al.*, "Tools and methods in participatory modeling: Selecting the right tool for the job," *Environ. Model. Softw.*, vol. 109, pp. 232–255, Nov. 2018.

[44] J. Solana-Gutiérrez, G. Rincón, C. Alonso, and D. García-de-Jalón, "Using fuzzy cognitive maps for predicting river management responses: A case study of the Esla River basin, Spain," *Ecol. Model.*, vol. 360, pp. 260–269, Sep. 2017.

[45] S. Gray, A. Chan, D. Clark, and R. Jordan, "Modeling the integration of stakeholder knowledge in social–ecological decision-making: Benefits and limitations to knowledge diversity," *Ecol. Model.*, vol. 229, pp. 88–96, Mar. 2012.

[46] P. J. Giabbanelli, T. Torsney-Weir, and V. K. Mago, "A fuzzy cognitive map of the psychosocial determinants of obesity," *Appl. Soft Comput.*, vol. 12, no. 12, pp. 3711–3724, 2012.

[47] P. J. Lewis, "Rich picture building in the soft systems methodology," *Eur. J. Inf. Syst.*, vol. 1, no. 5, pp. 351–360, 1992.

[48] E. A. Lavin and P. J. Giabbanelli, "Analyzing and simplifying model uncertainty in fuzzy cognitive maps," in *Proc. Winter IEEE Simulation Conf. (WSC)*, Dec. 2017, pp. 1868–1879.

[49] J. Banks, "Introduction to simulation," in *Proc. Winter Simulation Conf. (WSC)*, vol. 1, Dec. 1999, pp. 7–13.

[50] E. A. Lavin, P. J. Giabbanelli, A. T. Stefanik, S. A. Gray, and R. Arlinghaus, "Should we simulate mental models to assess whether they agree?" in *Proc. Annu. Simul. Symp.*, 2018, p. 6.

[51] R. Jordan *et al.*, "Twelve questions for the participatory modeling community," *Earth's Future*, vol. 6, no. 8, pp. 1046–1057, 2018.

[52] N. Tsolakis and L. Anthopoulos, "Eco-cities: An integrated system dynamics framework and a concise research taxonomy," *Sustain. Cities Soc.*, vol. 17, pp. 1–14, Sep. 2015.

[53] M. Cullen, "Cities on the path to 'smart': Information technology provider interactions with urban governance through smart city projects in Dubuque, Iowa and Portland, Oregon," Ph.D. dissertation, London School Econ. Political Sci., London, U.K., 2016.

[54] T. Verigin, P. J. Giabbanelli, and P. I. Davidsen, "Supporting a systems approach to healthy weight interventions in british columbia by modeling weight and well-being," in *Proc. 49th Annu. Simulation Symp.*, 2016, p. 9.

[55] A. Amirkhani, E. I. Papageorgiou, A. Mohseni, and M. R. Mosavi, "A review of fuzzy cognitive maps in medicine: Taxonomy, methods, and applications," *Comput. Methods Programs Biomed.*, vol. 142, pp. 129–145, Apr. 2017.

[56] E. I. Papageorgiou and J. L. Salmeron, "A review of fuzzy cognitive maps research during the last decade," *IEEE Trans. Fuzzy Syst.*, vol. 21, no. 1, pp. 66–79, Feb. 2013.

[57] M. Amer, T. U. Daim, and A. Jetter, "A review of scenario planning," *Futures*, vol. 46, pp. 23–40, Feb. 2013.

[58] E. I. Papageorgiou, *Fuzzy Cognitive Maps for Applied Sciences and Engineering: From Fundamentals to Extensions and Learning Algorithms*, vol. 54. Berlin, Germany: Springer, 2013.

[59] M. Glykas, *Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Tools and Applications*, vol. 247. Springer, 2010.

[60] A. J. Jetter and K. Kok, "Fuzzy cognitive maps for futures studies—A methodological assessment of concepts and methods," *Futures*, vol. 61, pp. 45–57, Sep. 2014.

[61] J. A. Dickerson and B. Kosko, "Virtual worlds as fuzzy cognitive maps," *Presence: Teleoperators Virtual Environ.*, vol. 3, no. 2, pp. 173–189, 1994.

[62] G. Nápoles, I. Grau, R. Bello, M. León, K. Vahoof, and E. Papageorgiou, "A computational tool for simulation and learning of fuzzy cognitive maps," in *Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE)*, Aug. 2015, pp. 1–8.

[63] J. Tisseau, M. Parenthoën, C. Buche, and P. Reignier, "Comportements perceptifs d'acteurs virtuels autonomes," *Techn. Sci. Inform.*, vol. 24, pp. 1259–1293, Oct. 2005.

[64] R. Gras, D. Devaurs, A. Wozniak, and A. Aspinall, "An individual-based evolving predator-prey ecosystem simulation using a fuzzy cognitive map as the behavior model," *Artif. Life*, vol. 15, no. 4, pp. 423–463, 2009.

[65] P. J. Giabbanelli, M. Fattoruso, and M. L. Norman, "Confluences: Simulating the spread of social influences via a hybrid agent-based/fuzzy cognitive maps architecture," in *Proc. ACM SIGSIM Conf. Princ. Adv. Discrete Simulation (PADS)*, 2019.

[66] A. K. Tsadiras, "Comparing the inference capabilities of binary, trivalent and sigmoid fuzzy cognitive maps," *Inf. Sci.*, vol. 178, no. 20, pp. 3880–3894, 2008.

[67] G. Nápoles, E. Papageorgiou, R. Bello, and K. Vanhoof, "Learning and convergence of fuzzy cognitive maps used in pattern recognition," *Neural Process. Lett.*, vol. 45, no. 2, pp. 431–444, 2017.

[68] V. K. Mago *et al.*, "Analyzing the impact of social factors on homelessness: A fuzzy cognitive map approach," *BMC Med. Inform. Decision Making*, vol. 13, no. 1, p. 94, 2013.

[69] P. P. Groumpos and C. D. Stylios, "Modelling supervisory control systems using fuzzy cognitive maps," *Chaos, Solitons Fractals*, vol. 11, nos. 1–3, pp. 329–336, 2000.

[70] P. J. Giabbanelli and R. Crutzen, "Creating groups with similar expected behavioural response in randomized controlled trials: A fuzzy cognitive map approach," *BMC Med. Res. Methodol.*, vol. 14, no. 1, p. 130, 2014.

[71] M. F. Hatwágner, E. Yesil, M. F. Dodurka, E. Papageorgiou, L. Urbas, and L. T. Kóczy, "Two-stage learning based fuzzy cognitive maps reduction approach," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 5, pp. 2938–2952, Oct. 2018.

[72] G. Nápoles, L. Concepción, R. Falcon, R. Bello, and K. Vanhoof, "On the accuracy–convergence tradeoff in sigmoid fuzzy cognitive maps," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 4, pp. 2479–2484, Aug. 2018.

[73] L. Leydesdorff and M. Deakin, "The triple helix model of smart cities: A neo-evolutionary perspective," *J. Urban Technol.*, vol. 18, no. 2, pp. 53–63, 2011.

[74] L. Drasic and P. J. Giabbanelli, "Exploring the interactions between physical well-being, and obesity," *Can. J. Diabetes*, vol. 39, pp. S12–S13, Apr. 2015.

[75] S. Gray, J. Hilsberg, A. McFall, and R. Arlinghaus, "The structure and function of angler mental models about fish population ecology: The influence of specialization and target species," *J. Outdoor Recreation Tourism*, vol. 12, pp. 1–13, Dec. 2015.

[76] P. J. Giabbanelli and A. A. Tawfik, "Overcoming the PBL assessment challenge: Design and development of the incremental thesaurus for assessing causal maps (ITACM)," *Technol., Knowl. Learn.*, pp. 1–8, Sep. 2017. [Online]. Available: https://link.springer.com/journal/10758/onlineFirst/page/3

[77] V. K. Gupta, P. J. Giabbanelli, and A. A. Tawfik, "An online environment to compare students' and expert solutions to ill-structured problems," in *Proc. Int. Conf. Learn. Collaboration Technol.* Springer, 2018, pp. 286–307.

[78] P. Girardi and A. Temporelli, "Smartainability: A methodology for assessing the sustainability of the smart city," *Energy Procedia*, vol. 111, pp. 810–816, Mar. 2017.

[79] G. C. Lazaroiu and M. Roscia, "Definition methodology for the smart cities model," *Energy*, vol. 47, no. 1, pp. 326–332, 2012.

[80] S. Ben Letaifa, "How to strategize smart cities: Revealing the SMART model," *J. Bus. Res.*, vol. 68, no. 7, pp. 1414–1419, Jul. 2015.

[81] E. Sofeska, "Understanding the livability in a city through smart solutions and urban planning toward developing sustainable livable future of the city of Skopje," *Procedia Environ. Sci.*, vol. 37, pp. 442–453, Jan. 2017.

[82] D. Węziak-Bialowolska, "Quality of life in cities–empirical evidence in comparative European perspective," *Cities*, vol. 58, pp. 87–96, Oct. 2016.

[83] T. Nam and T. A. Pardo, "Conceptualizing smart city with dimensions of technology, people, and institutions," in *Proc. 12th Annu. Int. Digit. Government Res. Conf., Digit. Government Innov. Challenging Times*, 2011, pp. 282–291.

[84] L. Ortolani, N. McRoberts, N. Dendoncker, and M. Rounsevell, "Analysis of farmers' concepts of environmental management measures: An application of cognitive maps and cluster analysis in pursuit of modelling agents' behaviour," in *Fuzzy Cognitive Maps*. Berlin, Germany: Springer, 2010, pp. 363–381.

[85] U. Özesmi and S. Özesmi, "A participatory approach to ecosystem conservation: Fuzzy cognitive maps and stakeholder group analysis in Uluabat Lake, Turkey," *Environ. Manage.*, vol. 31, no. 4, pp. 518–531, 2003.

[86] A. Meliadou, F. Santoro, M. R. Nader, M. A. Dagher, S. A. Indary, and B. A. Salloum, "Prioritising coastal zone management issues through fuzzy cognitive mapping approach," *J. Environ. Manage.*, vol. 97, pp. 56–68, Apr. 2012.

[87] C. Siokou, R. Morgan, and A. Shiell, "Group model building: A participatory approach to understanding and acting on systems," *Public Health Res. Pract.*, vol. 25, no. 1, 2014, Art. no. e2511404.

[88] E. Bardach, "Policy dynamics," in *The Oxford Handbook of Public Policy*. Oxford, U.K.: Oxford Univ. Press, 2006, pp. 336–366.

[89] J. A. Vennix, *Group Model Building: Facilitating Team Learning Using System Dynamics*. Hoboken, NJ, USA: Wiley, 1996.

[90] Global Center of Competence Cities. (2016). *Bandung Smart City: Peran Teknologi*. [Online]. Available: www.siemens.asia/ID/Libraries/Press_Attachment/Bandung_Study_Book_ID.sflb.ashx

[91] K. Kawamura, "Politics of inequality in Indonesia: Does democracy matter?" in *Emerging States at Crossroads*. Singapore: Springer, 2019, pp. 231–253.

[92] M. van Vliet, K. Kok, and T. Veldkamp, "Linking stakeholders and modellers in scenario studies: The use of fuzzy cognitive maps as a communication and learning tool," *Futures*, vol. 42, no. 1, pp. 1–14, 2010.

[93] M. E. Isaac, E. Dawoe, and K. Sieciechowicz, "Assessing local knowledge use in agroforestry management with cognitive maps," *Environ. Manage.*, vol. 43, no. 6, pp. 1321–1329, 2009.

[94] B. G. Giles, C. S. Findlay, G. Haas, B. LaFrance, W. Laughing, and S. Pembleton, "Integrating conventional science and aboriginal perspectives on diabetes using fuzzy cognitive maps," *Social Sci. Med.*, vol. 64, no. 3, pp. 562–576, 2007.

[95] P. J. Giabbanelli, J. Adams, and V. S. Pillutla, "Feasibility and framing of interventions based on public support: Leveraging text analytics for policymakers," in *Proc. Int. Conf. Social Comput. Social Media*, 2016, pp. 188–200.

HENDRA SANDHI FIRMANSYAH is currently pursuing the Ph.D. degree with the School of Electrical Engineering and Informatics, Bandung Institute of Technology (ITB), Indonesia. His research interests include smart city models, maturity models, and IT risk management.

SUHONO H. SUPANGKAT is currently a Professor with the School of Electrical Engineering and Informatics, Bandung Institute of Technology (ITB), Indonesia. He formerly served as the Head of the Smart City and Community Innovation Center. His research interests include smart cities concepts, smart city governance, and the Internet of Things.

ARRY A. ARMAN is currently an Associate Professor with the School of Electrical Engineering and Informatics, Bandung Institute of Technology (ITB), Indonesia. His main research interests include IT governance, enterprise architecture, smart cities governance, and speech recognition.

PHILIPPE J. GIABBANELLI is currently an Assistant Professor of computer science with Furman University. He has published almost 60 articles using data science techniques, such as machine learning, predictive analytics, and visualization. In particular, his work on predictive analytics often uses fuzzy cognitive maps for participatory modeling.

• • •