Fuzzy Analogical Reasoning in Cognitive Cities
A Conceptual Framework for Urban Dialogue Systems

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Abstract: This article presents a conceptual framework for urban dialogue systems to let them emulate human analogical reasoning by using cognitive computing and particularly soft computing. Since creating analogies is crucial for humans to learn unknown concepts, this article proposes an approach of urban applications to human cognition by introducing analogical reasoning as a sound component of their fuzzy reasoning process. Pursuing an approach derived from (transdisciplinary) design science research, two experiments were conducted to reinforce the theoretical foundation.

1 INTRODUCTION

Against the background of a strengthening urbanization (e.g., dwindling urban living space) and the increasing fuzziness in information (e.g., different perceptions of a family-friendly neighborhood), cities need to find new technological solution approaches to manage plenty of data to counteract urban challenges, such as natural resource use and human well-being. Thereby, a promising approach is to enhance existing urban systems with Web-based technologies (e.g., Web-of-things (D'Onofrio et al., 2018)) to sustain urban governance and mainly increase efficiency and sustainability, to finally establish smart cities (D'Onofrio and Portmann, 2017).

Recent technological advances, such as sensor technologies (Batty, 2013), have largely altered characteristics of urban data (e.g., real-time instead of past data). These advancements help to transform a formerly sparse knowledge to a much more sophisticated understanding of cities (Hurwitz et al., 2015). Building upon incoming civic data (e.g., through citizens' use of services), this understanding is required to design and implement urban services based on civic needs to shape human smart cities (i.e., becoming more human-oriented). By integrating citizens as "drivers of change" into the development of urban systems (e.g., civic tech movements), new forms of participatory governance may arise (Oliveira and Campolargo, 2015).

To foster information sharing in cities, existing urban services can be provided with cognitive capabilities, such as reasoning or learning abilities, to mimic human intelligence (cf. humanistic computing (Mann, 1998)). An approach, which might let urban systems emulate human cognition, is the application of cognitive computing. It enables supplementing systems with cognitive processes, such as analogical reasoning (Gentner, 1983), and, thus, accelerating urban development to foster cognitive cities (D'Onofrio and Portmann, 2017).

The authors present a conceptual framework for urban dialogue systems to emulate human analogical reasoning based on soft computing techniques (i.e., a vital component of cognitive computing (D'Onofrio and Portmann, 2017)), to suggest a new technological solution approach (i.e., fuzzy analogical reasoning), to improve existing urban systems with a focus on socio-technical systems.

This article is an outline of a work-in-progress. To this end, the authors use an approach derived from design science research (Hevner and Chatterjee, 2010) that is advanced by transdisciplinary research (Wickson et al., 2006) and follows the law of parsimony (Laird, 1919). Section 2 presents the theoretical background; the approach itself is outlined in Section 3 and discussed in Section 4; Section 5 concludes this article.

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2 BACKGROUND

By outlining how human smart cities may advance to cognitive cities, describing soft computing as a vital component of cognitive computing, and introducing structure-mapping theory, this section presents the theoretical foundation of the framework.

2.1 The Role of Technology and Humans in Urban Development

Building upon advanced Web-based technologies (e.g., Web-of-things (D'Onofrio et al., 2018)), smart urban systems, such as dialogue systems, represent potential starting points for enriching civic interaction. They enable the exchange of citizens' perceptions and knowledge among them and foster urban development, particularly regarding efficiency and sustainability. Moreover, they allow to build a collective knowledge base, supporting urban decisions on a data-driven basis (Finger and Portmann, 2016; Malone and Bernstein, 2015).

Based on aggregated data sets obtained through citizens' use of urban services (e.g., everyday questions through civic interaction), cities obtain an integrated view on issues (e.g., urban living space) and can involve affected stakeholders (e.g., citizens) specifically (Hurwitz et al., 2015). Hence, cities can take broad-based decisions to improve equity and sustainability of urban life. Thus, participative models of urban governance are established, allowing the development of human smart cities by putting citizens in foreground and giving them the possibility to shape their living environment through the expression of their needs or ideas for improvements (Oliveira and Campolargo, 2015).

Human smart cities can be further reinforced by being supplemented with cognitive computing. Cognitive cities build upon cognitive systems and processes (e.g., reasoning or learning processes) and are increasingly capable of dealing with a human living environment that is constantly changing and getting more complex (Mostashari et al., 2011). Due to natural language, which is seen as the main communication medium in cities, urban environment is also getting fuzzier. Therefore, cognitive cities enable developing collective and humanistic intelligence (i.e., citizens and urban systems are working together using natural language) (Malone and Bernstein, 2015; Mann, 1998), which significantly addresses urban resilience by helping to encounter challenges, such as urbanization and digitalization (D'Onofrio and Portmann, 2017).

2.2 Soft Computing

Fuzzy logic represents an extension of traditional logic where p can be true or false or have an intermediate truth value (Zadeh, 1988). This allows a generalization of conventional set theory, namely fuzzy set theory, where an element x of a finite or infinite set X is no longer either contained or not in a crisp subset A in X. Instead, it is possible to define a membership function $\mu_A(x)$, which shows to what degree an element x is contained in a fuzzy subset A in X (Zadeh, 1965):

$$\mu_A(x) \rightarrow [0, 1] \quad (1)$$

To build fuzzy sets, it is required that humans can break down information into various levels of abstraction by reflecting hierarchical structures of their environment upon the hierarchical organization of their knowledge (Yao, 2006). Thereby, the ability to decompose the complex and uncertain environment into simpler and tractable clumps (i.e., fuzzy information granules (Zadeh, 1997)) is crucial for human information processing (Hobbs, 1985). For instance, general words represent high levels of granularity, while specific words express high levels of detail, but low levels of granularity (Yao, 2006). Hence, fuzzy information granulation helps citizens to wrap up data and reduce information overload.

By using fuzzy information granules, computing with words (CWW) allows to describe human-like reasoning based on fuzzy logic (D'Onofrio and Portmann, 2015). Since most real-world constraints have a tolerance for fuzziness, the concept of a generalized constraint (GC) strives to define degrees of fuzziness based on CWW (Zadeh, 2005):

$$\text{GC: } X \text{ is} r \ R \quad (2)$$

Thereby, X is a constrained variable and R a fuzzy constraining relation. The modularity (i.e., semantics) of R is identified by r, an indexing variable that is adjustable (e.g., equal, possibilistic, probalistic) (Zadeh, 2005). Assuming possibilistic semantics of R, r is abbreviated to a blank space and a GC is adjusted as follows (Zadeh, 1996):

$$\text{GC: } X \text{ is } R \quad (3)$$

With possibilistic semantics, R constrains a variable X by playing the role of the possibility distribution of X. If u is a generic value of X, and μ_R is a membership function in R, the semantics of R can be defined as follows (Zadeh, 1996):

$$\text{Poss}\{X = u\} = \mu_R(u) \quad (4)$$

Hence, methods based on fuzzy logic foster human-like reasoning and facilitate, among others, analogical reasoning.

2.3 Structure-Mapping Theory

Analogy represents abstractions of higher-order human cognition (i.e., symbolic information processing), which involves humans mapping one situation onto another to process information, learn and acquire new knowledge. In the case of analogy, humans focus on relational similarity (i.e., structure-based similarity) between two situations, which is based on labelled relations (i.e., symbols) (Boteanu and Chernova, 2015). Hence, an analogy is apparent if a relation between a pair of data elements *d* and *e* is structurally similar to a relation between another pair of data elements *g* and *h* (e.g., *district is to city as chapter is to book*) (Barr et al., 2015).

Structure-mapping theory (SMT) explains not only analogical but also similarity reasoning and, thus, how humans map data elements of a familiar situation (i.e., base) onto data elements of an unfamiliar situation (i.e., target) to understand and draw new inferences about the latter. Each mapping comprises a set of correspondences either between attributes (i.e., features) of data elements or relations (i.e., structures) among one another. Depending on whether correspondences between data elements emphasize their attributes (i.e., objective similarity) or their relations among one another (i.e., relational similarity), different types of similarity (e.g., surface similarity, analogy) present the outcome of the mapping of two situations (Gentner, 1983).

Based on common patterns of entities (i.e., attributes, relations), which have emerged from the alignment of two situations, humans make new presumptions (i.e., candidate inferences) about the target. Pursuing structural consistency and systematicity, humans complete these patterns and familiarize with unknown data elements. An analogy occurs if and only if humans familiarize with a target by drawing inferences based on relational pattern completion (Gentner and Markman, 1997).

3 CONCEPTUAL FRAMEWORK

This section presents related work, the concept and the evaluation of the proposed framework for urban dialogue systems to emulate human analogical reasoning drawing on soft computing techniques.

3.1 Related Work

Dialogue systems aim to automatically deliver relevant and concise answers to humans' questions often posed in natural language (Ojokoh and Ayokunle, 2013). Such systems are of importance as they can help to sustain urban governance by enhancing the information exchange between cities and citizens. Since natural language consists of linguistic variables (e.g., words), the inclusion of soft computing techniques may improve dialogue systems (Zadeh, 2006). Although there have been developments of such reasoning methodologies (e.g., CWW-based system (Khorasani et al., 2009), perception-based system (Ahmad and Rahimi, 2006)), these applications, such as expert systems, typically do not foster reasoning and dialogue in such a way that humans process information by using, for instance, analogical reasoning (Zadeh, 2006).

Moreover, there have been aspirations to facilitate natural language processing (NLP) by means of analogical reasoning (e.g., denominal verb interpretation (McFate and Forbus, 2016), word sense disambiguation (Barbella and Forbus, 2013)). However, none of these systems constitute an approach to human cognition because attempts, such as NLP, do not account for fuzziness in the characterization of biological systems (Seising and Sanz, 2012). Since it is proposed that cognitive systems use soft computing techniques to become capable of understanding and extracting heterogeneously structured information from natural language (Zadeh, 2005), their ability to create analogies should also consider dealing with fuzzy information.

3.2 Concept

Based on previous work of Bouchon-Meunier and colleagues (Bouchon-Meunier et al., 2003; Bouchon-Meunier and Valverde, 1999), the proposed framework builds upon an analogical scheme for approximate reasoning to allow urban systems to interact with citizens in natural language. Starting with a citizen's question, for example "*How can I get a seasonal-work approval?*", the system decomposes it into data elements consisting of words or a sequence of words: *how*, *get*, *seasonal-work* and *approval*. By completing the granulation process (cf. Zadeh, 1997), the system needs to clarify through alignment with existing stored knowledge whether it understands single data elements. In this example, the following classification is possible: *how* belongs to certain degrees to the fuzzy set *factoid question* and that of *procedure*, *get* to the fuzzy set *infinitive*, and *seasonal-work* and *approval* remain unknown.

Resulting from the system's granulation process, two linguistic variables X and Y are assumed for the unknown information: X represents a domain with possible values p (e.g., *temporary-work*) and q (e.g., *seasonal work)*, and Y another domain that can take values r (e.g., *permit*) and s (e.g., *approval)*. Assuming furthermore possibilistic semantics of a fuzzy constraining relation R_Y, the system can formulate a GC for Y (Zadeh, 1996):

$$\begin{gathered} \text{GC: } Y \text{ is } R_Y, \\ \text{where Poss}\{Y = r\} = \mu_{RY}(r) \\ \text{and Poss}\{Y = s\} = \mu_{RY}(s) \end{gathered} \tag{5}$$

Next, the system may use resemblance relations (cf. Bouchon-Meunier and Valverde, 1999) to gain a somewhat known value for q based on a known relation R_X between the unknown data element q and a known data element p. Having retrieved a relation R_X between linguistic values p and q, the system becomes capable of drawing the analogical scheme to gain a known value for an unknown data element s (Bouchon-Meunier et al., 2003):

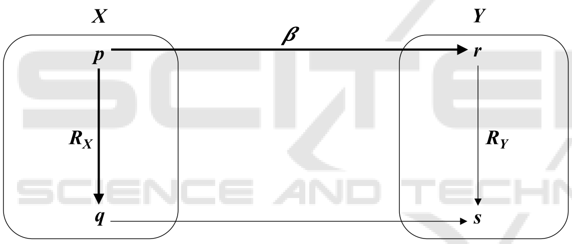

Figure 1: Analogical scheme.

Therefore, the system can use a fuzzy-based application of the compositional rule of inference (CRI) (i.e., approximate reasoning). The CRI is an extension of the familiar rule of inference (i.e., generalized modus ponens), which states *if X is true and implies Y, then Y is true*, and is applied as follows:

$$\mu_{RY}(r) = \max_{\mu}(\mu_{RX}(p) \wedge \mu_{\beta RXRY}(p, r)) \tag{6}$$

Based on resemblance relations (i.e., p and q are apparently known to be related by R_X), *temporary-work* and *seasonal-work* are approximately equal and, thus, *seasonal-work* is more or less *permit*.

Since the linkage β between p and r is also known (i.e., *temporary-work* belongs to the fuzzy set *permit* to a not negligible degree), it is possible to gain a known value for s, which is to q as r is to p, drawing an inference R_Y between data elements r and s (Bouchon-Meunier and Valverde, 1999). In terms of SMT, a structure-based correspondence is projected based on β (Gentner, 1983). Therefore, the system can project a mapping $R_{\beta RXRY}$, which provides it with a linguistic value for s based on relations β, R_X, R_Y, expressed by their membership grades in respective sets of fuzzy (sub-)sets of X and Y (i.e., μ_{RX}, μ_{RY}) (Bouchon-Meunier et al., 2003):

$$\begin{gathered} R_{\beta RXRY}\text{: } \mu_{RX}(p) \times \mu_{RY}(r) \times \mu_{RX}(q) \rightarrow \mu_{RY}(s), \\ \text{where } \beta \subset \mu_{RX}(p) \times \mu_{RY}(r) \\ \text{and } R_X \subset \mu_{RX}(p) \times \mu_{RX}(q) \\ \text{and } R_Y \subset \mu_{RY}(r) \times \mu_{RY}(s) \end{gathered} \tag{7}$$

Assuming that *approval* is to *seasonal-work* as *permit* is to *temporary-work*, the system creates a mapping to understand *approval* in relation to *seasonal-work*. The system ends the analogical reasoning process by classifying all data elements as known and may continue the dialogue with the citizen.

3.3 Evaluation

This subsection briefly outlines how the conceptual framework was evaluated through two experiments, both carried out by the authors, pursuing a methodological approach oriented towards design science research in information systems and transdisciplinary research to include citizens into the development process (Hevner and Chatterjee, 2010).

3.3.1 Workshop-based Experiment

In May 2017, the authors conducted a workshop to become more familiar with citizens' requirements for new (smart) urban systems and, simultaneously, get insights about the human reasoning process. Nine males and two females, all between 20 and 50 years old and with different professional backgrounds (e.g., computer science, geography), participated in the workshop. It lasted two hours in total, whereby the experiment took half an hour.

First, an introduction about cognitive computing and soft computing was given to build a theoretical foundation for the experiment. Afterwards, a discussion about the term *human-machine interaction* began, exchanging opportunities and threats of computer systems that are able to compute natural language (e.g., Alexa, Siri). Most participants were sceptical about systems that are taking over control or being able to autonomously make decisions. However, some participants stated that they are curious to test such "*intelligent*" systems (e.g., self-driving cars). They even considered using them in the future if such services would turn out to be advantageous for them.

After having discussed smart systems and, more concretely, their acceptance and usefulness for cities, the main experiment was conducted with the aim to reinforce the theories about the relation between questions and answers as well as to get constructive inputs regarding the human reasoning process. The experiment consisted of two parts.

The first part was about answering five *"W"-questions* (i.e., *who*, *where*, *when*, *how long*, *how*) stated in German. The results showed that almost every participant answered in the same way, even if the answers were not identically (e.g., *whole name* vs. *last name*). To grasp the essence of the results, some examples are presented: To the question "*Who leads the experiment?*", everyone answered with a name, obviously with the one of the moderating author. Asking "*Where does the experiment take place*", all participants stated a location. Their responses were only differing in their granularity (e.g., *Bern* vs. *Impact Hub Bern*). To the question "*How long does the workshop take?*", everyone answered with a time specification, however, also containing granular variances, such as mentioning hours or minutes. Considering the semantics of all answers, this experiment showed that *"W"-questions* influence humans in the way of how they give responses.

The second part consisted of responding to three questions that were impossible to answer because of their semantics (e.g., "*Where do lucky devils grow?*"). Even if the *"W"-word* provided hints on how to answer the question, no meaningful linking with existing knowledge was possible. Therefore, the participants were not able to give a reasonable answer. They tried to create analogies using familiar situations and, thus, responded with information that most likely matched them individually. Although the questions were obviously not meant serious, no one considered the possibility of stating that there is no answer (even though that would have been the correct answer) and instead gave unserious answers (e.g., *haunted forest*).

3.3.2 Laboratory Experiment

In May 2017, a laboratory experiment was conducted to evaluate the stableness of the conceptual framework's theoretical foundation. Its purpose was to document how far subjects would follow theoretical predictions of SMT if they created analogies to find relations between their existing knowledge and unknown concepts.

Seven males and three females, all between 25 and 30 years old, participated in the experiment, where everybody was of Swiss nationality and had an academic background. The paper-pencil experiment lasted 20 minutes in total and pursued double-blind anonymity as well as a 1x2 between-subject design. The two treatments split into an experimental treatment and a control treatment, completed by five subjects each.

SMT predicts that objective similarity is typically more likely to be retrieved by humans than relational similarity because it is represented by superficialities, which are easier to recollect (Gentner and Forbus, 2011). Hence, the tested hypotheses postulated this fundamental assumption and are outlined as follows:

H1: If humans need to retrieve a familiar situation (i.e., base) by their own memory to understand and draw new inferences about an unfamiliar situation (i.e., target), they tend to encode objective similarity (i.e., surface similarity) rather than relational similarity (i.e., analogy).

H2: If an unfamiliar situation (i.e., target) immediately comes with a familiar situation (i.e., base), which can be used to understand and draw new inferences about the former (e.g., analogical argumentation in a discussion), humans tend to encode relational similarity (i.e., analogy) rather than objective similarity (i.e., surface similarity).

The questionnaire used was in German, consisted of five tasks in two variations: One that was completed by the experimental treatment and another one by the control treatment. Thereby, the treatment variable described whether subjects needed to retrieve a familiar situation by their own memory to map any form of similarity onto an unfamiliar situation. Hence, the treatment variable was nominally scaled and took the values 0 (i.e., subject was in the control treatment) or 1 (i.e., subject was in the experimental treatment). Two graphical representations were used to illustrate such familiar or unfamiliar situations.

For both treatments, it was measured afterwards which form of similarity subjects had tended to encode either through their choices (i.e., control treatment) or their own drawings (i.e., experimental treatment). The dependent variable here was nominally scaled as well and took the values 0 (i.e., relational similarity) or 1 (i.e., objective similarity). These measurements served to investigate the statistical correlations and conditional probability distributions between the two elicited variables.

In H1, the descriptive univariate analysis indicated that subjects in the experimental treatment encoded relational and objective similarity equally. Although they needed to retrieve a base by their own memory, subjects did not tend to draw graphical representations that primarily shared an objective similarity with the target. In H2, conditional probability distributions of the control treatment suggested that subjects clearly tended to encode relational similarity rather than objective similarity, as they were given both target and base simultaneously. Finally, in H1 and H2, the descriptive bivariate data analysis indicated that there was a moderate correlation between the form of similarity, which subjects tended to encode, and whether they needed to retrieve a familiar situation by themselves to map this similarity onto an unfamiliar situation.

4 DISCUSSION

The conceptual framework builds upon an analogical scheme for approximate reasoning, which denotes a type of reasoning that is neither quite precise nor quite imprecise and expresses humans' ability to take rational decisions in complex and uncertain environments. By applying the analogical scheme and linking analogical concepts to soft computing, (Web-based) urban dialogue systems might understand previously unknown data elements. Hence, if they do not understand one or several data elements during an interaction with a citizen, they may create an analogy to find a relation with existing stored knowledge (Bouchon-Meunier and Valverde, 1999). Since creating analogies is crucial for humans to learn unknown concepts and soft computing allows to understand and extract information from natural language, urban dialogue systems would become more oriented towards humans and perform and learn better (D'Onofrio and Portmann, 2017; Gentner, 2010).

To reinforce the theories, two experiments were conducted (independently from each other). In the workshop-based experiment, the focus was put on question-answering processes to get constructive inputs regarding the human reasoning process. Thereby, two valuable findings were gained: First, *"W"-questions* influenced the way of how to answer (e.g., *who* = person, *where* = location), and second, if the semantics of a question made no or little sense, participants tended to create analogies using familiar situations. As an illustration, the question in German "*Wo wachsen Glückspilze?*" (engl. "*Where do lucky devils grow?*") is presented here: Some participants mentioned to have tried to create analogies using *Pilz* (engl. *mushroom*). Being influenced by the question word *wo* (engl. *where*), participants searched for a possible place (e.g., *haunted forest*) as an answer, associating *Glück* (engl. *luck*) with a magical element. They largely justified their answers with an association to their childhood, in which they got to know fairy tales. Thus, they connected the unknown word (i.e., the growth place of lucky devils) with an element known from their knowledge base. Hence, creating analogies is crucial for human information processing and, therefore, for future urban dialogue systems, too.

In the laboratory experiment, the results mostly indicated a stable theoretical foundation of the developing reasoning process. However, not all tested hypotheses were provided with evidence in favour of SMT. The most interesting finding was that relational similarity (i.e., analogy) was equally encoded by subjects, even if they had completed a retrieval by themselves. Hence, support for the hypothesis behind that finding (i.e., H1) could not be drawn, which counters a theoretical prediction of SMT. Regarding dialogue systems emulating human analogical reasoning, this last finding contains a promising implication: Since systems at some point need to retrieve a relation based on the drawn analogical scheme, it would further improve urban services and be in favour of citizens, if systems were able to encode powerful relational similarity by default and did not provide citizens with answers based on objective similarity (Gentner et al., 1993).

By further emulating human information processing through analogical reasoning, cognitive systems might perform better in interaction with citizens, make human-computer interaction (HCI) even more human-centered and facilitate the urban learning process additionally (Gentner, 2010). This provides the foundation for a resilient urban network of knowledge that is driven by a constantly learning collective intelligence (Malone and Bernstein, 2015). Thereby, intelligence amplification denotes a visionary concept that outlines how continuous and complementary HCI may shape and augment urban intelligence and, thus, sustain society (D'Onofrio and Portmann, 2017). Shaping and increasing urban intelligence are not simple endeavors. This is because amounts of data storage, communication capacity and, hence, potential knowledge for humans are exponentially growing, human information processing however remains unchanged (Batty, 2013). Therefore, human-centered, mutual and constant HCI is increasingly necessary to enhance human reasoning and learning.

If cities integrate cognitive computing into urban applications that may also emulate human analogical reasoning, it is crucial that they pursue a business and an economic plan that ensure appropriate planning, procurement and delivery of corresponding technologies and infrastructures. Thus, an appropriate environment for a human-computer symbiosis can be established and collective and humanistic intelligence sustainably be created (Malone and Bernstein, 2015; Mann, 1998). This intelligence is needed eventually to strengthen urban resilience and sustain urban governance to tackle challenges of urbanization and digitalization (Finger and Portmann, 2016).

5 LIMITATIONS AND OUTLOOK

The presented framework for urban dialogue systems, which is conceptually designed in this article, represents an extract of a developing idea of a global reasoning process for urban systems and is part of a current research project. Therefore, most limitations and corresponding suggestions for future research focus on this research project.

More research needs to be done relating to how a system decomposes a citizen question and whether this is expedient at all. So far, data elements have received a meaning only after they were decomposed by granular computing into words or a sequence of words. However, data elements might have a different meaning if they are processed as part of an entire question (Chowdhury, 2003). A conductive thought can be that the system immediately tries to align the citizen question with existing stored knowledge, looking for similar questions that have been asked in the past and might help to classify the incoming one.

Furthermore, investigation of modern information retrieval (IR) techniques is needed. This is because techniques based on conventional models are not in favour of the IR process. Relating to a fuzzy IR process, there are promising approaches that might be specified for the proposed fuzzy reasoning process (Baeza-Yates and Ribeiro-Neto, 2011).

More specifications are necessary regarding the nature of a system's knowledge base. Known fuzzy sets first need to be collected and stored such that they can be associated with processed data elements afterwards. This brings up the question about an appropriate computer memory. The authors intend to use fuzzy cognitive maps (FCMs) as a memory basis stored in graph databases (cf. D'Onofrio et al., 2017). Since it would define relevance gradually, the system would answer questions effectively even if they were formulated imprecisely. Therefore, an alignment of FCMs with SMT might be an expedient next step.

Finally, it needs to be noted that this introduction of analogical reasoning as a sound component of the fuzzy reasoning process focuses on SMT because it is displayed in the analogical scheme, which links analogical reasoning to soft computing. However, there are several analogical concepts (e.g., metaphor, schema, transfer) that might also provide a basis for further development of the fuzzy reasoning process.

One last limitation relates to both experiments whose findings do not raise a claim to represent high-level scientific contributions, particularly not in methodological terms. The experiments served much more as an evaluation of the developing fuzzy reasoning process as a designed artefact, which is oriented towards the process of (transdisciplinary) design science research. The authors encourage further urban researchers to conduct experiments with citizens to grasp actual existing needs and, therefore, to develop meaningful urban systems.

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