Illuminating Smart City Solutions – A Taxonomy and Clusters

Claudius Jonas
University of Bayreuth, claudius.jonas@fim-rc.de

Kevin Schmitt
University of St. Gallen, kevin.schmitt@unisg.ch

Anna Maria Oberländer
FIM Research Center, University of Bayreuth, anna.oberlaender@fim-rc.de

Philipp Ebel
University of St. Gallen, philipp.ebel@unisg.ch

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Completed Research Paper

Claudius M. Jonas
Research Center for Information Management, Branch Business & Information Systems Engineering of the Fraunhofer FIT, University of Bayreuth, Germany
claudius.jonas@fit.fraunhofer.de

Anna Maria Oberländer
Research Center for Information Management, Branch Business & Information Systems Engineering of the Fraunhofer FIT, University of Bayreuth, Germany
anna.oberlaender@fim-rc.de

Kevin Schmitt
Institute of Information Management, University of St. Gallen, St. Gallen, Switzerland
kevin.schmitt@unisg.ch

Philipp Ebel
Institute of Information Management, University of St. Gallen, St. Gallen, Switzerland
philipp.ebel@unisg.ch

Abstract

With urban problems intensifying, Smart City solutions are recognized by researchers and practitioners as one of the most promising solutions to make urban areas economically, environmentally, and socially sustainable. While many elements of Smart City solutions have been explored, existing works either treat Smart City solutions as technical black boxes or focus exclusively on Smart City solutions' technical or non-technical characteristics. Therefore, to conceptualize the unique characteristics of Smart City solutions currently available, we developed a multi-layer taxonomy based on Smart City solution literature and a sample of 106 Smart City solutions. Moreover, we identified three clusters, each covering a typical combination of characteristics of Smart City solutions. We evaluated our findings by applying the Q-sort method. The results contribute to the descriptive knowledge of Smart City solutions as a first step for a theory for analyzing and enable researchers and practitioners to understand Smart City solutions more holistically.

Keywords: Smart City, Smart City solutions, Taxonomy, Clusters, Sustainability

Introduction

In the early 2020ies, 55% of the global population lived in urban areas; the United Nations projects this number to reach 68% by 2050 (UN 2018). Forecasts show that due to urbanization coupled with the overall global population growth, an additional 2.5 billion people will likely start residing in urban areas by 2050, with Asia and Africa accounting for nearly 90% of this increase (UN 2018). As a result, many countries, especially those in the Global South, face considerable challenges – like increased traffic volume or rapidly increasing demands on waste management in urban areas (Cohen 2006; Rana 2011). Smart City solutions are vital to assisting researchers and practitioners in tackling such pressing problems of ever-expanding urban areas by providing new digitally enabled solutions, e.g., for traffic monitoring or smart bins to reduce waste collection personnel (Brandt et al. 2018; Cocchia and Dameri 2013). Throughout the years, Smart City solutions have become synonyms for the digital technology-based solutions required to address the rising problems of urban areas, drawing the attention of researchers, businesses, and governments (Cocchia and Dameri 2013). The respective market potential of Smart City solutions is expected to reach USD 1380.2 billion by 2030 (Statista Research Department 2023).

Prior research has started investigating different facets of Smart City solutions, i.e., focusing on technical aspects (Ahmed et al. 2016, Muhammad et al. 2020; Nagel and Kranz 2020), non-technical aspects (Vasudavan and Balakrishnan 2019), or specific subfields of a Smart City (Benevolo et al. 2016; Christmann et al. 2022; Rana 2011). For example, Ahmed et al. (2016) developed a taxonomy to showcase possible communication enablers, network types, wireless standards, objectives, and characteristics of smart environment solutions. In comparison, Vasudavan and Balakrishnan (2019) focus on identifying the core factors of a Smart City, which represent non-technical characteristics of Smart City solutions, such as the application area or the created benefit. Furthermore, there is research that focuses on individual manifestations in the area of the Smart City, for example, mobility (Benevolo et al. 2016), urban agriculture (Christmann et al. 2022), or urban sustainability (Rana 2011). Barth et al. (2017) argue that by focusing on specific application areas of Smart City research, prior research has led to important but isolated and scattered pockets of understanding the whole concept. Therefore, despite their undeniable contribution to previous research, categorizing the existing and diverse Smart City solutions is needed as a foundation for meaningful future theorizing. Researchers will benefit from a categorization of Smart City solutions, as this knowledge will form the basis for future theoretical work, such as looking at how the Smart City phenomenon can be explained (Type II theory) or looking at how Smart City will evolve in the future (Type III theory) (Gregor 2006). Further, it helps urban planning professionals and consultancies to analyze Smart Cities and provides an easy tool for classifying solutions, which allows making informed implementation decisions. With this paper, we aim to fill this research need and conceptualize a categorization for Smart City solutions as a first step for a theory for analyzing (Gregor 2006). Thus, we pose the following research question: *How can Smart City solutions be conceptualized by combining technical as well as non-technical characteristics and the diverse Smart City subfields?*

To address this research question, we developed and evaluated a taxonomy of Smart City solutions covering technical and non-technical characteristics, as well as considering the subfields of Smart Cities. Using a taxonomy approach to answer the research question appears promising since a taxonomy adds to the descriptive knowledge, helping researchers and practitioners clarify the Smart City solution phenomenon (Kundisch et al. 2021; Nickerson et al. 2013). Furthermore, we applied Ward's Hierarchical Agglomerative Algorithm to develop clusters (Ward 1963). The derived Smart City solution clusters represent typical combinations of the developed taxonomy dimensions. Our paper complements the existing Smart City research by laying the groundwork for future theoretical work (Holmström et al., 2009). Similarly, for engineering managers and urban planners, analyzing Smart City solutions' characteristics is crucial to fully harness their potential and further improve the design of future Smart City solutions.

The paper is organized as follows: Section 2 introduces the theoretical background of the Smart City concept and sheds light on Smart City solutions. Next, Section 3 outlines the research method before the multi-layer taxonomy of Smart City solutions is presented, evaluated, and applied in Section 4. In Section 5, we calculate, evaluate, and apply the clusters. Then, in Section 6, we discuss the results and implications of this paper. Finally, the paper concludes in Section 7 with the limitations and the outlook.

Theoretical Background

The Smart City Concept and Smart City Solutions

Generally, recent work has already reviewed and discussed the dimensions, characteristics, variables, and elements of the Smart City concept from different perspectives over the last few decades and provided definitions and descriptions for Smart City (Albino et al. 2015; Giffinger et al. 2007; Praharaj and Han 2019; Toli and Murtagh 2020). Giffinger et al. (2007) split the concept of Smart City into six domains (smart economy, smart people, smart governance, smart mobility, smart environment, and smart living), which must be addressed. In line, Albino et al. (2015) analyze the Smart City concept, revealing its multifaceted nature, including people, communities, and information as well as communication technologies. They conclude that measuring a Smart City is challenging, and all-encompassing indexes may not be appropriate, as different cities have varying priorities and visions for achieving their objectives and highlight the need for integrated development of different aspects of a Smart City (Albino et al. 2015). Furthermore, especially in recent years, the perspective of sustainability has been added to the existing ways of thinking, emphasizing a combination of soft and hard features to deliver a sustainable, livable, and efficient city (Toli and Murtagh 2020). Toli and Murtagh (2020) propose a new definition that addresses these issues and emphasize holistic sustainability, inclusiveness, and respect for localities and their inhabitants. Lastly, the authors point out that future attempts to define Smart Cities should consider all dimensions of sustainability and the potential costs to society and the environment (Toli and Murtagh 2020). Moreover, there are also regional differences in the understanding of the Smart City (Praharaj and Han 2019). Hence, Praharaj and Han (2019) introduce a new dimension to the ongoing Smart City debate, which often fails to engage with the local realities and contextual variants while placing technology at the center stage of urban development. The findings show that the greater appeal of the humane and non-technology concepts among the leading urban stakeholders in characterizing the Smart City holds essential lessons for Smart City planners and policymakers.

Despite the Smart City concept being one of the most promising concepts to address the challenges of our ever-faster-growing urban areas, there is neither a single template for capturing the unique dimensions and characteristics of the Smart City concept nor a one-size-fits-all definition. However, looking at the literature, we can observe that the Smart City concept is predominantly concerned with the physical world and constrained by geographical borders (Cocchia and Dameri 2013; Toli and Murtagh 2020). Moreover, prior research aligns with the fact that the Smart City concept utilizes heterogeneous technologies and government policies to make urban areas economically, environmentally, and socially sustainable to foster the quality of city life (Bhattacharya et al. 2018; Cocchia and Dameri 2013; Toli and Murtagh 2020)

While the appropriate use of technology and government policies makes a city undoubtedly smarter, the city is an entity of multiple stakeholders seeking diverse and sometimes contradictory outcomes (Albino et al. 2015; Toli and Murtagh 2020). Our proposed working definition integrates the aspects mentioned above. For this paper, we propose and follow the following definition: Smart City is a concept of a transformed urban area into an economically, environmentally, and socially sustainable area by utilizing technologies and government policies to foster the quality of city life.

While the Smart City concept is primarily prescriptive (i.e., what should be), Smart City solutions are the real-world technological enablers (i.e., what can be) of this concept. Again, our proposed working definition integrates the aspects mentioned above. For this paper, we propose and follow the following definition: *Smart City solutions are technology-based applications that offer a way to reach a Smart City goal (i.e., economic, environmental, or social sustainability) to foster the quality of city life.*

The Need for a New Taxonomy

Taxonomies help researchers and practitioners understand complex phenomena by grouping objects based on common characteristics (Kundisch et al. 2021; Nickerson et al. 2013). Thus, it is unsurprising that prior research has already developed taxonomies that, to some degree, structure Smart City solutions' technical and non-technical dimensions and characteristics or focus on specific Smart City subfields. Nevertheless, those taxonomies inherit some needs for expansion.

To the best of our knowledge, only Perboli et al. (2014) researched Smart City solutions' technical and non-technical characteristics to some degree by analyzing 28 Smart City projects. They identified eight objectives: improvements in water management, e-governance, buildings, CO_2 emissions, energy management, security, social innovation, and transportation. Additionally, they identified technologies that were leveraged as part of the 28 Smart City projects, i.e., cloud computing, databases, decision support systems, information and communication technology, innovative sensors, legal and financial tools, other new technologies, portable smart devices, and smart grids. As Smart City solutions utilize different technologies, the dimension "Tools" in Perboli et al.'s (2014) taxonomy gives us first insights into the technologies engineers might use to build Smart City solutions. The taxonomy relies on a data set of 28 Smart City projects and thus may exclude emerging technologies rarely implemented as part of those projects (Perboli et al. 2014). In addition, the taxonomy of Perboli et al. (2014) focuses on structuring Smart City projects, which address multiple urban challenges, rather than individual Smart City solutions targeting specific problems.

Complementary, Vasudavan and Balakrishnan (2019) focus on identifying the core factors a Smart City addresses by reviewing academic literature and real-world implementations. The six identified Smart City core factors (i.e., Smart Governance, Smart Mobility, Smart Living, Smart People, Smart Environment, and

Smart Economy) overlap widely with Perboli et al.'s (2014) identified eight objectives of Smart City projects. Furthermore, there are several taxonomies in the context of Smart City that focus more on technical characteristics, e.g., on the Internet of Things (IoT) and Smart City (Ahmed et al. 2016), blockchain technology and Smart City (Nagel and Kranz 2020), or deep learning and Smart City (Muhammad et al. 2020). Overall, these approaches demonstrate, on the one side, the diversity in connection with Smart City and, on the other side, show that digital technologies are an important part of the Smart City concept. Therefore, we also consider taxonomies focusing not solely on smart cities but on smart services (Püschel et al. 2020; Jonas et al. 2022) as important building blocks for a holistic view of the Smart City concept.

As the before-mentioned taxonomies cannot holistically explain the Smart City solution phenomena, the transformation of urban areas is continuously changing and developing, and new technologies arise, we designed a new taxonomy incorporating relevant characteristics from the abovementioned taxonomies.

Research Method

Taxonomy Development

In Information Systems (IS) research, taxonomies describe a unidimensional or multidimensional classification system that structures knowledge by following detailed rules to group similar entities into classes (Kundisch et al. 2021; Nickerson et al. 2013). As a result of the many technology-driven changes over the last decades, the IS discipline is increasingly called upon to analyze, contextualize, structure, and explain newly emerging technological phenomena (Nickerson et al. 2013). We used Nickerson et al.'s (2013) iterative taxonomy development method to answer our research question.

For each iteration, the conceptual-to-empirical or the empirical-to-conceptual approach can be chosen. In a conceptual-to-empirical iteration, the layers, dimensions, and characteristics are based on the literature or the authors' knowledge. In an empirical-to-conceptual approach, a sample of real-world objects gets analyzed. After finishing an iteration, an initial or revised taxonomy is obtained, and the authors must check whether the ending conditions are met. The taxonomy development process continues until the ending conditions and evaluation goals are met (Nickerson et al. 2013).

For our taxonomy, the target user groups comprise Smart City researchers, urban planning professionals, and consultancies focusing on the public sector. The intended purpose of the taxonomy is to help target users holistically understand the Smart City solution phenomena. Following Nickerson et al. (2013), the authors must determine the meta-characteristic and ending conditions to start the taxonomy development process. In line with the research question, the meta-characteristic was "structuring of technical and non-technical characteristics and diverse subfields of Smart City solutions." Moreover, given the meta-characteristic, we adopted appropriate ending conditions. We adopted the following objective ending conditions: (1) each characteristic is unique within its dimension, (2) each dimension is unique and not repeated within the taxonomy, and (3) at least one object is classified per characteristic and dimension. Further, we chose five subjective ending conditions. They are met if we agree that the taxonomy is concise, robust, comprehensive, extendible, and explanatory (Nickerson et al. 2013). Preferably, taxonomies should consist of mutually exclusive dimensions (Nickerson et al. 2013). However, we cannot restrict the choice of some dimensions to be mutually exclusive, as relevant information and conciseness would be lost. Thus, the taxonomy would not adequately depict Smart City solutions' unique characteristics. Otherwise, a comprehensive taxonomy for Smart City solutions cannot be developed since multiple selections must be allowed in some dimensions. The corresponding dimensions are marked accordingly in the taxonomy. Following Kundisch et al. (2021) and in line with existing taxonomies like Püschel et al. (2020), Puschmann and Shiba (2021), or Schöbel et al. (2020), we allowed non-exclusive dimensions when necessary and when justified. Our taxonomy development process comprises four iterations.

1st Iteration: In the first iteration, we opted for the conceptual-to-empirical approach, as Smart City solutions comprise a relatively young and dynamic field of research. We conducted a short literature review via Google Scholar to accumulate sufficient information about taxonomies related to Smart City solutions and adjacent research fields as well as literature from the research field of Smart City in general. As part of generating a sample of relevant taxonomies, we used two keywords ("Smart City taxonomy" AND "City 4.0 taxonomy") in the search string. Using this approach, we identified five relevant taxonomy papers (Ahmed et al. 2016; Christmann et al. 2022; Muhammad et al. 2020; Nagel and Kranz 2020; Perboli et al. 2014;

Vasudavan and Balakrishnan 2019). Further, we relied on additional literature from the field of Smart City research (Albino et al. 2015; Bhattacharya et al. 2018; Giffinger et al. 2007; Toli and Murtagh 2020). In line with the proposed meta-characteristic, we extracted initial dimensions (i.e., analytics, data source, smartification, technology application, and value proposition) and their related characteristics from the identified literature to capture and structure the first distinct features of Smart City solutions. The conceptual-to-empirical approach led to a rudimentary taxonomy and built the foundation for the upcoming iterations. Since no Smart City solution was classified into any dimension and thus characteristic, the third objective ending condition was not met. Hence, we conducted a second iteration. ***2nd Iteration:*** We enhanced and validated the taxonomy's structure by applying the empirical-to-conceptual approach. We relied on Crunchbase, which claims to be the primary source of company insights (Crunchbase 2023). As part of generating a randomized sample from Crunchbase, we used two keywords ("Smart City" AND "City 4.0") in the search string. This approach led to a sample of 606 Smart City solutions. However, to guarantee comparability among Smart City solutions, we reduced the number of suitable Smart City solutions according to the following criteria: (1) the Crunchbase website or the Smart City solution company website must provide sufficient information, and (2) the Smart City solutions must comply with our definition of a Smart City solution (see Section "Theoretical Background"). Therefore, we limited the initial sample to 106 Smart City solutions, which we included in the taxonomy development process. Throughout the following iterations, we analyzed the sample. We analyzed the sample's first 20 Smart City solutions in the second iteration. Since not all characteristics of the data stream, technology application, and focused smartification area dimensions were utilized to classify Smart City solutions, the third objective ending condition was not met. Furthermore, the subjective ending condition comprehensive was violated, as five new dimensions (i.e., dependency, solution end-user, solution owner, main sustainability value, and value creation) and their characteristics were identified and added to the taxonomy. Also, we identified new characteristics for the focused smartification area and technology application dimension of the taxonomy. Thus, the smartification and technology application dimension violated the subjective ending condition comprehensive. Moreover, since the analytics dimension was not elucidative enough, the subjective ending condition explanatory was violated. Thus, we conducted the third iteration. ***3rd Iteration:*** We analyzed a greater variety of solutions in the third iteration by picking 60 out of 106 Smart City solutions. Since the solution end-user and solution owner dimensions were not explanatory, the subjective ending condition explanatory was violated. Moreover, the subjective ending condition comprehensive was violated, as we identified and added two characteristics to the technology application dimension of the taxonomy. Hence, a fourth iteration was conducted. ***4th Iteration:*** We analyzed the remaining 26 Smart City solutions in the fourth iteration. After minor modifications of the taxonomy, we agreed to have met the ending conditions and stopped the taxonomy development process.

Evaluation and Application of the Smart City Solution Taxonomy

After developing the taxonomy, we evaluated and applied the multi-layer taxonomy of Smart City solutions. As part of the taxonomy's evaluation, we assessed the taxonomy's validity (hit ratios) and reliability (Fleiss' Kappa coefficient) using the Q-sort method (Cohen 1960; Fleiss 1971; Moore and Benbasat 1991; Nahm et al. 2002). As part of the taxonomy's application, we classified all 106 Smart City solutions into the taxonomy and showcased the frequencies of the taxonomy's characteristics. ***Evaluation:*** To evaluate the taxonomy, we applied the Q-sort method. The Q-sort method is a widely accepted statistical approach to classifying objects (e.g., Smart City solutions) according to a predefined construct (e.g., taxonomy) by two or more judges (P-set) (Nahm et al. 2002). When using the Q-sort method, the judges' agreement forms the basis for assessing the validity and reliability of the predefined construct (Nahm et al. 2002). We conducted a survey for evaluation purposes. Moreover, we measured the agreement within the survey group using dimension-specific and object-specific hit ratios (McKelvey 1975). Furthermore, based on the calculated agreement (i.e., hit ratios) within the survey group, we gauged the validity of the taxonomy (Moore and Benbasat 1991). We rated 1 as an agreement and 0 as a disagreement to calculate the agreement for exclusive dimensions. As non-exclusive dimensions differ from exclusive dimensions, the agreement was rated differently, using an agreement scale from 0 to 1 (Posey et al. 2013). Moreover, we measured reliability via Fleiss' Kappa coefficient; the proportion of joint agreement within the survey group after the random agreement is excluded (Fleiss 1971). The judges must have a detailed understanding of the objects (e.g., Smart City solutions) to be classified when using the Q-sort method and thus should not be randomly selected (Carter et al. 2007). Therefore, we selected six people with an IS background and five Smart City solutions for the Q-set. Afterward, we calculated the validity (hit ratios) and reliability (Fleiss' Kappa coefficient) of the taxonomy (Fleiss 1971; Moore and Benbasat 1991). ***Application:*** First, we classified all 106 Smart City solutions into the taxonomy and calculated the frequencies of the taxonomy's characteristics. Calculating the frequencies made distributions within the taxonomy quantifiable and thus easier to recognize patterns.

Identification of Smart City Solution Clusters

Since the taxonomy provides 28,338,660 ways to classify Smart City solutions, we want to understand what characteristics of Smart City solutions typically co-occur. Whereas the taxonomy fosters an in-depth understanding of Smart City solutions, it is too specific for managerial and communication purposes.

We used a statistical data analysis technique – cluster analysis – to analyze the alikeness of the Smart City solutions (Field 2013; Hair et al. 2010). We used Ward's Hierarchical Agglomerative Algorithm to cluster the surveyed Smart City solutions, as we did not know the number of clusters needed before starting the analysis (Ferreira and Hitchcock 2009; Ward 1963). The chosen algorithm groups objects by similarity in an agglomerative manner (Everitt et al. 2011; Ferreira and Hitchcock 2009; Ward 1963). Thus, there are as many clusters as Smart City solutions at the beginning of the process (Ferreira and Hitchcock 2009). Following the linkage criterion of Ward's Hierarchical Agglomerative Algorithm, the clusters merge and move up the hierarchy (Ferreira and Hitchcock 2009; Ward 1963). Hence, clusters get merged based on the minimum variance criterion, which minimizes the increase in total within-cluster variance (Ferreira and Hitchcock 2009; Ward 1963). A distance measure is needed to find the pair of clusters at each step, leading to a minimum increase in total within-cluster variance. We used the Manhattan (City Block) distance as a distance measure. The Manhattan distance was picked as a distance measure because it is preferable to the Euclidean distance for high-dimensional spaces (Bora and Gupta 2014; Chahar et al. 2014).

Based on the taxonomy, we consider nominal and ordinal variables. Like nominal variables, ordinal variables are inherently categorical. A straightforward approach is to utilize this commonality, ignore the ordinal variables' order, and treat them as nominal variables. In this case, ignoring the order of ordinal variables is advantageous because the order is not essential to answering the research question. Moreover, we used one binary variable per characteristic to code the variables. Second, we normalized the distance between the Smart City solutions to treat them equally (Ferreira and Hitchcock 2009).

We determined the appropriate number of clusters in the next step. We looked at the agglomeration schedule coefficient to get an initial sense of the appropriate number of clusters needed. The agglomeration schedule coefficient describes the incremental increase in the cluster's dissimilarity after combining clusters in the n^{th} step (Ferreira and Hitchcock 2009; Ward 1963). If the dissimilarity increases sharply, it probably goes too far. Therefore, a rule of thumb is to reduce the number of clusters until the agglomeration schedule coefficient increases sharply and use the number of clusters immediately before the jump (Yim and Ack Baraly 2015). However, there is no guarantee that this approach will always lead to good decisions. Thus, we combined the approach with examining the different clusters, which led us to a three-cluster solution. We follow the same procedure for evaluating and applying the Smart City Solution clusters as for the taxonomy (see detailed description in the previous section). In sum, as part of the clusters' evaluation, we assess the clusters' validity (hit ratios) and reliability (Fleiss' Kappa coefficient) using the Q-sort method. As part of the clusters' application, we first classified all 106 Smart City solutions into their respective cluster and showcased every cluster's most frequent characteristic(s). Second, we applied the clusters by describing one archetypical Smart City solution from every cluster.

Multi-layer Taxonomy of Smart City Solutions

This section demonstrates the final taxonomy of Smart City solutions including the layers, dimensions, and characteristics. As shown in Table 1, the taxonomy encompasses ten dimensions and their related characteristics across three layers, i.e., solution context, technology, and value. Thereby, the solution context layer summarizes the different subfields and the Smart City solution owner and user, the technology layer focuses on the technical aspects, and the value layer on the economic aspects of the Smart City solution. Moreover, Table 1 specifies if a dimension is exclusive or non-exclusive. Combining the three layers and ten dimensions with their respective characteristics leads to the multi-layer taxonomy of Smart City solutions, enabling target users to analyze, classify, describe, and identify Smart City solutions. The dimensions and characteristics are defined using justificatory references.

	Dimension	Characteristics								
Solution Context	Focused Smartification Area	Building	Commerce	Community	Environment	Governance	Healthcare	Mobility		E
	Solution Owner	Citizen	Business	Government						NE
	Solution End-user	Citizen	Business	Government						NE
Technology	Technology Application	AI	Mobile App	BC	Camera	Cloud	IoT	PV	WT	NE
	Data Stream	Existing Data	New Data							NE
	Analytics	None	Fundamental	Extensive						E
Value	Main Sustainability Value	Economic	Environmental	Social						E
	Value Proposition	Thing-centric	Service-centric	Platform-centric						E
	Value Creation	Instantaneous	Delayed							E
	Dependency	Dependent	Independent							E

E = Exclusive dimension (one characteristic at a time); NE = Non-exclusive dimension (potentially multiple characteristics observable at a time);
AI = Artificial Intelligence; BC = Blockchain; PV = Photovoltaic panel; WT = Wind turbine

Table 1. Multi-layer Taxonomy of Smart City Solutions

The first layer – ***Solution Context*** – describes the subfields and beneficiaries of a Smart City solution and includes three dimensions, i.e., focused smartification area, solution owner, and solution end-user.

Focused Smartification Area: The smartification dimension encompasses seven characteristics, i.e., building, commerce, community, environment, governance, healthcare, and mobility. The smartification dimension answers what gets "smarter" by implementing and using the Smart City solution. For example, when the target of the smartification is the *building*, the focus is to control, manage, measure, prevent, and/or reduce the environmental effects of the building (Khajenasiri et al. 2017). A Smart City solution focuses on the smartification of *commerce* if the focus is to help retail-oriented businesses and/or restaurants become more successful and, thus, more profitable, like QUEQ (2023), who developed a mobile app for queue management for restaurants. When the target of the smartification is the *community*, the focus is to connect community residents and/or help residents participate in the community's development (PlaceSpeak 2023). If the Smart City solution targets the *environment*, the focus is to make the surroundings smarter to control, manage, measure, prevent, and/or reduce the environmental effects of urban areas (Dimonoff 2022; Jamil et al. 2015; Wu et al. 2010). Further, *governance* is the action or manner of governing. Hence, governance concerns structures and processes for decision-making, accountability, and control (Ruhanen et al. 2010). *Healthcare* focuses on preserving and improving health by preventing, diagnosing, and treating disease, injury, and other physical and mental health problems (Daniels 2001). When the target of the smartification is *mobility*, the focus is to provide new and novel ways to solve mobility-related problems (Benevolo et al. 2016). For example, SEEDiA (2023) offers universal e-mobility city chargers for e-scooters.

Solution Owner: The solution owner dimension is non-exclusive and comprises three characteristics, i.e., citizen, business, and government. The solution owner dimension answers who, from a legal perspective, the owner of the Smart City solution is. Ownership represents a legal position on a particular thing (Demsetz 1974; McCarty 2002). One also speaks of a so-called right to legal control in this context (McCarty 2002). The right to legal control means the owner can do whatever he wants with his thing as long as he does not violate other laws (Demsetz 1974; McCarty 2002). For example, the owner may exclude others from using the Smart City solution (McCarty 2002). As characteristics for this dimension, we can distinguish citizen, business, and government. A *citizen* is a private person and is a solution owner if he has the legal right to control the Smart City solution (Demsetz 1974; McCarty 2002). Tesla's solar roof is a Smart City solution, which a citizen owns, that replaces conventional roofing to maximize the roof's energy production (Tesla 2023). A *business* is a private entity that must generate sales and, thus, profits to sustain its operation (Enderle 2009). One example of a Smart City solution owned by a business is Yo-Waste, which is a private company that matches citizens and businesses needing waste collection with waste collectors and recyclers via a mobile app (Yo-Waste 2023). A *government* is a public entity that primarily finances itself by collecting financial charges and directing them to the public sector (Kormendi 1983). Cortica is an example of a Smart City solution that targets governments as solution owners as it provides a platform to monitor city-wide traffic and security systems (Cortica 2023).

Solution End-user: The solution end-user dimension comprises the same three characteristics as the solutions owner dimension, i.e., citizen, business, and government. The solution end-user dimension answers the question of who the end-user of a Smart City solution is. A solution end-user differs from a solution owner, as the person who legally owns a Smart City solution is not necessarily the end-user. A *citizen* is a solution end-user if he actively chooses to install and use the Smart City solution in a non-mandatory private setting (Kim et al. 2013). The already introduced QUEQ app is a Smart City solution targeted toward citizens as solution end-users (QUEQ 2023). A *business* is a solution end-user if it implements and uses a Smart City solution in a business setting. Singular Intelligence targets consumer retail (i.e., businesses) as solution end-users and focuses on maximizing profits by forecasting business performance under different scenarios with the help of Artificial Intelligence (AI) (Singular Intelligence 2023). A *government* is a solution end-user if the government decides to implement and use a Smart City solution in a government setting, e.g., managing traffic to ease congestion, controlling public streetlights' energy consumption, or fill level monitoring public bins (Asura 2023; Bevir et al. 2003; GreenQ 2023).

The second layer – ***Technology*** – focuses on the technological foundation needed to generate value and comprises three dimensions, i.e., technology application, data source, and analytics.

Technology Application: This dimension answers what technologies get leveraged to build Smart City solutions. Among the technologies leveraged to build Smart City solutions are AI, mobile apps, blockchain, cameras, cloud technology, IoT, photovoltaic panels (PV), and wind turbines (WT). *AI* describes the ability of a machine to simulate the human mind by interpreting and learning from data it receives and using that experience to perform tasks (Helm et al. 2020). Further, a *mobile app* is an application designed for a portable device such as a smartphone, *blockchain* is a decentralized transaction and data management technology, and a *camera* is a device that records video alone or in tandem with audio (Kim et al. 2013; Yli-Huumo et al. 2016). *Cloud technology* represents a large pool of readily available and usable resources. Those resources can be reconfigured dynamically to adjust to a variable scale and configured for maximum resource utilization (Vaquero et al. 2009). The *IoT* refers to physical objects that can be connected to other devices and systems via a communication network to exchange data (Oberländer et al. 2018). Furthermore, IoT devices can monitor, control, visualize, and/or listen to their operating environment (Goumagias et al. 2021). We exclude mobile phones, smartphones, and tablets from being labeled as IoT devices (Oberländer et al. 2018). *PV* panels transform radiation energy, such as sunlight, into electricity utilizing materials that display a photovoltaic effect (Sampaio and González 2017), and lastly, a *WT* is a wind-powered rotor that generates electricity. In this dimension, some Smart City solutions combine several technologies, such as QUEQ, which combines the characteristics mobile app and AI (QUEQ 2023).

Data Stream: In the context of Smart City solutions, data plays an essential role, as all surveyed Smart City solutions utilize data as part of their service offering. The data source dimension answers what kind of data a Smart City solution utilizes to generate value (Jonas et al. 2022; Püschel et al. 2020). The data source dimension is divided into two non-exclusive characteristics, i.e., existing and new. *Existing data* refers to data points supplied by, for example, existing sensors, websites, cameras, tracking devices, and enterprise information systems (Jonas et al. 2022). Simplicity is an example of using existing data; their service relies on existing news websites to summarize and aggregate news articles for citizens (Simplicity 2023). On the other side, *new data* refers to data points generated by the newly installed Smart City solution, like Bin-e, which relies on new waste bins with sensor technology to enable their service (Solar Outdoor Media 2023).

Analytics: The exclusive analytics dimension differentiates between none, fundamental, and extensive analytic capabilities. The analytics dimension answers what type of analytics the Smart City solution utilizes to generate value. For example, suppose the Smart City solution does not have an analytic element. In that case, the solution is classified as *none*, e.g., capturing the state of the environment but not making the data collected serviceable or running any analyses, like the provided air sensor by Green Ideas Technology to measure air pollution, which can collect data but cannot visualize or analyze the data (Green Ideas Technology 2023). *Fundamental* analytics makes data concerning the state, environment, and/or operation of a product or system serviceable, e.g., visualizing data via charts or numbers (Delen and Demirkan 2013). *Extensive* analytics refers to analytic, diagnostic, predictive, and prescriptive data use (Delen and Demirkan 2013; Jonas et al. 2022; Püschel et al. 2020). For example, LILEE System offers a Smart City solution that transforms ordinary buses into autonomous vehicles, seeks to determine optimal actions to make autonomous transport safe, and is defined in our taxonomy as extensive analytics (LILEE Systems 2023).

The third layer – ***Value*** – describes what kind of sustainability value the Smart City solution promotes, in what form the Smart City solution primarily delivers its value, how fast the value is delivered, and if the solution depends on other functions or inputs to sustain its operation and generate value.

Main Sustainability Value: The sustainability dimension consists of three characteristics, i.e., economic, environmental, and social. The sustainability value dimension answers what kind of sustainability value the Smart City solution aims to promote. *Economic* sustainability focuses on increasing profits and/or saving costs (Lehtonen 2004). Japa offers a Smart City solution that overcomes the challenges associated with parking lot management (Japa 2023). Automating and streamlining data collection of each parking space increases revenue and efficiency and is an example of economic sustainability. *Environmental* sustainability focuses on preserving resources and safeguarding the environment by controlling, managing, monitoring, and/or optimizing environmental parameters, e.g., monitoring air quality, controlling the energy consumption of streetlights, and optimizing waste collection (Lehtonen 2004; Toli and Murtagh 2020). Lastly, *social* sustainability focuses on the well-being of the city's citizens (Lehtonen 2004; Toli and Murtagh 2020). PlaceSpeak allows citizens to actively participate in the city's decision-making process by providing feedback to the administration, and thus, they focus on providing a Smart City solution that embodies the social aspect of sustainability (PlaceSpeak 2023).

Value Proposition: This dimension answers in what form a Smart City solution primarily delivers its value. Hence, this dimension differentiates between thing-centric, service-centric, and platform-centric (Jonas et al. 2022; Püschel et al. 2020). The physical product represents the core element in a *thing-centric* value proposition and predominantly serves a thing-related purpose, possibly supplemented by a digital service, which can be found with Bin-e, where the core element is a physical bin to collect waste (Solar Outdoor Media 2023). In a *service-centric* value proposition, the service represents the core element like PlaceSpeak, which provides a service to connect citizens with the city's decision-making process PlaceSpeak 2023). Even though a physical underlying is possible, it cannot or hardly produce any value unassisted from the service (Püschel et al. 2020). *Platform-centric* means that the platform offered represents the core element of the value proposition, like Yo-Waste. They provide a platform to connect citizens and waste organizations for more accessible and efficient waste management (Yo-Waste 2023).

Value Creation: The value creation dimension answers how fast a Smart City solution can deliver value to its users. The value creation dimension is divided into two exclusive characteristics, i.e., instantaneous and delayed. The value creation is defined for this taxonomy as *instantaneous* when solution end-users do not have to perform any time-consuming process to make the Smart City solution function properly and generate value, like with GoDee. GoDee offers public transportation services via a mobile website and app (GoDee 2023). The value creation is *delayed* when solution end-users must perform some time-consuming installation to make the Smart City solution function properly and generate value, like the parking lot management by Japa, where the parking spaces have to be retrofitted first (Japa 2023).

Dependency: The dependency dimension answers under what conditions the Smart City solution generates value. We distinguish between dependent and independent. A Smart City solution is *dependent* if it relies on third-party service offerings or inputs to sustain its operation and provide value, e.g., third-party data, and *independent* if it works on its own. Simplicity news relies on existing news websites and articles for a region and, therefore, is dependent, whereas the Bin-e waste bin works independently (Simplicity 2023; Solar Outdoor Media 2023).

Evaluation of the Smart City Solution Taxonomy

In the evaluation, we aimed to verify the validity and reliability of the taxonomy using the Q-sort method (Nahm et al. 2002). The group achieved a dimension-specific hit ratio of more than 70.0% per dimension and an average dimension-specific hit ratio of 86.9%. In addition, the participants achieved an object-specific hit ratio of at least 80.6% and an average object-specific hit ratio of 86.9%. A taxonomy with a high degree of proper placement of objects can be considered to have high construct validity, indicating a high potential for a good reliability score (Moore and Benbasat 1991). Since all dimension-specific and object-specific hit ratios are at least 70.0% and thus have a high degree of correct placement, the taxonomy can be considered to have high construct validity and a high potential for a good reliability score (Moore and

Benbasat 1991). We calculated Fleiss' Kappa coefficient to test this assumption in the next step. We measured reliability via Fleiss' Kappa coefficient; the proportion of joint agreement within the survey group after the random agreement is excluded (Fleiss 1971). The survey group achieved a Fleiss' Kappa coefficient of 0.68. As the calculated Fleiss' Kappa coefficient is greater than 0.60, there is substantial agreement within the survey group (Landis and Koch 1977). In summary, we conclude that the taxonomy has a high construct validity and reliability.

Application of the Smart City Solution Taxonomy

First, we classified the 106 Smart City solutions into the taxonomy, guided by the definitions of the characteristics. Then, based on the classification, we calculated the frequencies for the characteristics of the taxonomy. During the classification process, we discussed extreme and ambiguous examples to ensure the quality of the process. From the analysis of the frequencies, further insights into the taxonomy can be gained: 39.6% of the classified Smart City solutions focus on the smartification of mobility, while 37.7% of the classified Smart City solutions focus on the smartification of the environment. Solving mobility-related problems in an increasingly urbanized world is one of the most central tasks of cities today (Benevolo et al. 2016; Zawieska and Pieriegud 2018). Moreover, making the city environment smarter to reduce, manage, control, and prevent the environmental effects of a city is the second most prominent focus of the surveyed Smart City solutions. With many cities facing increasing air pollution, waste pollution, and other kinds of pollution, it is no surprise that the smartification of the city's environment plays such a dominant role within the sample (Cohen 2006; Rana 2011). 72.6% of the Smart City solutions examined have businesses, and 78.3% have governments as solution owners. Citizens (1.9%) play only a minor role as solution owners. Hence, based on the sample, transforming an ordinary city into a Smart City is primarily an endeavor of both the private and public sectors, even though the focus of the smartification might differ. Only 32.1% of all Smart City solutions have citizens as solution end-users; thus, businesses (62.3%) and governments (70.8%) are the most common solution end-users.

60.4% of Smart City solutions leverage IoT technology to capture and create value. However, it is noteworthy that 30.2% of the surveyed Smart City solutions leverage AI, and 30.2% leverage mobile apps to capture and create value. Most Smart City solutions surveyed use newly generated data (79.2%). Hence, the surveyed solutions indicate that more than the already collected data by citizens, businesses, and governments may be needed to make a city a Smart City (Hashem et al. 2016), and therefore, new data points are collected. Moreover, the focus is on fundamental (51.9%) and extensive analytic services (40.6%). With 40.6% of Smart City solutions using extensive analytics techniques, it is evident that sophisticated techniques are needed to gain insight into increasingly complex and interconnected city systems (Al Nuaimi et al. 2015; Nikitas et al. 2020).

For 52.8% of all Smart City solutions surveyed, the sustainability value is environmentally focused. The dominant presence of Smart City solutions that focus on environmental aspects contradicts the position of Hollands (2008). Hollands (2008) emphasizes that the way the Smart City concept is advertised is more akin to a high-tech version of an entrepreneurial city concept. Hence, the Smart City concept and its real-world enablers, Smart City solutions, might not be as progressive and environmentally driven as they portray themselves (Hollands 2008). However, the Smart City solutions analyzed address various aspects of a Smart City, and all three aspects of sustainability are considered, i.e., economic (26.4%), environmental (52.8%), and social (20.8%) sustainability. In addition, 12.3% of the Smart City solutions surveyed have a thing-centric value proposition, 62.3% have a service-centric value proposition, and 25.5% have a platform-centric value proposition. The frequencies indicate that while a physical product can be part of a Smart City solution, it mainly serves as a vehicle for service delivery (Püschel et al. 2020). 84.0% of the Smart City solutions surveyed have delayed value creation due to the extensive implementation required to make a solution work properly. Most Smart City solutions that create value instantaneously (16.0%) for their solution end-users utilize mobile apps. The dependency dimension is dominated by one characteristic, as 94.3% of all Smart City solutions surveyed have a dependent value creation, showing the required integration into a city's existing systems, concepts, and services.

In summary, the analyzed Smart City solutions occupy different positions across the taxonomy, reinforcing the need to structure Smart City solutions systematically.

Smart City Solution Clusters

The clusters are displayed in Table 2. Moreover, we showcase each cluster's most frequent characteristic(s) per dimension. For exclusive dimensions, we incorporated the most frequent characteristic. We incorporated all characteristics covered by more than half of a cluster's Smart City solutions for non-exclusive dimensions. The most frequent characteristics were selected if no characteristic within a dimension was covered by at least half of a cluster's Smart City solutions. Furthermore, in line with the results from the cluster analysis, we derived meaningful names for the identified clusters: environmentally-focused IoT, mobility-focused data analytics, and citizen-focused everyday mobile apps.

	Cluster	Environmentally-focused IoT	Mobility-focused Data Analytics	Citizen-focused Everyday Mobile Apps
Solution Context	Focused Smartification Area	Environment	Mobility	Commerce, Community, Mobility
	Solution Owner	Business, Government	Business, Government	Business
	Solution End-user	Business, Government	Business, Government	Citizen
Technology	Technology Application	IoT	AI, IoT	Mobile App
	Data Stream	New	New	Existing, New
	Analytics	Fundamental	Extensive	Fundamental
Value	Main Sustainability Value	Environmental	Economic	Economic
	Value Proposition	Service-centric	Service-centric	Service-centric
	Value Creation	Delayed	Delayed	Instantaneous
	Dependency	Dependent	Dependent	Dependent

Table 2. Smart City Solution Clusters

Evaluation of the Smart City Solution Clusters

We evaluated the validity and reliability of the clusters using the Q-sort method (Nahm et al. 2002). We calculated the agreement within the survey group using hit ratios. The participants obtained a hit ratio of 100% for the first, 100% for the second, and 75.0% for the third cluster. Clusters with a high degree of proper placement of objects can be considered to have high construct validity, indicating a high potential for a good reliability score (Moore and Benbasat 1991). Since all hit ratios are at least 75.0% and thus have a high degree of correct placement, the clusters can be considered to have high construct validity and a high potential for a good reliability score (Moore and Benbasat 1991). We calculated Fleiss' Kappa coefficient to test this assumption in the next step. We measured reliability via Fleiss' Kappa coefficient; the proportion of joint agreement after the random agreement is excluded (Fleiss 1971). The participants obtained a Fleiss' Kappa coefficient of 0.74. As the calculated Fleiss' Kappa coefficient is greater than 0.60, there is substantial agreement within the survey group (Landis and Koch 1977). In summary, the clusters have high construct validity and reliability.

Application of the Smart City Solution Clusters

We identified three Smart City Solution clusters (Table 2), which we present and describe in the following. The first cluster *environmentally-focused IoT* consists of 40 Smart City solutions of our sample. Smart City solutions within this cluster are mainly leveraging IoT technology (97.5%) and focus on the smartification of the environment (95.0%). The solutions in this cluster have a clear focus on environmental sustainability (100%). The solution owners (97.5%) and solution end-users (90.0%) are predominantly governments, although businesses also play a crucial role as solution owners (77.5%) and solution end-users (72.5%). Smart city solutions from this cluster can thus be described as solutions that focus on improving the environment with the help of IoT technologies and are both operated and used by businesses and the government. An archetypical example of a Smart City solution from this cluster is GreenQ. GreenQ leverages sensor technology to monitor the fill levels of underground garbage containers. The data gathered empowers municipalities in their decision-making process. Thus, municipalities can reduce vehicle-related emissions by only emptying underground containers when full (GreenQ 2023).

The second cluster *mobility-focused data analytics* contains 50 Smart City solutions of our sample. Corresponding solutions focus on the smartification of mobility (70.0%). Similar to the previous cluster, the solution owners (78.0%) and solution end-users (74.0%) are predominantly governments, although businesses also play a crucial role as solution owners (66.0%) and solution end-users (64.0%). Solutions in this cluster mostly rely on extensive analytics (66.0%) and mostly rely on AI (54.0%) and/or IoT (50.0%) as technology applications. Therefore, we summarized the solutions in this cluster as addressing mobility-related problems using a data-driven approach. Asura is an archetypical example of a solution from the second cluster. With Asura, cities can manage the traffic environment much more cost-effective. Asura uses cameras and AI technology to automate traffic surveillance (Asura 2023). The technology can count vehicles, recognize specific brands, models, and license plates, and recognize as well as report traffic violations. (Asura 2023) The benefit of automatized traffic surveillance is that fewer police officers are needed to monitor the areas within a city. Hence, more information and insights are generated while spending less on local police headcount, creating economic value for the government.

The third cluster *citizen-focused everyday mobile apps* consists of 16 Smart City solutions of our sample. Commerce (25.0%), community (25.0%), and mobility (37.5%) play the most dominant role in the smartification dimension of this cluster. Moreover, most solution owners are businesses (81.3%), and citizens (100%) are the primary solution end-users. Further, the technology application is a mobile app (100%), and the used value proposition is service-centric (100%). We summarized the solutions in this cluster as solutions to make the lives of citizens easier by providing a mobile app for diverse application areas. An archetypical example of a Smart City solution is GoDee from Vietnam. GoDee is a private Smart City mass transit company that owns buses and services 20 routes throughout Ho Chin Min City in Vietnam (GoDee 2023). The mission of GoDee is to enable the 8.9 million citizens of Ho Chin Min City to use GoDee's public transport system stress-free and convince people to switch from scooters and cars to public transport, thereby improving the air quality in the city (GoDee 2023). The provided service provides citizens with new types of transportation possibilities, digital payment options, and related information by constantly updating travel and arrival times.

Discussion and Implications

Given the enormous growth and growing relevance of urban areas, Smart City solutions have attracted considerable attention in recent years. Smart City solutions have the potential to solve many of our urban problems, such as waste disposal, growing energy demand or increased traffic volumes (Jamil et al. 2015; Khajenasiri et al. 2017; Nikitas et al. 2020; Zawieska and Pieriegud 2018). As the examples demonstrate the wide range of Smart City solutions, a categorization, i.e., a taxonomy of Smart City solutions, is needed as a foundation for meaningful future theorizing. Building on prior research (Ahmed et al. 2016; Christmann et al. 2022; Muhammad et al. 2020; Nagel and Kranz 2020; Perboli et al. 2014; Vasudavan and Balakrishnan 2019), complemented by a sample of 106 Smart City solutions, we developed a taxonomy combing technical and non-technical aspects as well as considering the diverse subfields of Smart Cities. Researchers benefit from a combined understanding of Smart City solutions' characteristics, as this knowledge will form the basis for future theoretical work (Holmström et al. 2009). Likewise, from the perspective of an engineering manager and urban planning, a combined understanding of Smart City solutions' characteristics is critical to tapping their full potential.

Thus, our work's theoretical contribution is threefold: First, we contribute to the descriptive knowledge of Smart City research by proposing a taxonomy for Smart City solutions based on Smart City literature, existing Smart City taxonomies, and real-world examples. The taxonomy complements and extends the existing taxonomies in the field of Smart City (Ahmed et al. 2016; Christmann et al. 2022; Muhammad et al. 2020; Nagel and Kranz 2020; Vasudavan and Balakrishnan 2019) in two ways: On the one hand, our taxonomy covers technical and non-technical aspects of the Smart City solution architectures. On the other hand, it provides a holistic overview of Smart City solutions beyond specific subfields that have been in focus. Hence, we structured the currently highly fragmented research in the field of Smart City solutions and incorporated insights from the Smart City solution market to shed light on the anatomy of those solutions. Thus, our final taxonomy fosters an in-depth understanding of the Smart City solutions phenomenon, increases the general expertise on Smart Cities, and provides researchers with a holistic foundation for future research. The taxonomy transforms Smart City solutions' features into measurable and comparable dimensions and characteristics. It enables researchers to theorize beyond the level of individual Smart City solutions and focus on purpose-related Smart City solutions clusters. To do so, the taxonomy provides nomenclature and definition for researchers to be consistent and specific when referring to Smart City solutions. Future research can use the taxonomy to study and hypothesize relationships among Smart City solutions and their characteristics, e.g., the relationship between the solution owner and the main sustainability value. Second, the derived clusters abstract from the high combinatorial diversity of Smart City solution characteristics and provide high-level insights into the sample. The clustering allows researchers to target a specific type of Smart City solutions, as every cluster we have found contains a specific set of characteristics. Therefore, future research could focus only on specific Smart City clusters and rely on the elaborated clusters. Further, the taxonomy and clusters facilitate the discussion of similarities and differences in Smart City solutions, serving as a critical foundation for scientific progress. Third, the taxonomy and clusters allow for more precise explanations (e.g., towards a Type II theory) of the effects of Smart City solutions for different phenomena and lay the foundation for future theoretical work (Gregor 2006). For example, Marrone and Hammerle (2018) found out that citizens tend to be underrepresented in discussions on smart cities. Future research could leverage our results to differentiate what positive and negative effects arise from which types of Smart City solutions and related characteristics, examining their impact on the citizens and the city itself. Future research can use our taxonomy to assess and identify specific characteristics that are likely to cause a positive or negative impact on stakeholders in a Smart City.

The results also have several managerial implications for urban planning professionals and consultancies, especially in the public sector: First, our work helps to improve their under-standing of Smart City solutions and provides an easy tool for analyzing and classifying solutions by combining technical and non-technical aspects. For example, the taxonomy and clusters can be used by consultancies to analyze the status quo of existing Smart City solutions in the city and, based on this, to make decisions on where there is still room for improvement. The taxonomy and clusters are also suitable as a tool to compare the Smart City solution landscape of different cities with each other and to perform more in-depth analyses based on them. Second, the taxonomy and clusters can aid in the improvement and redesign of existing Smart City solutions, as well as the development of new ones. There is enormous potential for new product offerings and city-wide implementations. Third, the taxonomy and clusters help match the unique characteristics of Smart City solutions with the needs of solution end-users and the constraints faced by solution owners to derive design and implementation recommendations. Hence, the taxonomy and clusters aid in determining which Smart City solutions are appropriate for specific scenarios. This knowledge is especially crucial for urban planning professionals in developing countries, who disproportionally must deal with problems of rapid urbanization but often lack the necessary capabilities (Bhattacharya 2002; Cohen 2006; Rana 2011).

Limitations and Outlook

As in any research endeavor, we must point out that this work has its limitations, thus providing stimuli for further research. First and foremost, the scope of the analysis may not be exhaustive. Although 106 Smart City solutions were carefully selected, the sample is limited to a specific period. Considering the fast pace at which novel technologies evolve, previously underrepresented characteristics will become more prevalent, and new characteristics will emerge. We followed Nickerson et al.'s (2013) taxonomy design process to respond to this scenario. Hence, the taxonomy is revisable and expandable. Moreover, the taxonomy should be reevaluated regularly to reflect new developments and account for the abovementioned limitations. Also, governance-focused and healthcare-focused Smart City solutions might be underrepresented in the sample because a broader audience refers to them differently, e.g., e-governance and e-healthcare. Additionally, we did not find education-focused Smart City solutions in our sample, even though the re-skilling and up-skilling of employees are highly discussed and encouraged actions to keep economies economically sustainable in the long run. Thus, future research could extend the taxonomy by including additional keywords. Furthermore, future research could apply other clustering methods. While our clusters have produced three extensive clusters, other clustering techniques (e.g., k-means) could also produce finer, more detailed clusters suitable for more detailed analysis. As a possible next step in the research, the developed clusters can be further developed into archetypes, such as those proposed by Baier et al. (2023) or Fischer et al. (2020). In addition, transforming a city into a Smart City is a global phenomenon. However, the investigated sample heavily represents Smart City solutions from Europe and North America, and other regions, such as Africa, Asia, and South America, are underrepresented. Future research should include more Smart City solutions from underrepresented regions to identify possible regional differences in the solutions offered. In addition, future research should also explore how end-users want to use Smart City solutions. Finally, the findings stimulate future research on the Smart City phenomenon. From a descriptive perspective, the identified characteristics can serve as inputs for research on factors that foster the adoption of Smart City solutions. The identified characteristics can also serve as a basis for future explorations of opportunities presented by those solutions. Finally, our results aim to inspire further research into methods for engineering Smart City solutions and expand existing product design from a prescriptive standpoint.

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