Driving Towards a Sustainable Future: A Multi-Layered Agent-Based Digital Twin Approach for Rural Areas

Stephanie C. Rodermund[1], Annegret Janzso[1], Ye Eun Bae[1], Anna Kravets[1], Alexander Schewerda[1], Jan Ole Berndt[1] and Ingo J. Timm[1,2]

[1]*Cognitive Social Simulation, German Research Center for Artificial Intelligence, Behringstr. 21, 54296 Trier, Germany*

[2]*Business Informatics, Trier University, Universitaetsring 15, 54296 Trier, Germany*

Keywords: Digital Twin, Agent Decision-Making, Sustainability, Rural Development.

Abstract: The production of CO_2, a major contributor to global emissions, is significantly caused by human activities, with transportation accounting for approximately 25% of worldwide emissions. Fostering pro-environmental behaviors (PEB) is vital for achieving emission reduction. Individual decision-making to adopt PEBs is complex, influenced by personal characteristics, situational factors, and externally sourced information. This position paper introduces a conceptual framework for a multi-layered agent-based Digital Twin (DT) designed to facilitate experimentation with various scenarios and intervention approaches promoting PEB among residents in rural regions. As a use case, we outline how to apply the DT to a specific rural area in Germany.

1 INTRODUCTION

Climate change has been a significant concern over the past decade and escalating global temperatures are precipitating adverse consequences such as extreme weather and natural disasters (Shukla et al., 2019). Carbon dioxide (CO_2), among various greenhouse gases, stands out as one of the predominant contributors to climate change (National Academies of Sciences et al., 2020). Numerous human activities contribute substantially to the production of CO_2, with the transportation sector alone responsible for approximately one-quarter of global CO_2 emissions (Agency and Environment, 2022).

Under the 2015 Paris Agreement, nations agreed to cap the rise in global average temperature at 1.5°C above pre-industrial levels, thereby preventing more pronounced and deleterious consequences of climate change (Masson-Delmotte et al., 2022). To bring about a meaningful reduction in emissions within a limited timeframe, it becomes imperative not only to substitute fossil fuels with other alternative fuels in the long-term but also to change human behavior in the short-term (Chapman, 2007).

An international survey reveals that 85% of German respondents believe that climate change is mostly caused by human activities (Leiserowitz et al., 2022). This awareness, however, does not always translate into pro-environmental actions. For instance, while the environmental benefits of public transport over private transport are known, many still opt for the latter, preferring immediate convenience to long-term sustainability. Such social dilemma, choosing between immediate and long-term reward (Dawes, 1980), is particularly evident in rural areas of Germany, where private transport is often favored due to infrastructural inadequacy (Süddeutsche Zeitung, 2022).

We aim to provide a framework that enables experimenting with various scenarios and intervention approaches promoting pro-environmental behaviors (PEB) among residents in rural areas, with a focus on transportation. This approach is grounded in the capabilities of Digital Twin (DT) to support decision-making in promoting sustainable behaviors with a virtual representation of the area and implementing simulation as well as reasoning (cf. Wang et al. 2023). The DT framework is designed to offer insight into how individuals make decisions under a complex interplay of their internal and external factors without requiring a change into the actual physical infrastructure.

The paper is structured as follows: Section 2 gives a brief introduction to DT and discusses the results of a systematic literature review. In Section 3, the proposal of our conceptual DT framework - consisting of a spatial, individual and social layer - is introduced. For this, we represent individuals with artificial agents under consideration of cognitive and social concepts using Agent-based Social Simulation (ABSS). In Section 4, the DT framework is applied to a use case of

Rodermund, S., Janzso, A., Bae, Y., Kravets, A., Schewerda, A., Berndt, J. and Timm, I.
Driving Towards a Sustainable Future: A Multi-Layered Agent-Based Digital Twin Approach for Rural Areas.
DOI: 10.5220/0012460100003636

In *Proceedings of the 16th International Conference on Agents and Artificial Intelligence (ICAART 2024) - Volume 1*, pages 386-395
ISBN: 978-989-758-680-4; ISSN: 2184-433X

Table 1: Search Queries and Results from Structured Literature Research.

”Digital Twin” AND	Hits	Relevant
”Urban”	37	16
”City”	43	
”Smart City”	33	
”Town”	1	
”Rural”	1	
”Agent”	33	
”Sustainability” OR ”Sustainable”	31	
”Emission”	3	
Backward	75	3
Forward	11	
Sum	**268**	**19**

a rural area. Finally, Section 5 summarizes the paper and addresses the limitations and future work.

2 BACKGROUND: DIGITAL TWINS OF INHABITED AREAS

DTs were initially conceptualized as a virtual or digital equivalent to a physical product. The concept was first mentioned in the context of product lifecycle management (Grieves, 2014). This transformative concept has found a variety of applications and continues to evolve into new industries and use cases. Various types of DTs exist, from device-level models for individual machines to city-level replicas for urban planning. The concept of DT is constantly evolving, leading to a lack of a unified consolidated definition that distinguishes it from other technologies (VanDerHorn and Mahadevan, 2021). When DTs are applied to urban settings, usually entire cities are replicated, enabling the analysis and optimization of complex systems such as transportation networks and infrastructure.

To get an insight into current DT approaches of inhabited areas, we conducted a structured literature review using a simplified version of the snowballing technique, originally introduced by Wohlin (Wohlin, 2014). We focused on the computer science bibliography *dblp*[1] using several search queries in conjunction with “Digital Twin” (cf. Table 1). Beyond queries with general terms synonymous with populated regions, we incorporated “Agent” as a specific term to appropriately represent individuals. Agent-based Modeling (ABM) and Multi-agent systems (MAS) allow for investigating the effect of individual characteristics on decision-making on the micro level and emergent behavior on the macro level which arises from communication and interaction (Bonabeau, 2002). We retrieved 268 publications in total using a backward and forward search, from which we identified 19 as relevant. The following subsection analyzes the publications in terms of relevant components for representing rural areas and discusses our research focus.

[1]https://dblp.org/

2.1 Aspects of Digital Twins of Inhabited Areas

As stated in Section 1, human activities have a significant impact on CO_2 emissions. Hence, in addition to spatial circumstances, individual and collective behavior need to be addressed when providing a DT framework that enables experimenting with aspects impacting PEB. Therefore, we analyzed the retrieved publications with a special focus on spatial, individual, and social aspects. Table 2 displays an overview of the occurrence of those aspects in the publications.

Spatial Aspects. Taking a closer look at spatial aspects is relevant for assessing the proximity of individuals to their preferred locations such as public transportation or supermarkets, calculating population density, and dividing the overall population into groups such as households, communes, neighborhoods. Some key aspects thereof are granularity, structure, and representation within the DT.

Granularity is concerned with how the area is represented. This can be on the level of individual districts or neighborhoods, or more fine-grained on the level of individual blocks or buildings. Major et al. (2021) represent geographical as well as building as-

Table 2: Spatial, Individual and Social Aspects in Publications.

	spatial aspects	**individual aspects**	**social aspects**
Barat et al. (2022)	✓	✓	✓
Clemen et al. (2021)	✓	✓	
Adreani et al. (2023)	✓		
Yun et al. (2023)	✓	✓	
Mohammadi and Taylor (2019)	✓	✓	✓
Ahn et al. (2020)	✓	✓	
Mavrokapnidis et al. (2021)	✓	✓	
Bujari et al. (2021)	✓	✓	
Meta et al. (2021)		✓	✓
Major et al. (2022)	✓	✓	
Pan et al. (2022)	✓		
Sottet et al. (2022)	✓		
Mohammadi and Taylor (2020)	✓		
Van Den Berghe (2021)	✓		
Major et al. (2021)	✓		
Le Fur et al. (2023)	✓	✓	✓
Bellini et al. (2022)	✓		
Ferreira et al. (2013)	✓		
Fan et al. (2022)	✓	✓	

pects, while the DT of Adreani et al. (2023) consists of individual buildings for the purpose of a photorealistic model of the city. Van Den Berghe (2021) and Mohammadi and Taylor (2020) include most of the physical objects in their DT. Le Fur et al. (2023) operates on a finer level, and even includes a detailed representation of interiors, in addition to the buildings. A fine level of granularity has also been chosen for infrastructure representation by Major et al. (2022), Ferreira et al. (2013) and Bellini et al. (2022), giving information i.e. on road type, direction, and capacity, whereas Pan et al. (2022) show a high-level focus on infrastructure.

The structure describes how items are represented and distributed under the chosen granularity. For example, Barat et al. (2022) present the city as areas with different types of buildings and numbers of people in each area. The areas thereby differ from each other in the ratio of building types, to represent residential or industrial areas. Clemen et al. (2021) and Bujari et al. (2021) structure DTs by coordinates, giving the start and end point of each commute, thereby eliminating the need of a detailed representation of infrastructure. The structure can also be presented as a graph with nodes at geographic coordinates, which can then be connected via links and structured in individual sections (Yun et al., 2023; Sottet et al., 2022).

Finally, it is important to determine what needs to be represented within the DT. This can include infrastructure and points of interest (POIs), as well as vegetation or terrain aspects. As an example, Adreani et al. (2023) choose a very fine-grained representation for their DT, and thereby included buildings, road shapes, names, paths, areas, terrain, and other structures, as well as markers for POIs.

Individual Aspects. Addressing individual aspects is crucial in the context of inhabited areas, especially with regard to behavioral adoption concerning CO_2 reduction. This was diversely reflected in half of the publications we reviewed. For instance, the influence of individuals can be regarded on a community level by including an aggregated impact of their behavior on the respective city (cf. Mavrokapnidis et al. 2021; Bujari et al. 2021). Another option is to only include the results of an analysis concerning a specific group of people. For example, Ahn et al. (2020) investigate the distress of elderly people in pedestrian situations and identify the best paths for minimal emotional or physical distress. Mohammadi and Taylor (2019) use a game-theoretic approach including groups of stakeholders (citizens, government, industry) that represent diverse interests. Fan et al. (2022) focus on the individual level and define trajectories of people in the city in a two-stage process using a coarse and fine-grained level to predict human mobility.

Among publications that deal with human factors six of them use ABM. Agents here utilize rather simple, mostly reactive, architectures, as these are often used for generating crowd behavior on the macro level. Le Fur et al. (2023) map agents' behavior with existing data to define daily routines of real inhabitants of a city, and abstract to behavioral groups, e.g., moving between locations, sleeping or eating. Papers with health-related approaches focus on where agents interact with each other to compute the probability of disease transmission. For instance, Barat et al. (2022) model agents using characteristics such as demographic data and profession to define behavioral patterns, i.e., movements and amount or type of contacts. Similarly, publications in transport focus on the presence of agents at a particular location and how they move between places, e.g., Clemen et al. (2021) model agent decisions in favor of the specific type of transport based on travel time required. Meta et al. (2021) test the adaptability of a City Physiology framework designed for urban DTs within the testbed of a virtual stadium. Pedestrian movement patterns are affected by an individual's characteristics and knowledge as well as changes in the environment, e.g., an event or behavioral change of other agents. Yun et al. (2023) develop a DT for testing scenarios regarding garbage collection in a city to optimize the operating policy. The agent decision model is a binary decision about whether to dump trash into containers or empty a full container.

Social Aspects. When modeling inhabited areas, not only individual behavior but also potential interactions between those individuals are relevant as they result in emergent effects. There were four publications that utilized some kind of social relationship between individuals. Those publications consider social behavior as a result of simple contact at a certain location. Barat et al. (2022) use contacts to determine infection spread in the population. Here, agents are given archetypes to implement different contact patterns. Meta et al. (2021) include social behavior by implementing crowd dynamics considering movement directions. A similar approach is used by Le Fur et al. (2023), where human-animal interaction occurs. A detailed model for human agents is not elaborated upon. The only paper that mentions more complex concepts such as the values of citizens still remains on a simple level, viewing citizens as merely consumers of the infrastructure services (Mohammadi and Taylor, 2019).

Our Research Focus. It is noticeable that the term "rural" returned only one result in the literature search, which indicates the need for additional research. To build upon insights from papers we retrieved, we aim to incorporate existing research and address some of its drawbacks. We intend to operate at a less detailed spatial level compared to the retrieved publications. Since our focus is on transportation, representing terrain is less relevant for our framework, we rather put an emphasis on POIs and sustainable infrastructure like public transportation. Our DT is intended to be used as an experimental framework, i.e., to compare scenarios and test the effect of interventions on behaviors and the overall system. For this, agents must be capable of deliberation considering options, which was not tackled in detail in the retrieved publications. Furthermore, they often overlook the dynamic nature of the intricate aspects of social organization and structure. Incorporating insights from social theorists could enhance the models' ability to simulate and predict outcomes in real-world scenarios more accurately, especially in the context where human behavior and social structures play a pivotal role (cf. Helbing 2012). Whether and how these aspects could be implemented in a DT will be discussed in the following section.

3 A MULTI-LAYERED DIGITAL TWIN APPROACH FOR RURAL AREAS

When creating a DT of an inhabited area, an enormous amount of data from multiple sources at different granularity has to be integrated. In examining an inhabited area, we focus on what is classified as a "complex system", (cf. Helbing 2012). One of the ways to approach a complex system is via structural complexity, hence a multi-layer framework. Figure 1 depicts the conceptual layers of our DT framework with the *spatial layer* at the bottom. Additionally, an essential component of a DT is the population of the focused area. Individual behaviors (*individual layer*) and relationships between people (*social layer*) can impact the overall system and lead to, e.g., fluctuations of CO_2 emissions. This may be triggered by actions that have a direct impact (e.g., the choice of means of transportation) or an indirect impact (e.g., information exchange between people that might affect their decision-making). The decision for or against PEB does not only depend on individual preferences, goals, and habits, but also on situational circumstances or information gathered from external

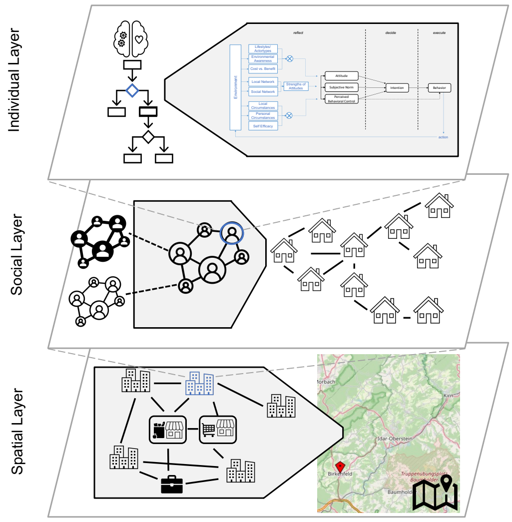

Figure 1: Layers of the DT Structure.

sources. These complex relationships can be realized by MAS and ABM as it has established itself in the representation of cognitive decision-making in varying application areas (Bonabeau, 2002; An, 2012). This requires the use of additional psychological concepts. The box in the center connects individual and spatial layers and considers the social structure, which emerges as a result of connections between individuals and their spatial and social proximity.

Layers comprising our DT are introduced in the following order: the spatial layer in Section 3.1, the individual layer in Section 3.2 and the connecting social layer in Section 3.3.

3.1 Spatial Layer

One main aspect of the spatial layer is the possibility to represent location, and thereby show individuals at given places, where they can interact with one another. Generally, locations in this layer are represented as cities, places, and POIs. The infrastructure network defined by streets and public transport options connects individual locations. The overall population is distributed in residential- and workplaces.

As described in Section 2.1, this layer is presented in different levels of granularity. Here, we take an approach of representing multiple towns to demonstrate commutes between places. A region is further defined by individual zones and areas (cf. Barat et al. 2022). At the finer level of granularity, zones are further divided into individual neighborhoods. Further, a neighborhood is depicted as a group of buildings. This is a common approach when building a DT of a city (cf. Adreani et al. 2023; Le Fur et al. 2023), especially when they incorporate a strong visual component. Higher levels of granularity are of advantage, as they enable a thorough overview of the relevant steps while keeping processing times low. Other aspects, such as areas of vegetation or details on terrain, are omitted at this stage.

Our focus is on a rural region in Germany, consisting of several towns and villages. This is why it is essential to consider places of work such as offices and POIs. These are determined for each region with OpenStreetMap[2] (OSM) data with relevant tags of places located within the area. In our use case, this is particularly relevant since key locations might not be within a single town, requiring residents to travel farther to adhere to their daily routines. Therefore, we use data reflecting the positions of relevant points in locations and infrastructure, which can be obtained from OSM data.

3.2 Individual Layer

Similar to spatial aspects, the complexity of portraying individual decisions depends on the application context and purpose of DTs. For instance, in urban, energy, or mobility planning, the use of reactive behavior models of individuals or groups is usually sufficient to represent the impact of small structural changes that affect the overall system. As the focus of our research is identifying suitable intervention strategies for an inhabited area with varying spatial and infrastructural circumstances (e.g., state of the public transport) as well as generational diversity, a more elaborated representation of individuals is required.

In the case of our DT framework, this implies that the individual behavior is modeled two-fold. First, agents are equipped with a realistic time schedule representing their daily life including the specific geographic places where the agent is spending time, e.g., the workplace or POIs, as well as how the agent travels to these places (e.g., by car or public transport) (cf. Le Fur et al. 2023; Barat et al. 2022). Second, agents have a deliberative component that refers to PEB in the specific scenarios. These situations can occur at any step of the daily schedule, e.g., if a certain demand arises or a need is triggered. Agents can exhibit almost automatic responses that become habitual. Similarly, if agents have a certain level of awareness of the impacts of their actions on the environment, this can lead to a more complex decision process. Hence, aspects that have an impact on their decision-making include the agent's general lifestyle, preferences, perceived environmental threat posed by environmental hazards, and group dynamics of their social network.

[2]https://www.openstreetmap.de/

When looking at related works on agent decision-making in the context of PEB, one of the focuses is on the identification of decision-relevant factors. For instance, Tong et al. (2018) investigate under which circumstances agents decide on an option concerning recycling and waste disposal, Granco et al. (2019) focus on the conservation and protection of natural habitats. Mostly, these models utilize psychological theories to represent the complex decision processes. One of those is the Theory of Planned Behavior (TPB) (Ajzen, 1991) that is increasingly used in the context of long-term set goals, i.e., PEB, (cf. Anebagilu et al. 2021). Personal aspects, like the general attitude towards a behavior or the perceived behavioral control, affect the formation of an intention to act. Additionally, the social network plays an important role in this theory, e.g., by forming behavioral norms through interactions with the social network. Furthermore, Yuriev et al. (2020) claim that the TPB is well-suited for the design of behavioral interventions.

To adequately utilize TPB within an agent architecture, agents must be capable of reflecting on their own situation, desires, goals, and events. For this, the Belief-Desire-Intention (BDI) model is particularly suitable (Bratman, 1987; Berndt et al., 2018): individual goals (desires), information (beliefs) and action-oriented measures (intentions) are organized into mental states. Intentions are derived from beliefs and desires using a deliberation process. TPB is used to adapt the deliberation process to map the requirements of the application area by selecting the necessary internal and external factors for decision-making.

3.3 Social Layer

Our DT framework acknowledges that the spatial and individual layers are linked through a social layer, a complexity often overlooked in DTs. The literature review showed that important aspects of social organization and structure are frequently excluded in such models (cf. Section 2.1).

Literature highlights the pivotal role of social norms in fostering PEB (Cialdini and Jacobson, 2021), influencing travel choices (Doran and Larsen, 2016), and specifically affecting travel mode choices (Eriksson and Forward, 2011). Travel attitudes of a region's inhabitants are significant predictors of travel-related CO_2 emissions, as exemplified in the context of the Netherlands (Ettema and Nieuwenhuis, 2017). Other research illustrates the impact of social learning in virtual environments on the adoption of pro-environmental lifestyles (Chwialkowska, 2019) and the uptake of eco-conscious products (Zhang et al., 2021). Research therefore suggests that these concepts are integral to PEB. However, they are often viewed merely as extensions of the TPB (cf. Eriksson and Forward 2011; Doran and Larsen 2016; Cialdini and Jacobson 2021), an approach that risks neglecting the dynamic interactions within the social sphere.

To better understand the origins and spread of attitudes and norms, a clear understanding of the social structures and network dynamics is essential. This knowledge is also crucial to effectively model possible emergent behaviors and to identify challenges in its adoption. Therefore, we treat the social layer as a separate level of complexity in our analysis. This essentially implies consideration of both the local and the social network. The local network is bound to the geolocation we described in the spatial layer. The social network consists of connections and relationships which are not identifiable on the map.

When looking at human networks in inhabited geographic areas, it is crucial to consider that physical proximity does not necessarily translate into social proximity. This is particularly vivid from the research on support networks[3]. Blokland et al. show how social networks are susceptible to the effects of mobility and digitization. The authors challenge traditional views of social networks, which previously focused on neighborhood ties, suggesting that these ties are not solely defined by physical proximity but are increasingly influenced by digital interactions and trans-local mobility (cf. Small 2017).

For us, it is vital to conceptualize the social network in a broader sense, encompassing both digitalization and mobility factors. Prior research on changes in PEB emphasizes the vital role online communication plays on social learning (Chwialkowska, 2019; Zhang et al., 2021). Our DT framework incorporates potential pathways for the dissemination of PEB that have been overlooked in prior studies, due to their limited scope in defining the social domain.

To consider social networks in our DT framework, while keeping the individual layer in mind, we focus on two types of information flow. Agents acquire information from their local and social networks either through direct observation or via knowledge and views disseminated by others. This information is then channeled to the individual layer, and processed within the agent's deliberation. The outcome results in an intention, tailored to each agent's specific circumstances, that potentially influences opinion dynamics within their environment. The social layer plays a pivotal role in shaping agents' perception of their environment and how their behaviors impact others within the social network.

Incorporating these social aspects into MAS for the purpose of conducting experiments leads to the development of Agent-Based Social Simulation (ABSS) (Davidsson, 2002). ABSS has proven to be a good fit to enable interaction between agents while considering social concepts; it offers a controlled environment for experimenting, e.g., with different scenarios or psychological and social concepts (Squazzoni et al., 2014).

4 USE CASE: DIGITAL TWIN OF A RURAL AREA

This section addresses specifics of and required data for our rural area use case. Essentially, the area consists of numerous small communities. Typical for this region are various demographic changes, i.e., rural migration and a high proportion of commuters within and between rural districts (Dauth and Haller, 2018). Due to poorly developed public transport infrastructure, people largely depend on private vehicles for work, leisure activities, and daily supply. To mitigate the impact of inadequate infrastructure, approaches in cooperative mobility and logistics are explored.

Figure 2 displays the general processes required to model the use case. *Data Processing and Model Building* shows the sub-models of the layers defined in Section 3. *Theories* contains theories applied in the respective layers. For the spatial layer, we use a network generator to filter the given data and build the required networks. Together, these boxes comprise a generic representation of the DT model. Expanding this DT using data enables adaptation to the region in focus and validation of the model components. *Data input* and theories are interrelated, e.g., theories determine which data is needed. Lastly, *Experimental Setup* and *Output* are required for simulation studies that can be conducted using the implemented model. An experiment consists of testing hypotheses referring to the specific scenarios and interventions (Lorig et al., 2017). The parameter setting depends on the structure of the model and available data. The output generally refers to the ratio of adopted behavior by individuals on the micro and macro levels.

A baseline scenario is the usual shopping behavior where inhabitants order goods online or buy them from the nearest shop using their preferred transport option. As an option for PEB, we introduce crowd delivery supported by commuters. Crowd delivery in logistics is an approach to unburden delivery services

[3] Support network is conceptualized as a system through which individuals exchange resources, with an emphasis on the varying strength of ties and the closeness these ties might represent (Blokland et al., 2021)

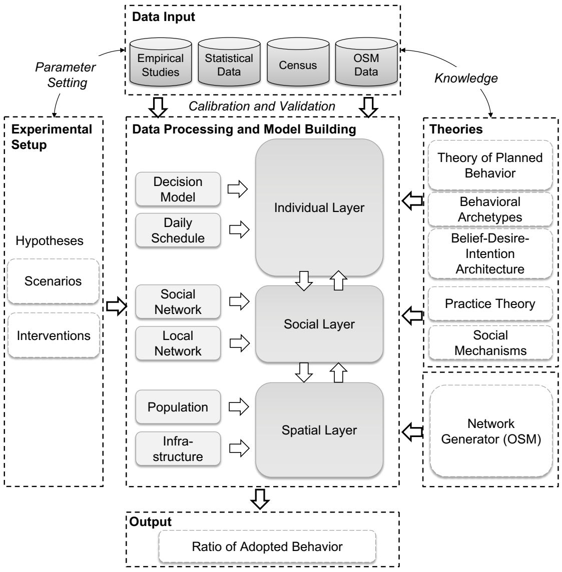

Figure 2: Processes, Data Use and Theories.

and improve the last mile in terms of parcel delivery time (cf. Asdecker and Zirkelbach 2020). Inhabitants are provided with an additional option, i.e., to commission a commuter who travels from, to, or through the community of the inhabitant. Interventions seek to encourage residents to utilize this additional option, for example, by promoting social norms (social pressure) that emerge through interactions or by providing information about its environmental benefits. The intended output would be, e.g., an increased ratio of people adopting the new option that helps to identify the most effective interventions for real-life application.

To build the model components for each DT layer, a variety of data sources are needed. The spatial layer requires georeferenced data including buildings and streets with tags and an overview of public transport. For this, we use OSM data. While OSM provides a collection of data for a general area, data for the focus area has to be extracted by removing all data outside the outermost longitude and latitude values of the area. Of the remaining data, workplaces, and POIs are filtered using relevant tags. Additionally, we utilize census data[4] to generate an artificial population that represents the demographic characteristics of respondents, including age, gender, and living situation, at the time of the survey.

In the following step, inhabitants are represented by agents with a daily schedule and a decision-making model. To understand individual aspects, it is essential to conduct empirical studies, specifically, surveys focused on rural areas. These surveys should encompass a broad range of topics, including subjective personal attitudes, preferences, and habits (e.g., shopping behavior, travel choices, and daily routines). Additionally, they need to shed light on the influences inspiring PEB, aiming to map out individuals' social networks and pinpoint other significant external factors.

An agent's daily schedule, on the one hand, is influenced by the person's workplace. Hence, we include statistical data regarding commuters in the area using the Pendleratlas[5] (Commuter atlas), which tells how many people commute between and within communities. On the other hand, the schedule is shaped by leisure activities (e.g., meeting friends), necessary activities (e.g., grocery shopping), and the respective travel choices, for which we use empirical studies and statistical data (e.g., Datenreport Umwelt, Energie und Mobilität (Data report environment, energy, and mobility) by Brockjan et al. (2021)). For the TPB in the Decision Model we derive data from empirical studies. Additionally, we utilize archetypes based on survey results or theoretical constructs, e.g., social actor types (Dittrich and Kron, 2002).

The local network, defined by data from the spatial layer, includes an individual's household and can extend to neighbors. Social networks consist of people who might not live in the same neighborhood but have a strong impact on an individual's behavior. To map the social network of our agents, the social network is analyzed based on survey data. Importantly, our social network analysis centers on the study of practices (Blokland et al., 2021) rather than predefined ties. This approach reflects the fluidity of modern social interactions and incorporates diverse communication methods.

For validation, we utilize publicly available data (i.e., commuter statistics, census data, OSM data). This also facilitates the transferability to other rural regions. Furthermore, we utilize traffic count data from the selected region to assess the number of commuters and their daily travel routes. The data gathered from empirical studies is employed to initialize and calibrate our model and to verify assumptions regarding the model's behavior.

5 CONCLUSION

This paper aims to understand and foster pro-environmental behaviors in rural areas. For that, we first conducted a literature review on the theme of Digital Twins and inhabited areas. We then addressed

[4]https://ergebnisse2011.zensus2022.de/datenbank/online/

[5]https://www.pendleratlas.de/

current research gaps, and guided by our research focus, outlined a framework for developing a Digital Twin. Our framework is distinctive in its multi-layered approach, integrating spatial, individual, and social aspects to offer a holistic understanding of the factors influencing pro-environmental behavior. Our framework was created with a real-world use case of a rural area in mind. We accounted for the unique characteristics of this region and established the basis for a DT which could facilitate the search of sustainable solutions, without necessitating significant changes to physical infrastructure. As a next step, we plan to implement the conceptual structure into a computational model. Our model can support decision-making by enabling the exploration of various scenarios and interventions that promote pro-environmental behavior. However, we also acknowledge certain limitations of this paper. Firstly, our literature review was confined to a single database, which, while comprehensive, may have led to the exclusion of relevant publications from other sources.

Secondly, our approach focused on integrating the specific psychological and social theories while omitting others. Future research could benefit from incorporating a wider range of theories to capture a more diverse array of behavioral influences and dynamics. Additionally, our conceptualization of the social network has been primarily informed by the research applicable to urban areas, it is therefore yet to be determined how well these theoretical considerations will perform in the rural setting. Third, besides the Digital Twin's level of granularity that we addressed in the spatial layer, other characteristics of DTs to describe their capability of representing its physical twin can be discussed in more detail, e.g., fidelity, maturity or consistency (Su et al., 2023).

Lastly, it is important to consider the potential variability in the applicability of our framework across different rural and urban contexts as inhabited areas are diverse in their geographic and socio-economic characteristics. However, our approach is promising as it includes the identification of key characteristics and establishes basics for an adaptable conceptual framework by building upon openly available data.

ACKNOWLEDGEMENTS

This work is funded by the Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection (Bundesministerium für Umwelt, Naturschutz, nukleare Sicherheit und Verbraucherschutz) (BMUV, No. 67KI31073A).

REFERENCES

Adreani, L., Bellini, P., Fanfani, M., Nesi, P., and Pantaleo, G. (2023). Design and develop of a smart city digital twin with 3d representation and user interface for what-if analysis. In *ICCSA 2023*, pages 531–548. Springer.

Agency and Environment, E. (2022). *Transport and environment report 2022 - Digitalisation in the mobility system - Challenges and opportunities*. Publications Office of the European Union.

Ahn, C., Ham, Y., Kim, J., and Kim, J. (2020). A digital twin city model for age-friendly communities: capturing environmental distress from multimodal sensory data. In *HICCS 2020*.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*, 229:25–36. Modeling Human Decisions.

Anebagilu, P. K., Dietrich, J., Prado-Stuardo, L., Morales, B., Winter, E., and Arumi, J. L. (2021). Application of the theory of planned behavior with agent-based modeling for sustainable management of vegetative filter strips. *Journal of Environmental Management*, 284:112014.

Asdecker, B. and Zirkelbach, F. (2020). What drives the drivers? a qualitative perspective on what motivates the crowd delivery workforce. In *HICSS 2020*, pages 1–10.

Barat, S., Paranjape, A., Parchure, R., Darak, S., and Kulkarni, V. (2022). Agent based simulatable city digital twin to explore dynamics of covid-19 pandemic. In *WSC 2022*, pages 557–568. IEEE.

Bellini, P., Bilotta, S., Palesi, A. L. I., Nesi, P., and Pantaleo, G. (2022). Vehicular traffic flow reconstruction analysis to mitigate scenarios with large city changes. *IEEE Access*, 10:131061–131075.

Berndt, J. O., Rodermund, S. C., and Timm, I. J. (2018). Social contagion of fertility: An agent-based simulation study. In *WSC 2018*, pages 953–964. IEEE.

Blokland, T., Krüger, D., Vief, R., and Schultze, H. (2021). Where we turn to: Rethinking networks, urban space, and research methods. In *Spatial Transformations*, pages 258–268.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proc. of the national academy of sciences*, 99(suppl_3):7280–7287.

Bratman, M. (1987). *Intention, Plans, and Practical Reason*. Cambridge, MA: Harvard University Press, Cambridge.

Brockjan, K., Maier, L., Kott, K., and Seqald, N. (2021). Umwelt, Energie und Mobilität. Auszug aus dem Datenreport 2021. Technical report, Statistisches Bundesamt.

Bujari, A., Calvio, A., Foschini, L., Sabbioni, A., and Corradi, A. (2021). A digital twin decision support system for the urban facility management process. *Sensors*, 21(24):8460.

Chapman, L. (2007). Transport and climate change: a review. *Journal of transport geography*, 15(5):354–367.

Chwialkowska, A. (2019). How sustainability influencers drive green lifestyle adoption on social media: The process of green lifestyle adoption explained through the lenses of the minority influence model and social learning theory. *Management of Sustainable Development*, 11(1):33–42.

Cialdini, R. B. and Jacobson, R. P. (2021). Influences of social norms on climate change-related behaviors. *Current Opinion in Behavioral Sciences*, 42:1–8.

Clemen, T., Ahmady-Moghaddam, N., Lenfers, U. A., Ocker, F., Osterholz, D., Ströbele, J., and Glake, D. (2021). Multi-agent systems and digital twins for smarter cities. In *ACM SIGSIM-PADS 2021*, pages 45–55.

Dauth, W. and Haller, P. (2018). Berufliches Pendeln zwischen Wohn-und Arbeitsort: Klarer Trend zu längeren Pendeldistanzen. Technical report, IAB-Kurzbericht.

Davidsson, P. (2002). Agent based social simulation: A computer science view. *Journal of artificial societies and social simulation*, 5(1).

Dawes, R. M. (1980). Social dilemmas. *Annual review of psychology*, 31(1):169–193.

Dittrich, P. and Kron, T. (2002). Complex reflexive agents as models of social actors. In *Proc. of the SICE Workshop on Artificial Society/Organization/Economy*, volume 25, pages 79–88.

Doran, R. and Larsen, S. (2016). The relative importance of social and personal norms in explaining intentions to choose eco-friendly travel options. *International Journal of Tourism Research*, 18(2):159–166.

Eriksson, L. and Forward, S. E. (2011). Is the intention to travel in a pro-environmental manner and the intention to use the car determined by different factors? *Transportation Research Part D: Transport and Environment*, 16(5):372–376.

Ettema, D. and Nieuwenhuis, R. (2017). Residential self-selection and travel behaviour: What are the effects of attitudes, reasons for location choice and the built environment? *Journal of Transport Geography*, 59:146–155.

Fan, Z., Yang, X., Yuan, W., Jiang, R., Chen, Q., Song, X., and Shibasaki, R. (2022). Online trajectory prediction for metropolitan scale mobility digital twin. In *SIGSPATIAL 2022*, pages 1–12.

Ferreira, N., Poco, J., Vo, H. T., Freire, J., and Silva, C. T. (2013). Visual exploration of big spatio-temporal urban data: A study of new york city taxi trips. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2149–2158.

Granco, G., Heier Stamm, J. L., Bergtold, J. S., Daniels, M. D., Sanderson, M. R., Sheshukov, A. Y., Mather, M. E., Caldas, M. M., Ramsey, S. M., Lehrter II, R. J., Haukos, D. A., Gao, J., Chatterjee, S., Nifong, J. C., and Aistrup, J. A. (2019). Evaluating environmental change and behavioral decision-making for sustainability policy using an agent-based model: A case study for the smoky hill river watershed, kansas. *Science of The Total Environment*, 695:133769.

Grieves, M. (2014). Digital Twin: Manufacturing Excellence through Virtual Factory Replication. Technical report, Michael W. Grieves, LLC.

Helbing, D. (2012). *Social self-organization: Agent-based simulations and experiments to study emergent social behavior*. Springer.

Le Fur, J., Sall, M., and Dembele, J.-M. (2023). A Digital Twin Simulator Approach as a Support to Develop an Integrated Observatory of the Epidemic Risk in a Rural Community in Senegal. In *SIMULTECH 2023*, pages 134–142. SCITEPRESS.

Leiserowitz, A., Carman, J., Buttermore, N., Neyens, L., Rosenthal, S., Marlon, J., Schneider, J., and Mulcahy, K. (2022). International public opinion on climate change 2022.

Lorig, F., Lebherz, D. S., Berndt, J. O., and Timm, I. J. (2017). Hypothesis-driven experiment design in computer simulation studies. In *WSC 2017*, pages 1360–1371. IEEE.

Major, P., Li, G., Hildre, H. P., and Zhang, H. (2021). The use of a data-driven digital twin of a smart city: A case study of ålesund, norway. *IEEE Instrumentation & Measurement Magazine*, 24(7):39–49.

Major, P., Torres, R., Amundsen, A., Stadsnes, P., et al. (2022). On the use of graphical digital twins for urban planning of mobility projects: a case study from a new district in ålesund, norway. In *ECMS 2022*.

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., et al. (2022). *Global Warming of 1.5 C: IPCC special report on impacts of global warming of 1.5 C above pre-industrial levels in context of strengthening response to climate change, sustainable development, and efforts to eradicate poverty*. Cambridge University Press.

Mavrokapnidis, D., Mohammadi, N., and Taylor, J. (2021). Community dynamics in smart city digital twins: A computer vision-based approach for monitoring and forecasting collective urban hazard exposure. In *HICSS 2021*.

Meta, I., Serra-Burriel, F., Carrasco-Jiménez, J. C., Cucchietti, F. M., Diví-Cuesta, C., García Calatrava, C., García, D., Graells-Garrido, E., Navarro, G., Làzaro, Q., et al. (2021). The camp nou stadium as a testbed for city physiology: a modular framework for urban digital twins. *Complexity*, 2021:1–15.

Mohammadi, N. and Taylor, J. (2019). Devising a Game Theoretic Approach to Enable Smart City Digital Twin Analytics. In *HICCS 2019*.

Mohammadi, N. and Taylor, J. (2020). Knowledge discovery in smart city digital twins. In *HICSS 2020*.

National Academies of Sciences, E., Medicine, et al. (2020). Climate change: evidence and causes update 2020. *The National Academies Press, Washington*, 17226:25733.

Pan, X., Mohammadi, N., and Taylor, J. E. (2022). Smart city digital twins for public safety: A deep learning and simulation based method for dynamic sensing and decision-making. In *WSC 2022*, pages 808–818.

Shukla, P. R., Skea, J., Calvo Buendia, E., Masson-Delmotte, V., Pörtner, H. O., Roberts, D., Zhai, P., Slade, R., Connors, S., Van Diemen, R., et al. (2019). Ipcc, 2019: Climate change and land: an ipcc special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

Small, M. L. (2017). *Someone to Talk to*. Oxford University Press, New York.

Sottet, J.-S., Brimont, P., Feltus, C., Gâteau, B., and Merche, J. F. (2022). Towards a lightweight model-driven smart-city digital twin. In *MODELSWARD*, pages 320–327.

Squazzoni, F., Jager, W., and Edmonds, B. (2014). Social simulation in the social sciences: A brief overview. *Social Science Computer Review*, 32(3):279–294.

Su, S., Nassehi, A., Hicks, B., and Ross, J. (2023). Characterisation and evaluation of identicality for digital twins for the manufacturing domain. *Journal of Manufacturing Systems*, 71:224–237.

Süddeutsche Zeitung (2022). Mehrheit der Menschen würde häufiger ÖPNV nutzen. https://www.sueddeutsche.de/wirtschaft/verkehr-mehrheit-der-menschen-wuerde-haeufiger-oepnv-nutzen-dpa.urn-newsml-dpa-com-20090101-220111-99-665040. 2022-01-11.

Tong, X., Nikolic, I., Dijkhuizen, B., van den Hoven, M., Minderhoud, M., Wäckerlin, N., Wang, T., and Tao, D. (2018). Behaviour change in post-consumer recycling: applying agent-based modelling in social experiment. *Journal of Cleaner Production*, 187:1006–1013.

Van Den Berghe, S. (2021). A processing architecture for real-time predictive smart city digital twins. In *IEEE Big Data 2021*, pages 2867–2874. IEEE.

VanDerHorn, E. and Mahadevan, S. (2021). Digital twin: Generalization, characterization and implementation. *Decision Support Systems*, 145:113524.

Wang, H., Chen, X., Jia, F., and Cheng, X. (2023). Digital twin-supported smart city: Status, challenges and future research directions. *Expert Systems with Applications*, page 119531.

Wohlin, C. (2014). Guidelines for snowballing in systematic literature studies and a replication in software engineering. In *EASE 2014*, pages 1–10.

Yun, T.-S., Park, M., and Moon, I.-C. (2023). Modeling and calibrating digital twin of automatic garbage collection system in sejong city. In *ANNSIM 2023*, pages 572–583. IEEE.

Yuriev, A., Dahmen, M., Paillé, P., Boiral, O., and Guillaumie, L. (2020). Pro-environmental behaviors through the lens of the theory of planned behavior: A scoping review. *Resources, Conservation and Recycling*, 155:104660.

Zhang, W., Chintagunta, P. K., and Kalwani, M. U. (2021). Social media, influencers, and adoption of an eco-friendly product: Field experiment evidence from rural china. *Journal of Marketing*, 85(3):10–27.