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Green choices in rural settings: analyzing community adoption of eco-friendly shopping alternatives through agent-based modeling

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To address the high CO₂ emissions from private car use in rural areas, largely due to limited infrastructure and few public transport options, there is a need for innovative, locally accessible services that support sustainable practices. Understanding what drives rural communities to adopt such alternatives is essential for effective intervention. This study demonstrates the development of a toolkit, employing a multi-agent model to analyze how a rural community reacts to the introduction of a local, eco-friendly shopping alternative—a container store—compared to a common grocery store facility. We integrate the diffusion of innovation theory, the theory of planned behavior, and a spatially and socially explicit agent-based model (ABM) to simulate individual and collective decision-making processes regarding this new shopping method. We illustrate how the theoretical foundations are operationalized within the model. Our experiments explore the effects of store attributes, location, and initial adopter groups on community adoption rates. Results across scenarios reveal variations in adoption rates, illustrating how the applied toolkit effectively captures the influence of store attributes, location accessibility, and community network structures on sustainable consumer behaviors.

KEYWORDS

sustainability, agent-based modeling, community adoption, diffusion of innovation, theory of planned behavior, preferential attachment model

1 Introduction

This study examines pro-environmental behaviors aligned with achieving net-zero emissions targets (Marteau et al., 2021), focusing specifically on shopping as a fundamental daily activity. Our use case emphasizes the adoption of local shopping alternatives accessible by foot or bicycle, offering a practical strategy to reduce emissions while fostering sustainable mobility. Promoting such behaviors is particularly challenging in rural areas, where residents often travel significantly longer distances for daily needs compared to their urban counterparts. In rural Germany, for instance, individuals travel an average of 43 kilometers daily, with 49% of these trips made by private cars (Nobis and Kuhnimhof, 2018), primarily due to limited alternatives (Süddeutsche Zeitung, 2022). This reliance on private vehicles exacerbates CO₂ emissions, which contribute to climate change (Lee and Romero, 2023). Cutting these emissions would not only mitigate climate change but also

yield significant health benefits by reducing air pollution—currently the greatest external threat to human health (Lee and Greenstone, 2021).

However, merely situating shopping alternatives locally does not guarantee a reduction in car travel. Handy and Clifton (2001) showed that in the US context, nearby supermarkets or grocery stores may not always reduce driving, as shorter distances can lead to more frequent trips, offsetting the benefits of proximity. Conversely, Cao et al. (2006) highlight that local commercial area characteristics, such as pedestrian-friendly design and proximity, play a significant role in encouraging utilitarian walking, like shopping trips. Moreover, Carling et al. (2012) indicate that strategically locating shopping locations can reduce consumer travel emissions. Feng et al. (2014) emphasize the critical role of context in understanding travel mode choices, noting that differences in socio-cultural, economic, and urban structures across countries can lead to significant variations in travel behavior and the explanatory power of e.g., socio-demographic factors. In sum, context matters, and we need to look into the specificities of the region which we work with.

Germany's retail landscape, especially in rural areas, has long shifted as traditional Tante-Emma-Läden¹ vanish due to competition from large supermarkets. To address this issue, innovative cashier-less stores are emerging (Rampe, 2024), offering 24/7 access to essential goods in underserved areas. These automated shops aim to reduce the need for long car trips by providing local, convenient alternatives.

In this study, we assume that local container stores offer a solution to reduce CO₂ emissions by providing convenient, nearby shopping alternatives in rural areas. We therefore focus on studying the factors, which hinge the success of their adoption within the community and propose a simple model, which can be used as foundation for further exploration of community adoption.

To better understand the community adoption of shopping at the local container store, we want to look into how do *spatial proximity*, *pricing strategies*, *goods offered*, and *opening hours* influence the dynamics of community adoption for container stores as a sustainable shopping alternative in rural areas. These variables shape individual decision-making, modeled through behavioral intention and eventual adoption. Using agent-based modeling, we simulate interactions between human agents (local residents) and non-human agents (supermarkets and container stores) within a spatially defined rural environment. The model integrates core principles from the diffusion of innovation theory (Rogers et al., 2014) and the theory of planned behavior (Ajzen, 1991), focusing on behavioral and contextual drivers of adoption. To enhance the representation of human cognitive decision-making, the model incorporates the belief-desire-intention framework (Bratman, 1987), while the preferential attachment model (Topirceanu et al., 2018) is employed to better capture the structure and dynamics of social networks. By illustrating how these theoretical

foundations can be operationalized within a simulation framework, the study offers a methodology for exploring adoption dynamics in rural contexts.

This paper focuses on demonstrating a methodological toolkit for studying the adoption of local shopping alternatives. Of specific interest to us is to allow for an analysis of how store attributes, individual decision-making, and social network dynamics collectively influence sustainable consumer behaviors, highlighting the potential for strategic interventions to promote green choices. The experiment design investigates community adoption dynamics through three scenarios that analyze the impact of (1) container store attractiveness, (2) its placement across different municipalities, and (3) initial adopter groups—on adoption rates within a simulated rural environment.

In the following Section 2, we begin with the theoretical toolkit and a related work review, offering an overview of relevant literature and theoretical foundations, including the diffusion of innovation theory, the theory of planned behavior, and the preferential attachment model as well as their integration into agent-based modeling using the belief-desire-intention framework. This is followed by a detailed explanation of the conceptual model, demonstrating how these theories are integrated into our agent-based model and formalized within its framework. Next, we describe the simulation scenarios and the experiment design used. The Results Section 3 evaluates the outcomes of the simulation experiments, focusing on our key metric: adoption rate. In the Section 4, we highlight the implications of our findings for promoting sustainable behaviors in rural areas, and outline limitations and potential avenues for future research. Finally, in line with best practices in agent-based modeling research, we include the Overview, Design concepts and Details (ODD) protocol (Grimm et al., 2020) for transparency. The ODD protocol systematically documents the model, providing a structured description, ensuring clarity and facilitating understanding of the model's structure and function.

By integrating theories like diffusion of innovation theory and theory of planned behavior within a simulation framework, our research provides insights into how individual decisions and social dynamics influence community behavior toward sustainable practices. This approach supports the practical development and testing of interventions—such as targeted local initiatives before large-scale implementation. This is particularly relevant for stakeholders in rural development, environmental policy, and retail planning who are looking to implement and assess interventions that encourage pro-environmental behaviors in rural communities.

2 Materials and methods

2.1 Theoretical toolkit

In the subsections that follow, we introduce the theoretical frameworks that form the backbone of this study: diffusion of innovation theory, theory of planned behavior, and the methodologies involved in agent-based modeling in the context of sustainability.

¹ Tante-Emma-Läden are small, local retail shops that emerged around 1,860 during the industrial era, offering a wide range of everyday goods in both urban and rural areas. Easily accessible on foot, these stores served as key points for distributing industrial products but have largely disappeared, replaced by supermarkets and chain stores (Jessen-Klingenberg, 2006).

2.1.1 Understanding innovation adoption: diffusion of innovation theory

To establish a foundation for understanding the community adoption process, we frame it through the lens of the behavior adoption process outlined in the diffusion of innovation theory (Rogers et al., 2014), since it provides a theoretical framework for explaining how and why an idea or technology spreads within a population. Diffusion of innovation theory emerged in the field of rural sociology during the 1920s and 1930s, focusing on how farmers adopted new technologies (Ryan and Gross, 1943). Since then, the theory has been widely applied across various fields, including marketing (Gatignon and Robertson, 1989) and public health (Berwick, 2003). Among the numerous studies on diffusion of innovation, the book by Rogers et al. (2014) is the most renowned due to its comprehensive coverage of topics, drawing on insights from 508 diffusion studies conducted over an extensive period of 40 years.

According to Rogers et al. (2014), the diffusion of innovation framework offers a perspective for understanding adoption processes by introducing adoption rate as a key metric and identifying factors that influence it. There are five key elements that influence the spread of a new idea or technology: (1) the perceived attributes of the innovation, (2) the type of innovation-decision, (3) the communication channels, (4) the characteristics of the social system, and (5) the extent of change agent's promotion effort.² In formalizing adoption rate, diffusion of innovation theory emphasizes the perceived attributes of the innovation and the environment where adoption occurs. This framework allows for adjustment of these attributes within the decision-making model, ensuring their relevance to the adoption process. Additionally, diffusion of innovation theory highlights the critical role of communication channels as mechanisms for information exchange and the spread of innovation among people, providing a room for specifying characteristics of communication such as type of network individuals have with each other. Another defining feature of the diffusion of innovation framework is its focus on the nature of social system, particularly the influence of cultural norms and the degree of how highly the communication network is interconnected, which significantly shape adoption processes within a community. Furthermore, diffusion of innovation theory categorizes adopters into distinct groups and identifies their behavior patterns, offering valuable insights into adoption dynamics. For example, early adopters or influencers often lead the adoption process, making their behavior pivotal for promoting or marketing new innovations. This classification enables the integration of individual characteristics, such as environmental awareness and situational circumstances, into the model, facilitating the design of strategies to foster adoption effectively.

Several studies have utilized diffusion of innovation theory to investigate adoption processes within communities, reinforcing

its relevance as a framework for understanding community-level adoption dynamics. For example, Magsamen-Conrad and Dillon (2020) examined the spread of communal computing facilities among urban poor communities, incorporating all five key elements of diffusion of innovation theory. Their findings underscored the importance of the social system in driving adoption. Similarly, Nanyonjo et al. (2012) explored the adoption of a healthcare strategy across different communities, identifying critical factors such as the relative advantage of the innovation, observable results, and the influence of the social system in the decision-making process. Furthermore, Magsamen-Conrad and Dillon (2020) investigated the adoption of mobile technology in community contexts and highlighted the significant impact of interpersonal communication and relationships on the adoption process. These examples demonstrate how diffusion of innovation theory provides a structured lens for analyzing community-based adoption, emphasizing the importance of how the innovation is communicated among people and how it is perceived by individuals.

As discussed, diffusion of innovation theory introduces adoption rate as a measurable outcome and identifies five key factors influencing it. It is important to consider these factors in more detail in order to apply diffusion of innovation theory's framework to a specific use case. According to Rogers et al. (2014), the *perceived attributes* of an innovation account for 49% to 87% of the variance in adoption rates. These attributes include relative advantage, (1) compatibility, (2) complexity, (3) trialability, and (4) observability.

Relative advantage refers to the extent to which an innovation is perceived as superior to the behavior or idea it replaces. In our model, this includes the advantages of container stores, such as longer opening hours or closer proximity, which may positively influence individuals' attitudes toward adopting this alternative. Compatibility measures how well the innovation aligns with the existing values, past experiences, and needs. For instance, if the alternative aligns with environmental values, reduces resource use or emissions, it is more likely to be adopted. Complexity captures the perceived difficulty of adopting the innovation; in our case, the alternative is unlikely to present significant technical or behavioral challenges. Trialability reflects the extent to which an innovation can be tested or experimented with before commitment, which, in our model, depends on e.g., proximity of the store. Together, complexity and trialability shape the challenges that people might face when adopting the innovation. Lastly, observability refers to how visible the outcomes of the innovation are to others, reinforcing social norms and shaping the social pressure to adopt the behavior.

For the second element of diffusion of innovation theory, the *type of innovation decision*, our model adopts an individual-optional approach. This means that each agent independently evaluates the innovation, taking into account their circumstances. *Communication channels*, the third element, are operationalized through two networks: local and broader social networks. Both networks facilitate the interpersonal diffusion of information, enabling agents to observe and be influenced by their peers' adoption behaviors. The fourth element, the *characteristics of social system*, is formed by social norms and the interconnectedness of network structure among agents. In our

² It refers to the degree of effort invested by an individual or organization (the "change agent") in promoting the adoption and diffusion of an innovation within a target population (Rogers et al., 2014). Notably, the term 'agent' in this context differs from its use in the framework of agent-based modeling.

model, this interconnectedness is differentiated into local networks and social networks, reflecting varying levels of interaction and influence.

In general, diffusion of innovation theory provides an appropriate framework for understanding the diffusion of sustainable behaviors and community responses by covering various aspects of the innovation, the environment and network structure where the information and social norm are being exchanged. This flexibility and applicability of diffusion of innovation theory offers us a great foundation to model our use case using agent-based model. Despite the benefits of diffusion of innovation theory, it also has some limitations that were noted by the original author (see Rogers et al., 2014). Pro-innovation bias, for example, refers to the tendency of researchers to focus on the complete and successful diffusion of an innovation, often overlooking the possibility of discontinuation of the innovation. Similarly, individual blame bias disproportionately attributes innovation failures to individuals rather than considering social system factors. These limitations are covered in our model by theory of planned behavior that is integrated in our model as well. The further description of how diffusion of innovation theory and theory of planned behavior compliment each other follows in Section 2.1.2 and the demonstration of how these theoretical elements of diffusion of innovation theory are implemented and operationalized in our agent-based model follows in Section 2.2.

2.1.2 Understanding individual decision-making: theory of planned behavior

The community adoption process cannot be fully understood without first examining the adoption process at the individual level. To explore this individual deliberation, we employ the theory of planned behavior. As an extension of the Theory of Reasoned Action (Fishbein and Ajzen, 1977), the theory of planned behavior identifies the key factors that influence an individual's decision to engage in a specific behavior (Ajzen, 1991).

According to Ajzen (1991), the theory of planned behavior posits that an individual's behavior is primarily driven by their intentions, which act as motivational forces. These intentions are shaped by three core factors: attitude, subjective norms, and perceived behavioral control. Attitude refers to the individual's positive or negative evaluation of the behavior. Subjective norms capture the perceived social pressure to perform or refrain from the behavior, based on the expectations of the individual's social network. Perceived behavioral control reflects the individual's confidence in their ability to perform the behavior, considering both internal capabilities and external constraints.

Recent bibliometric analyses highlight the widespread application of theory of planned behavior in environmental science, particularly in studying pro-environmental behaviors such as waste management, green consumption, and sustainable transportation (Si et al., 2019; Zulkepli et al., 2024; Yuriev et al., 2020). Key variables like environmental awareness, consciousness, knowledge and education have been shown to play an important role in understanding and promoting sustainable actions (Zulkepli et al., 2024). However, despite theory of planned behavior's extensive use, many studies overlook indirect variables influencing behavior or fail to report the explained variance, limiting the robustness of

the theory (Yuriev et al., 2020). To address these gaps, researchers are encouraged to follow guidelines, including carefully selecting the theoretical framework, considering extensions to the original model, employing robust methods, and conducting thorough result analyses to enhance consistency and relevance (Yuriev et al., 2020). Zulkepli et al. (2024) highlight new trends and opportunities and provide a roadmap for utilizing the theory of planned behavior in the study of pro-environmental behaviors. The authors state that there is a lack of combining multiple theories in pro-environmental behavior research, i.e., theory of planned behavior with behavioral or social psychological theories. With diffusion of innovation theory as a sociological theory that explains the spread of innovations within a population, we would like to make a contribution to this with this paper by combining theory of planned behavior and diffusion of innovation theory in a specific use case. Furthermore, in addition to the theory of planned behavior, which cannot predict emotional states, more attention should be paid to irrational aspects that can also influence behavior in order to better understand pro-environmental behavior. In addition, the authors emphasize the application of the theory of planned behavior in different (industrial) application areas and scenarios, as different types of contexts as well as desired behaviors have specific requirements and can lead to the identification of varying decision-relevant factors. This is particularly relevant if, for example, a behavior, such as the use of a new innovation, is to be specifically promoted through interventions. To this end, the decision-relevant factors and their influence on behavior must first be examined. A toolkit can be a first step in this process. Additionally, Yuriev et al. (2020) emphasize theory of planned behavior's suitability for designing behavioral interventions, such as targeting specific decision factors within the framework to, e.g., reduce perceived barriers or influence attitudes.

In summary, theory of planned behavior enriches the diffusion of innovation theory's framework by deepening the theoretical basis for understanding individual behavior change. Adding theory of planned behavior broadens the explanatory power of models considering individual decision-making in the context of green choices, providing a more detailed analysis of innovation diffusion through individual deliberation processes. While diffusion of innovation theory deals with the characteristics of the innovation, theory of planned behavior deals with characteristics of individuals who decide whether to adopt or reject the innovation (Weigel et al., 2014). Moreover, theory of planned behavior enables overcoming the limitations of diffusion of innovation theory mentioned in Section 2.1.1, namely pro-innovation bias and individual blame bias, with diffusion of innovation theory focusing on the adoption process at population or community level whereas theory of planned behavior putting emphasis at individual level. By addressing these environmental factors that influence individual perceptions, individual blame bias can be mitigated. Individuals not only evaluate their willingness to adopt the innovation, but also check whether their circumstances allow them to do so. These constraints may stem from the characteristics of innovation itself or from external factors, such as infrastructure that affects access to the knowledge or opportunities to try the innovation in the first place. Moreover, the combination of both theories can reduce the pro-innovation bias by considering factors across all available decision options, e.g., to adopt or not to adopt the

innovation. This dual-option framework enables a more detailed analysis of the factors that are particularly important in the decision-making process.

2.1.3 Related work: agent-based modeling in community and environmental studies

According to Wooldridge an agent is a

“(...) computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives.” (Wooldridge, 2000, p. 29ff).

Agents act autonomously, they are able to interact with other agents (social ability), can react to changes in their environment (reactivity) and can also act proactively to pursue a behavior in a targeted manner (Wooldridge and Jennings, 1995). It enables researchers to experiment with and observe the complex dynamics of systems where individual behaviors and interactions can lead to emergent phenomena (Bonabeau, 2002). Agent-based modeling is increasingly recognized as an effective method for exploring complex social interactions and decision-making processes within community settings, offering insights critical to environmental and behavioral research. Agent-based modelings flexibility in incorporating diverse social and environmental variables (see, for instance, Bonabeau, 2002; Berndt et al., 2018; Lebherz et al., 2018) makes it a powerful tool for testing potential interventions and for understanding how sustainable practices may be adopted in specific community contexts. The approach is particularly suitable for sustainability studies because it enables simulation of both individual and collective responses to environmental interventions, providing actionable insights for interventions aimed at reducing ecological impact.

Agent-based modeling faced criticism for its tendency to oversimplify human behavior, often failing to capture the complexities of social dynamics. Conte and Paolucci (2014) warned that many agent-based models relied on *ad-hoc*, minimal rules, prioritizing macro-level outcomes over the detailed internal mechanisms driving individual decision-making. This approach, shaped by the “KISS” (Keep It Simple, Stupid) principle (Axelrod, 1997), raised concerns about the models’ explanatory power and empirical validity. However, in the years since, the field has advanced considerably. Researchers have developed more sophisticated methods to strike a balance between simplicity and complexity, particularly in community and environmental studies.

The “KISS” contrasts with the “KIDS” (Keep it Descriptive, Stupid) principle proposed by Edmonds and Moss (2004), which emphasizes the importance of descriptive adequacy over simplicity in modeling complex social phenomena. Edmonds and Moss (2004) argue that while simplicity can make models easier to understand, analyze, and communicate, it often sacrifices realism, particularly when applied to systems with intricate dynamics. The “KIDS” approach, by contrast, advocates beginning with models as descriptively rich as the available evidence and resources allow, incorporating qualitative, anecdotal, and expert data. Simplification

here is justified only when evidence supports it, ensuring the model maintains fidelity to the observed complexity.

Recent studies have demonstrated how agent-based modeling can incorporate rather complex theoretical frameworks such as the diffusion of innovation theory to improve the modeling of adoption processes. For instance, Christensen et al. (2020) present a methodology for designing agent-based simulations that explore technology adoption behaviors. Their work emphasizes that incorporating factors such as compatibility, complexity, trialability, and observability enhances the realism and accuracy of adoption models. This nuanced understanding of innovation characteristics offers a more comprehensive view of how sustainable behaviors spread within communities. This is further evidenced by Schramm et al. (2010), who modeled brand and product diffusion at both macro- and micro-level, while taking individual characteristics and emergent phenomena into consideration; and Zhang et al. (2011), who explored the adoption of eco-innovative technologies through social interactions, such as word of mouth. Talebian and Mishra (2018) also coupled diffusion of innovation theory with agent-based modeling to simulate the adoption of connected autonomous vehicles. They demonstrated how innovation diffusion unfolds within a social network, emphasizing factors like communication channels and social norms. Similarly, Bohlmann et al. (2010) explored the effects of market network heterogeneity on innovation diffusion using agent-based modeling. Their work highlighted how variations in network structures and interpersonal communications significantly influence adoption rates and diffusion dynamics.

Similarly, the theory of planned behavior has been leveraged in agent-based modeling to simulate individual and collective decision-making in environmental contexts. For example, Anebagilu et al. (2021) investigate under which circumstances farmers use vegetative filter strips depending on whether other farmers in the social network do. Pakpour et al. (2014) observed that the recycling behavior of households in Iran is strongly dependent on theory of planned behavior factors, especially with regard to moral expectations, which can be set by the influence of external factors such as the media, but also by social pressure from the attitudes of surrounding households. Furthermore, the role of social networks is highlighted by Tong et al. (2018), who analyzed how social influences affect decisions on recycling and waste disposal methods, successfully using the model to predict real regional data. Rai and Robinson (2015) utilize agent-based modeling in a study of solar technology adoption in Texas, emphasizing that social influence—particularly through peer networks—can substantially affect technology uptake. Zsifkovits (2015) also highlights that agent-based modelings ability to model diverse agents and their interactions allows for a more realistic depiction of environmental innovation diffusion in sectors requiring complementary infrastructure, such as green mobility. Also Meles and Ryan (2022) examine adoption of renewable heating systems in Ireland using agent-based modeling, demonstrating the impact of economic incentives, social influence, and psychological drivers on adoption rates.

Several studies have integrated elements from both diffusion of innovation theory and theory of planned behavior into agent-based modeling to enhance the simulation of innovation diffusion

across various contexts. Schwarz and Ernst (2009) developed an agent-based model to explore the diffusion of water-saving technologies in Southern Germany, using theory of planned behavior to simulate decision-making processes within households, showcasing how innovations spread across different lifestyles. Roberts and Lee (2012) applied agent-based modeling to predict the spread of safe teenage driving behaviors through online social networks, illustrating how social norms and behavioral intentions influence adoption. Jensen and Chappin (2017) introduced the “Schwarz flexible” (see Schwarz and Ernst, 2009) and theory of planned behavior models to automate the diffusion modeling process, focusing on water-saving showerheads and adjusting model parameters to fit empirical data dynamically. More recently, Pakravan and MacCarty (2021) coupled elements from diffusion of innovation theory and theory of planned behavior to study the adoption of clean technologies in low-income regions, emphasizing the importance of targeted information campaigns and the empowerment of specific social groups. Finally, Sadou et al. (2021) presented an agent-based model approach that uses formal argumentation combined with theory of planned behavior to simulate the diffusion of innovations, aiming to enhance the realism and predictive power of diffusion models. Building on those studies, we combine diffusion of innovation theory and theory of planned behavior to demonstrate the development of a toolkit for simulating the diffusion of a new grocery shopping option.

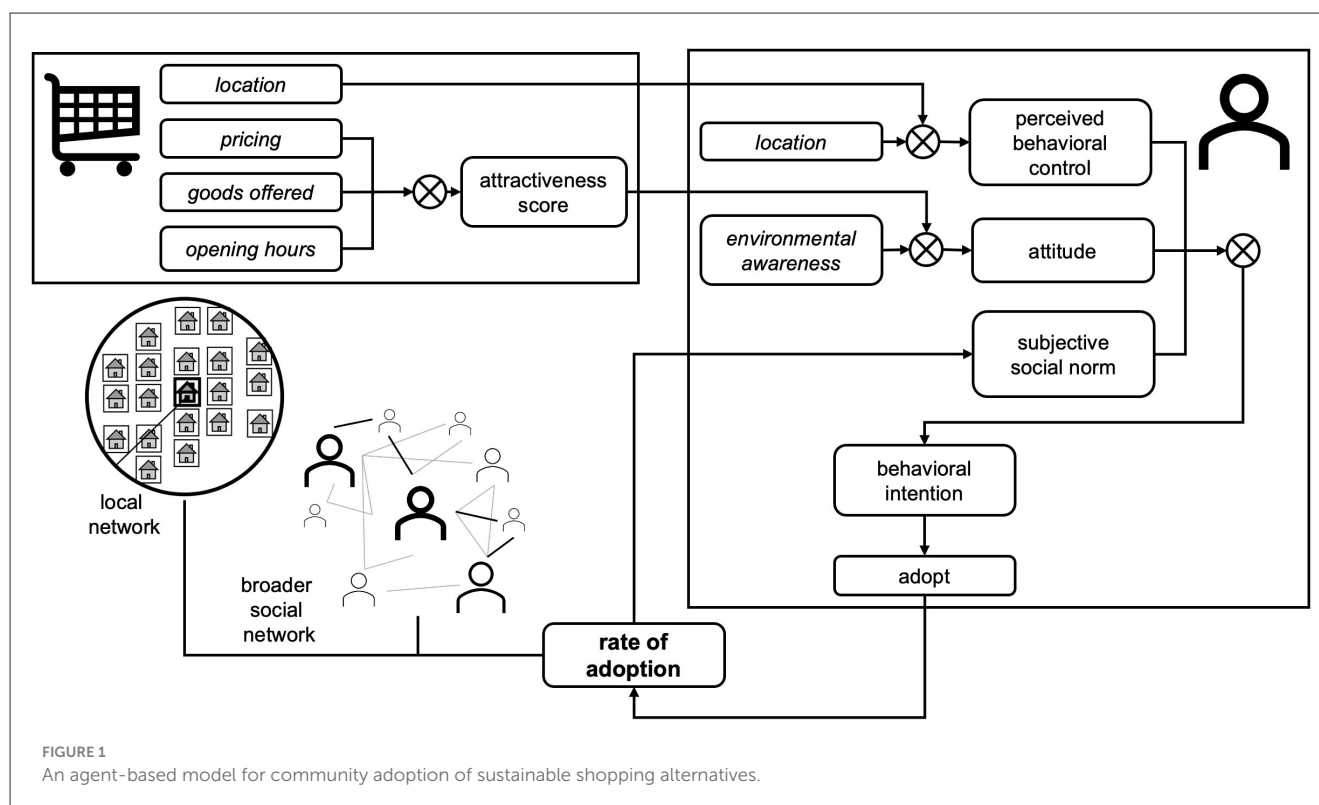
Integrating theory of planned behavior within an agent architecture requires nuanced considerations, as agents must reflect their circumstances and aspirations. One of the wide-spread approaches to tackle this is to implement the belief-desire-intention model (Bratman, 1987). A belief-desire-intention agent is a model for autonomous, intelligent software agents that is based on the mental states Beliefs, Desires and Intentions. These states represent an agent’s knowledge of the world, its goals and the actions planned to achieve these goals (Bratman, 1987). Theory of planned behavior and belief-desire-intention framework are similar enough in approach and scope that they can be combined within an agent-based model (cf. Andrews et al., 2011). Intentions in a belief-desire-intention model are derived from beliefs and desires by means of a deliberation process. Theory of planned behavior can be used to adapt the deliberation process to the requirements of the application area by selecting the necessary internal and external factors for decision-making (Rodermund et al., 2024). The fusion of theory of planned behavior and belief-desire-intention framework in agent-based modeling has been explored in various contexts to enhance prediction in human behavior modeling. For instance, Andrews et al. (2011) propose an agent-based framework for simulating the behavior of building occupants to improve the usability of design, especially for innovative buildings. Setiawan et al. (2020) integrate the theory of planned behavior with norm activation theory to create a more comprehensive model for predicting pro-environmental behavior, especially in waste segregation. Robbins and Wallace (2007) propose a multi-agent decision support system to support ethical problem solving that incorporates normative theories as criteria. It is important to note that the concept of intentions differs between psychological and sociological theories and the belief-desire-intention model (see Kurchyna et al. (2022)). In theory of planned behavior, intentions represent an agents desires—what the agent wants to

do—whereas in the belief-desire-intention model, intentions refer to the agents planning and actions—what the agent actually does. This distinction must be accounted for when integrating theory of planned behavior into belief-desire-intention framework, as the planning step inherent in belief-desire-intention framework is not explicitly addressed in the original formulation of theory of planned behavior.

Studies highlight agent-based modeling’s ability to incorporate social structures into simulations (Pakravan and MacCarty, 2021; Anebagilu et al., 2021; Pakpour et al., 2014; Tong et al., 2018; Rai and Robinson, 2015; Zsifkovits, 2015; Meles and Ryan, 2022). These social structures enable the modeling of how social influence can shape the adoption of new behaviors, particularly in the context of innovation diffusion. Yet, a key consideration lies in determining how exactly these networks should be constructed. One effective approach is the use of the Preferential Attachment Model (Barabási and Albert, 1999; Albert et al., 2000), which provides a framework for analyzing how connections within a community evolve, highlighting the disproportionate influence of highly connected individuals in driving the diffusion of behaviors. Preferential attachment model shows that social ties often cluster within similar groups, with highly connected individuals more likely to gain additional ties, amplifying their influence (Topirceanu et al., 2018). Specifically in context of agent-based modeling, preferential attachment model was for instance utilized by Ringa (2009) to examine how social influence affects the adoption of organic food consumption. Their findings support the hypothesis that social influence plays a significant role in shaping consumer behaviors, which can be extrapolated to other areas such as sustainable shopping practices. Moreover, preferential attachment model is instrumental in modeling the diffusion of information, as demonstrated by Pandey et al. (2015), enhancing our understanding of how behaviors spread through social networks.

Agent-based modeling has proven to be a powerful tool for modeling the adoption of sustainable practices, particularly when enriched with theoretical frameworks like diffusion of innovation theory, theory of planned behavior, belief-desire-intention framework, and preferential attachment model. These frameworks enable the exploration of both individual and social dimensions of adoption, providing a comprehensive understanding of community-level dynamics. By capturing the interplay between spatial, social, and psychological factors, agent-based modeling offers valuable insights for designing effective interventions. For environment, avoiding the time and resource constraints of testing in a real-world environment. The simulation allows us to abstract the scenario, focusing on specific factors, such as the aspects of social interaction and influence, without the complexities of a real population. By applying the above described theories and frameworks, we can model various influences on the adoption rate of an innovation - specifically, a new, environmentally friendly grocery shopping option in a rural area. The integration of multiple theories brings the model closer to reflecting the complexity of the real-world.

The following section builds on these insights, presenting a conceptual model that integrated diffusion of innovation theory, theory of planned behavior, belief-desire-intention framework and preferential attachment model. This model is tailored to simulate



the adoption of sustainable shopping practice within a rural community, laying the groundwork for experimentation.

2.2 Theoretical framework for an agent-based model of green choices

Our study integrates diffusion of innovation theory, theory of planned behavior, and preferential attachment model to offer an approach to modeling community adoption. This method facilitates a multidimensional analysis of the adoption process, encompassing the diffusion of innovation, individual decision-making intricacies, and social network dynamics. Specifically, our simulation employs diffusion of innovation theory to get informed about the variables that influence the adoption rate (Rogers et al., 2014). Thereby the model focuses on attributes like 24/7 accessibility of the container store and how these characteristics interact with the community's social system, including prevalent environmental attitudes and social norms (Section 2.1.1). Theory of planned behavior is utilized to delve deeper into individual decision-making by examining attitudes, perceived social norms, and perceived behavioral control (Ajzen, 1991), complementing diffusion of innovation theory by shedding light on the personal and societal pressures that can influence adoption rates (Section 2.1.2). Furthermore, preferential attachment model is integrated to examine the community's social network dynamics, highlighting the role of social ties and the potential of prominent community members to accelerate the diffusion of sustainable shopping practices (see Section 2.1.3).

The proposed conceptual framework seeks to analyze the adoption mechanisms of sustainable shopping alternatives, such as container stores, within rural communities. To illustrate these dynamics, Figure 1 presents a conceptual agent-based model developed for this purpose. The model consists of three main components: non-human agents (on the left), agents representing humans (on the right), and the environment, which encompasses the network connecting human agents and serves as the context in which both agent types operate.

Non-human agents in the model represent container stores and supermarkets and are defined by their attributes, including $location(x, y)$, where $x, y \in \mathbb{R}$, $pricing \in [0, 1]$, $goods_offered \in [0, 1]$, and $opening_hours \in [0, 1]$. These are also the innovation attributes under diffusion of innovation theory's concepts, influencing the adoption rate (see Section 2.1.1).

These attributes contribute to an overall *attractiveness_score* of a non-human agent j , which plays a pivotal role in shaping human agents' attitudes toward adoption. The components of the attractiveness score: pricing and goods offered reflect widely recognized store selection factors identified in empirical studies (Zulqarnain et al., 2015), while opening hours are specific to our use case. To simplify our conceptual model, we assume that the attractiveness score is influenced by the factors to the same extent. Hence, this score is the arithmetic mean of the three values, representing the non-human agent's perceived advantages (Equation 1).

$$attractiveness_score_j = \frac{pricing_j + goods_offered_j + opening_hours_j}{3} \quad (1)$$

Human agents (set *Human_Agents*) represent community members, each characterized by their *location* and *environmental_awareness* $\in [0, 1]$. These agents make decisions based on the principles of the theory of planned behavior (see Section 2.1.2). Specifically, a human agent *i*'s *attitude* $\in [0, 1]$ toward a non-human agent *j* is influenced by both agent *i*'s level of environmental awareness and the objective attractiveness score of the store *j* (see Equation 2). If agent *i* has not yet visited the container store, the attractiveness score is neglected, which means that environmental awareness is the decisive factor in this decision (see Equation 3).

$$\text{attitude}_{i,j} = \text{environmental_awareness}_i + \text{visited}_{i,j} \cdot \text{attractiveness_score}_j / 1 + \text{visited}_{i,j} \quad (2)$$

where

$$\text{visited}_{ij} = \begin{cases} 1, & \text{if agent } i \text{ has visited store } j, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

Perceived_behavioral_control, another critical factor, is calculated based on the Euclidean distance between human agent *i* and container store *j*, representing the perceived feasibility of the shopping behavior (see Equation 4).

$$\text{perceived_behavioral_control}_{i,j} = \text{dist}(\text{location}_i, \text{location}_j) \quad (4)$$

Finally, subjective social norms, as theorized by Ajzen (1991), are determined by the strength of normative beliefs and weighted by the motivation to comply with the norms. For an agent *i*, these norms are shaped by interactions with agents in its social network ($\text{Network}_i \subseteq \text{Human_Agents}$ for an agent *i*). The influence of peers who have already adopted the use of a container store is captured quantitatively by Equation 5. This formulation conceptualizes social norms as the aggregated influence of an agent's network, where the adoption behaviors of connected peers create a perceived pressure to conform. The model includes two types of social networks to account for varying levels of influence: (1) a local network, representing immediate social connections within a defined geographical radius, and (2) a broader social network, constructed using preferential attachment model, capturing wider, potentially more influential ties beyond the local sphere. These networks enable the dynamic propagation of social norms, illustrating how both localized and broader social influences collectively shape individual decision-making processes.

$$\text{social_norm}_i = \frac{1}{|\text{Network}_i|} \cdot \sum_{k=1}^{|\text{Network}_i|} \text{adopt}_k \quad (5)$$

To effectively implement the complex decision-making processes of human agents, determined by the relevant factors of the theory of planned behavior, in an agent-based model, it is essential to provide a framework for deliberation on objectives. This is achieved through the belief-desire-intention architecture, which defines the mental states necessary for decision-making:

beliefs *B*, desires *D* and intentions *I*. The set of beliefs encompasses everything the agent knows is true about itself and its environment: $B_i = \{\text{attractiveness_score}_i, \text{location}_i, \text{environmental_awareness}_i, \text{perceived_behavioral_control}_i, \text{attitude}_i\}$.

Based on its beliefs, the agent determines its desire. In our model, the agent has one desire, its behavioral intention, representing the willingness to use the nearest container store instead of the supermarket: ($D_i = \{\text{behavioral_intention}_i\}$). As mentioned in Section 2.1.3, behavioral intention in the context of theory of planned behavior reflects what the person desires to do. In contrast, in the belief-desire-intention framework, an intention refers to what an agent plans to do to fulfill this desire—a plan that may involve one or more actions. When integrating theory of planned behavior into belief-desire-intention framework, we represent behavioral intention as the agent's desire in the sense of belief-desire-intention framework. This desire encapsulates a trade-off between egoistic concerns, such as convenience (e.g., proximity to the nearest shopping option, opening hours), and the agent's conscience regarding environmentally conscious behavior (e.g., environmental awareness). Our model adopts a simplified version of the belief-desire-intention framework, where the agent has only one desire in the belief-desire-intention sense—its behavioral intention. Unlike typical belief-desire-intention framework implementations that often involve conflicting desires requiring resolution, our model assumes no conflicting desires. The *behavioral_intention* of agent *i* is calculated based on the three factors: attitude (which includes environmental awareness and the attractiveness of the respective store), perceived behavioral control (which refers to the proximity to the store), and social norms (which reflects the perceived social pressure from its environment) (see Equation 6).

$$\text{behavioral_intention}_{i,j} = \text{attitude}_i + \text{perceived_behavioral_control}_{i,j} + \text{social_norm}_i / 3 \quad (6)$$

Finally, the agent updates its intention based on its beliefs and desires. The intention determines whether the agent adopts the behavior and chooses to use the container store ($I = \{\text{adopt}\}$). Following Jensen et al. (2016), adoption occurs when the behavioral intention exceeds a specified *threshold* $\in [0, 1]$ for agent *i*. This threshold defines alternate behaviors, e.g., the preference to use the container store compared to other shopping options as well as a potential delay caused, for example, by the cost of behavior change (see Equation 7) (see Jensen et al., 2016). An adopt value of 1 means that the agent adopts container use as a behavior, while 0 means that the default behavior such as visiting the supermarket is continued.

$$\text{adopt}_i = \begin{cases} 1, & \text{if } \text{behavioral_intention}_i \geq \text{threshold} \\ 0, & \text{else} \end{cases} \quad (7)$$

The *adoption_rate* represents the cumulative proportion of agents within the simulated community who have adopted this behavior. This decision-making process is captured in the models flow, where agents iteratively evaluate their intention to adopt based on changes in store attributes, their social environment,

and spatial proximity (see Equation 8). This conceptualization is somewhat similar to the product adoption model developed by Bass (1969), who modeled the diffusion of innovation as a process driven by two key mechanisms: innovation, where adoption occurs independently of others, and imitation, where adoption is influenced by interactions within the social environment. Equation 8 operationalizes this concept in the context of a simulated community by aggregating the individual adoption states of agents.

$$\text{adoption_rate} = \frac{1}{|\text{Human_Agents}|} \cdot \sum_{i=1}^{|\text{Human_Agents}|} \text{adopt}_i \quad (8)$$

The proposed agent-based model design simulates how individual behaviors aggregate to produce community-level adoption patterns. By integrating diffusion of innovation theory's emphasis on innovation characteristics, theory of planned behaviors framework for individual decision-making, and preferential attachment models simulation of social network dynamics, the model provides an understanding of how sustainable innovations diffuse within rural settings. It highlights how spatial proximity, product attributes, and social interactions collectively drive the adoption of container stores, which can potentially offer insights for designing effective interventions aimed at promoting sustainable consumer behavior. We emphasize that the model equations are not empirically calibrated but serve as theoretically grounded simplifications. All equations, particularly those using additive and equally weighted components, are *ad hoc* choices made for conceptual clarity. These imply behavioral assumptions, such as substitutability between decision factors, that may not hold empirically. While such simplifications are common in early-stage modeling (Axelrod, 1997), they should be treated with caution (Edmonds and Moss, 2004). To support transparency and reproducibility, we document all modeling decisions in detail using the ODD protocol in the Appendix.

3 Results

3.1 Simulation experiments and experiment design

The simulation aims to demonstrate the practical applicability of the developed toolkit in researching community adoption dynamics. It seeks to provide actionable insights into how different factors, such as location, network structure, and agent attributes, influence adoption behavior. The scenarios are designed to illustrate the toolkit's capability to model complex social processes and identify strategies for fostering sustainable consumer practices. The experiments focus on three main aspects of container store adoption: the role of store attributes, the impact of geographic placement, and the influence of initial adopter groups. By tracking key metrics like adoption rates and behavioral shifts, the experiments offer a comprehensive view of how individual and community-level factors interplay in shaping collective behavior. Each experiment is carefully structured to isolate and analyze the effects of specific variables, highlighting the potential

of this simulation approach to support data-driven decision-making.

The simulation explores community adoption dynamics. It operates through an iterative process comprising several key stages. *Initialization* sets the models foundation by assigning initial attributes to agents and establishing local and social network connections. Non-human agents (container stores and supermarkets) are spatially positioned within a simulated rural setting in Rhineland-Palatinate, Germany. This setting encompasses a simulated population of 610 individuals spread across three small villages: Buhlenberg with 426 inhabitants, Ellenberg with 71 inhabitants, and Gollenberg with 113 inhabitants, all located near the small town of Birkenfeld.³ Due to the lack of shopping facilities, residents typically travel to the nearest supermarket in Birkenfeld for groceries. The proximity of each village to Birkenfeld influences this dynamic; Ellenberg is the closest, while Buhlenberg and Gollenberg are slightly further, affecting residents' accessibility to shopping at the Birkenfeld supermarket.⁴ The entire simulation is crafted in Python using the Mesa framework. Local network connections are confined to a 75-meter radius, while the broader social network is generated using the preferential attachment model network generator from the NetworkX Python library. The simulation employs a time abstraction where each step corresponds to a single decision iteration.

During the *interaction* phase, human agents dynamically update their behavioral intentions based on evolving store attributes, spatial proximity, and social norms. In each step of the adoption decision stage, agents compare their behavioral intention against a predefined threshold to determine whether to adopt the shopping behavior at the local container store. This feeds into a feedback loop, where adoption decisions influence social norms, altering the behavior of connected agents in subsequent iterations. Finally, the *data collection* phase tracks critical metrics, such as adoption rates, spatial patterns of shopping behavior, and the impact of social norms, providing insights for analysis.

3.1.1 Analyzing container store adoption: experiments on attributes, location, and initial adopter group impact

In order to investigate the effect of the container's attributes, the agents' networks as well as location-specific aspects, in the following sections we present three experiments. Each experiment tracks the key metric *adoption rate* for the whole population and for individual municipalities (Gemeinden).

Experiment 1: Impact of containers' attractiveness score on community adoption dynamics. This experiment examines how the *attractiveness score* of container stores influences community adoption dynamics. We test four different scenarios regarding the containers' *attractiveness score*:

3 These numbers result from a synthetic population generated using the German census data from 2011: <https://www.zensus2011.de>.

4 To determine location and size of the communities we make use of data from OpenStreetMap: <https://www.openstreetmap.org>.

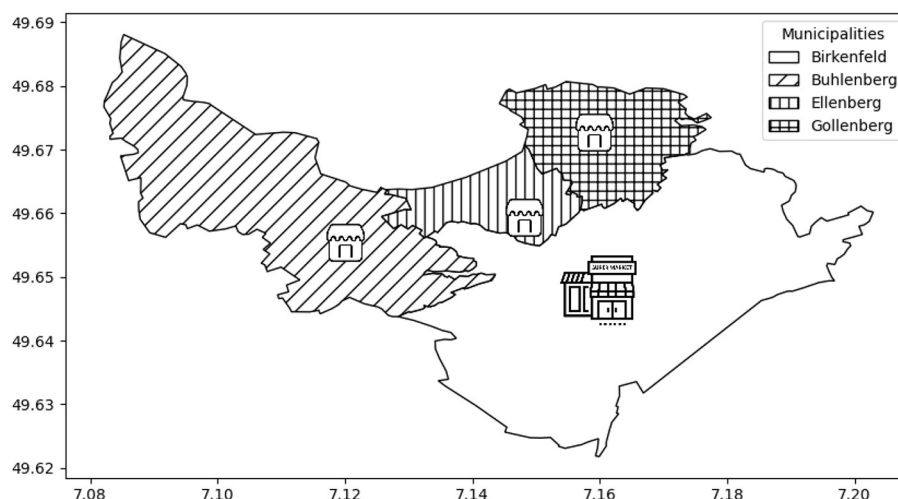


FIGURE 2
Simulated rural region in Rhineland Palatinate, Germany.

1. **Very high attractiveness score** due to only optimal properties (pricing, goods offered, opening hours).
2. **High attractiveness score** due to two optimal and one suboptimal property.
3. **Low attractiveness score** due to one optimal and two suboptimal properties.
4. **Very low attractiveness score** due to only suboptimal properties.

Depending on the specific scenario and respective *attractiveness score*, the option of using the container becomes more or less attractive compared to the supermarket. This experiment operates under the hypothesis that higher *attractiveness scores* for container stores will lead to increased *adoption rates* and faster transition toward the new shopping practice. The goal is to analyze how shifts in *attractiveness scores* influence agents *attitudes*, and ultimately their *behavioral intentions*. This experiment highlights the critical role of objective attributes in driving community adoption and provides insights into optimizing container store attributes to encourage sustainable consumer behavior.

Experiment 2: Impact of containers' location on community adoption dynamics. This experiment examines the influence of container store placement on community adoption dynamics within three distinct geographic communities; it is structured around two strategic placement approaches:

1. **Uniform distribution:** One container store is placed in each of the three geographic communities, ensuring equitable access across all regions.
2. **Single location access:** A single container store is placed in one of the three geographic communities for each experiment run, creating varied access levels across the communities.

This setup aims to understand how container store *accessibility* affects community adoption rates and explores the broader implications of store placement strategies on local shopping behaviors. Regarding theory of planned behavior,

the effects of *perceived behavioral control* and the *social norm* are particularly taken into account in this experiment. **Figure 2** illustrates the simulated region with the uniform container distribution strategy. This leads to a container in each simulated municipalities population centroid and a supermarket in Birkenfeld.

Experiment 3: Impact of initial adopter groups on community adoption dynamics. This experiment examines how the *adoption rate* of the container store evolves based on the initial 16% of adopters, which represent the first two groups of the diffusion of innovation theory: *innovators* (2.5%) and *early adopters* (13.5%) (Rogers et al., 2014). Selecting a sufficient amount of *initial adopters* creates an initial momentum in the communities which allows easier adoption for the majority groups. We explore the following three group selection strategies:

1. **Random selection:** 16% of agents are chosen randomly, serving as a baseline.
2. **Environmentally-conscious group:** The top 16% of agents with the highest environmental awareness are selected to test the impact of pro-environmental attitudes.
3. **Socially-connected group:** The most highly-connected 16% of agents are targeted, leveraging their network influence.

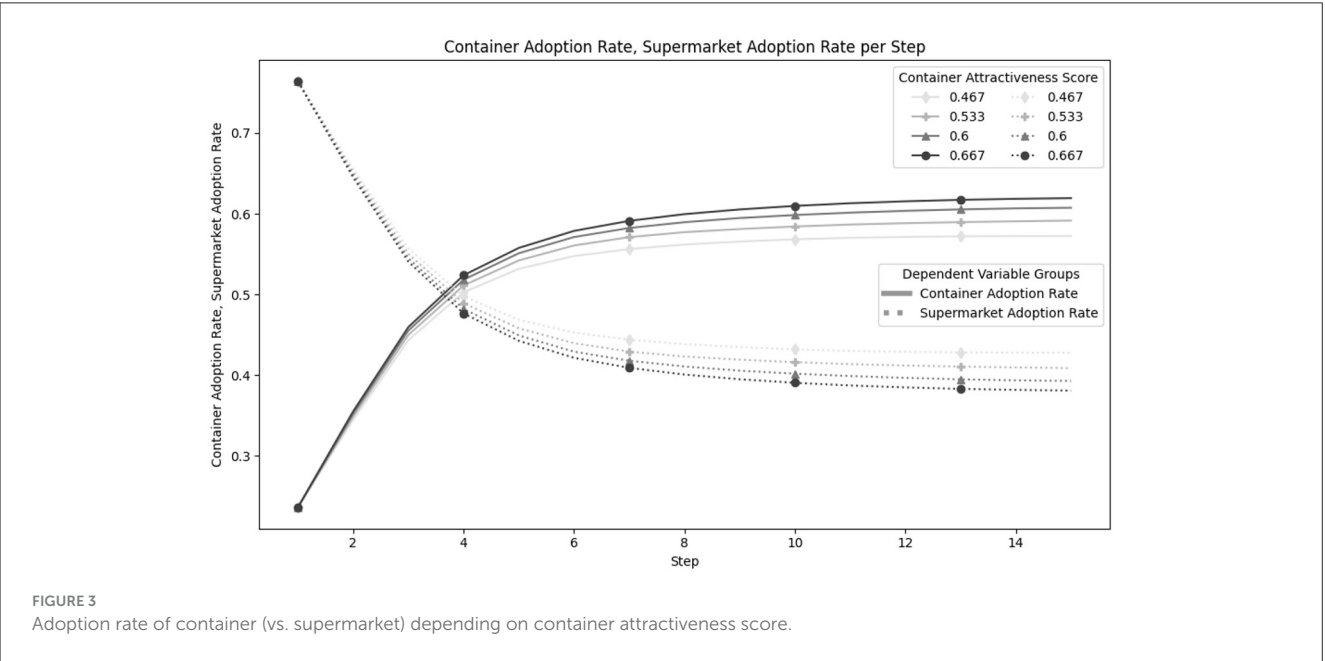
This experiment is designed to show the relevance of targeted *early adoption* strategies in accelerating sustainable behavior diffusion. By comparing the *adoption rates*, it can highlight the varying roles that *social network* configurations and individual *behavioral drivers* play in the diffusion process.

3.1.2 Experiment design

To investigate the above described experiments, this study is conducted using a full factorial design with the independent variable levels listed in **Table 1**. We compare up to four levels of input factors that refer to either human agents or non-human

TABLE 1 Independent variable levels for simulation experiment.

Entities	Attributes	Levels			
		Level 1	Level 2	Level 3	Level 4
Agent (human agent)	Environmental awareness	Normal	Right-skewed	Left-skewed	
	Initial user group	Random	Most-connected	Highest EA	
Container (non-human agent)	Goods offered	0.4	0.6		
	Pricing of goods	0.4	0.6		
	Opening hours	0.6	0.8		
	Location	Buhlenberg	Gollenberg	Ellenberg	All three
Supermarket (non-human agent)	Goods offered	0.6	0.8		
	Pricing of goods	0.6	0.8		
	Opening hours	0.4	0.6		
	Location	Birkenfeld			



agents (containers and supermarkets). The resulting experiment design comprises $3^2 \times 2^6 \times 4 \times 1 = 2,304$ unique experiments each running for 10 iterations (replications) with a varying seed leading to 23,040 simulation runs in total.

The key observed metric is the *adoption rate* of the container. This variable and those that correlate strongly with it, such as the *social norm*, are the best indicators for the success of an innovation. The *adoption rate* thus serves as a proxy for the environmental benefit the innovation provides.

3.2 Experiment results

The following subsections present the outcomes of our simulations, which, despite the model's simplicity, reveal underlying trends and tendencies in community adoption

dynamics. Further subsections detail the specific experiments conducted and the implications of their findings.

3.2.1 Impact of containers' and supermarket's attractiveness score on community adoption dynamics

Figure 3 illustrates the adoption rate of container stores over the course of the simulation, with the attractiveness score of the container store as the independent variable. The adoption rate of container stores is shown with solid lines, while supermarket usage is represented by dotted lines. The varying shades correspond to different attractiveness scores: the darker shades indicate higher attractiveness scores, highlighting how increased attractiveness influences the preference for container stores over supermarkets.

One can see the increase in the usage of the container store throughout the time for all levels of attractiveness score from

0.467 to 0.667. Symbols along the lines clarify these values of attractiveness score: a diamond stands for the lowest value of score, a plus sign (0.533) and a triangle (0.6) mark intermediate values, and a circle (0.667) indicates the highest value. The curves show an inverse relationship: when the use of containers increases, the use of supermarkets decreases by the same amount. The increase at the beginning is relatively strong: the adoption rate of a container rises in 15 steps from just over 0.2 to around 0.6, while supermarket usage falls from below 0.8 to around 0.4. Overall, the attractiveness score has a consistent, although not particularly strong, influence on the choice of shopping alternatives.

3.2.2 Impact of containers' location on community adoption dynamics

The results of the second experiment, examining the impact of container stores' spatial distribution on adoption dynamics within communities, are presented in [Figure 4](#). This figure displays four histogram clusters: Uniform Distribution for *Buhlenberg*, *Gollenberg*, *Ellenberg* on the left and Single Location Access for each *Buhlenberg*, *Ellenberg*, and *Gollenberg* municipalities. The histograms represent the average container adoption rate and standard deviation at the final simulation step across all runs. The order of bars on the comparative histogram corresponds to the geographic positioning of the communities on the map: *Ellenberg* is placed in the center, with *Buhlenberg* to the west and *Gollenberg* to the east, maintaining the same relative order as their locations on the map.

In the first histogram scenario, where each municipality is equally served by centrally located containers, adoption rates are consistently high across *Buhlenberg*, *Gollenberg*, and *Ellenberg*, suggesting that proximity strongly favors container use. This aligns with the expectation that easier access to a nearby container store significantly reduces the likelihood of residents opting for more distant supermarkets.

In specific scenarios like the one represented in the second histogram where the container is only located in *Buhlenberg*, a marked increase in container store utilization is observed within *Buhlenberg*, with usage values peaking around 0.8. Conversely, *Gollenberg* and *Ellenberg*, lacking a local container, show much lower adoption rates, around 0.2. This pattern repeats in the fourth histogram where the container is placed in *Gollenberg*, resulting in the highest container usage there. However, *Gollenberg*'s smaller size means its residents' social networks likely extend beyond local boundaries. This introduces a social norm bias against adopting the *Gollenberg* container, as non-resident influences dominate.

Ellenberg presents a distinct case; even with container presence, the proximity to *Birkenfeld*'s supermarket affects residents' choices, leading to a balanced usage between the container and the supermarket. This phenomenon is due to the supermarket's competitive attractiveness, such as better pricing and a broader range of goods, which can deter residents from switching exclusively to the container store. As a result, while the container's location still attracts residents from neighboring municipalities (*Buhlenberg* 0.45, *Gollenberg* 0.4), the adoption rates in *Ellenberg* itself do not reach full potential due to some residents' decisions to stick with the supermarket option.

The results indicate that while container usage can approach full saturation, particularly in scenarios with highly accessible containers as seen in the first pair of histograms, there is never a complete transition away from supermarket usage. This persistence of supermarket use in *Ellenberg* can be attributed to its proximity to a supermarket and the influences of perceived behavioral control, which encompasses factors like convenience and ease of access. Additionally, individual attitudes and social norms play crucial roles in shaping decisions. For example, if an individual in *Ellenberg* possesses low environmental awareness and is less influenced by social opinions, they are more inclined to continue using the supermarket, despite the nearby container's availability.

The results highlight that proximity to the nearest container store influences agent decision-making. As distance decreases, perceived behavioral control increases, strengthening the intention to use the container. As defined in Section 2.2, social norms, shaped by both local and broader social networks, also play a crucial role. Agents within similar local network distances experience enhanced perceived behavioral control effects, making them more likely to opt for the environmentally friendly choice of using the nearby container, thereby reinforcing their behavioral intentions.

3.2.3 Impact of initial adopter groups on community adoption dynamics

The third experiment refers to the effect of different selections of first adopters on the adoption rate in the model. To investigate the effect of specifically chosen initial users, three initial user groups are distinguished, namely agents with the highest environmental awareness (depicted with a diamond sign in the line), agents that have the most connections to other agents in the model (plus sign in line) and randomly chosen agents. The graph in [Figure 5](#) thus shows the development of container usage throughout the simulation steps. The line with diamonds represents the adoption rate when the initial user group consists of individuals with the highest environmental awareness. In contrast, the line with plus signs depicts the adoption rate when the most connected agents form the initial user group, while the line with triangles illustrates the adoption rate when the initial users are selected at random.

As shown, all three lines have a somewhat similar progression, starting at a smaller value, shortly progressing in a concave manner during the first two steps and continuing with a more convex course thereafter.

The highest value from start to end of the simulation is shown in the scenario with the most connected users as the initial group, with a starting value of almost 0.4 and an end value of 0.7. The adoption rate starts with a relatively high value and continues to grow over time due to the influence of many connections. The initial user group has a strong influence on the behavior of the connected users, creating a cascading effect. This dynamic is further reinforced when more agents within the same network use the container, which increases the overall adoption rate until step 15. This scenario shows the effect of the social norm, which has the greatest effect when the initial user group can influence as many other agents as possible.

The line referring to a random initial user group starts with a value close to 0 and a final value of almost 0.5 after 15 steps.

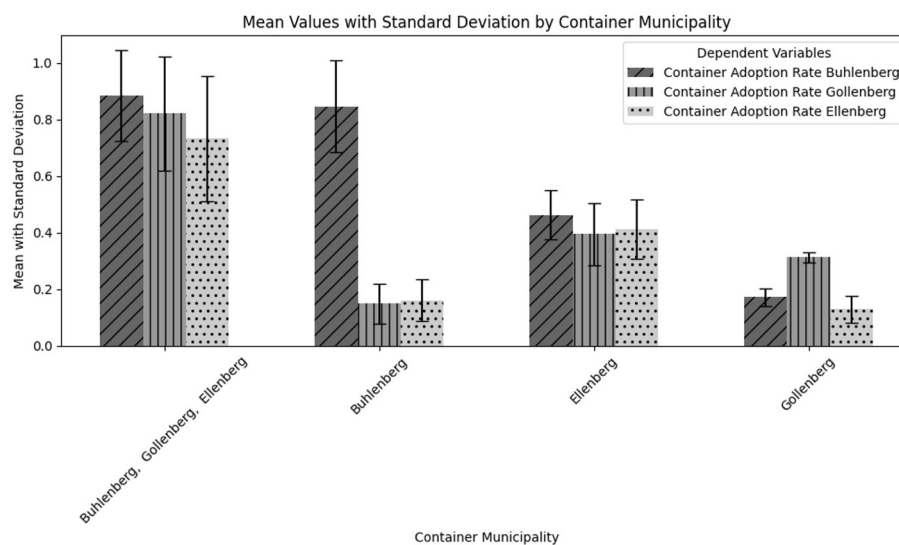


FIGURE 4
Container adoption in the communities.

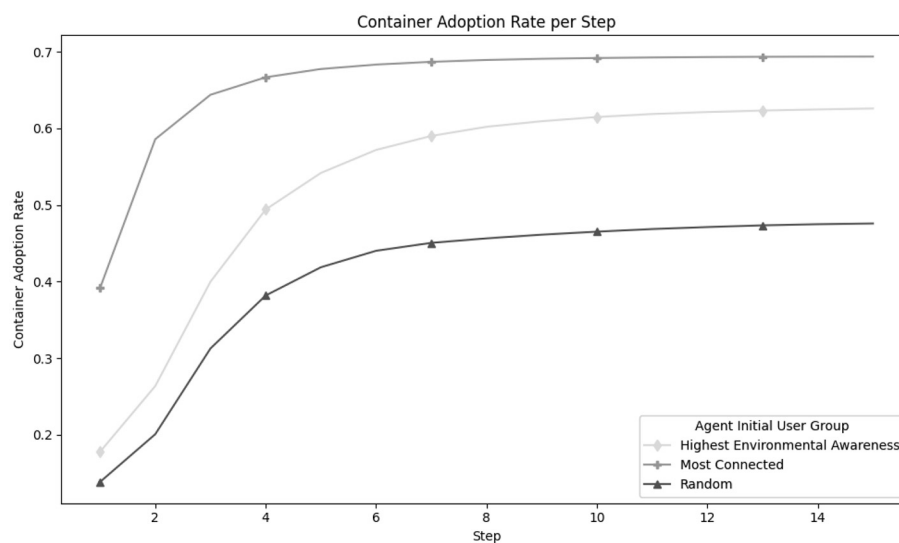


FIGURE 5
Adoption rate depending on initial user group.

Over time, more users adopt the use of the container than those in the most connected scenario. Early adopters in this scenario may have less objective reasons for using the container (based on the decision function) and often drop the usage quickly, resulting in a low initial adoption rate. Over time, individuals motivated by factors such as local proximity (perceived behavioral control), social environment (social norm) or their own environmental awareness (attitude) begin to adopt the behavior, leading to a relatively strong increase in usage of almost 0.5.

The middle line represents the adoption rate when the agents with the highest environmental awareness are selected first. The

initial value is relatively low (ca. 0.18). Agents that have a sufficient environmental awareness (attitude) and whose proximity to the container store (perceived behavioral control) is small enough keep adopting the container store as their shopping choice. Therefore, the starting value is still higher than that of the randomly chosen agents. However, if the next container store has a higher distance, agents might not adopt this option or drop it right away. Over time, more agents are added that have such a high level of environmental awareness that they would use the container regardless, further stabilizing and maintaining the adoption rate.

4 Discussion

The German context, with its historical attachment to the concept of Tante-Emma-Läden and the emergence of innovative business models like cashier-less supermarkets (Rampe, 2024), provides a unique backdrop for simulating the implementation of container stores. Designing such simulations requires careful consideration of context-specific factors. With our model, we aimed to demonstrate the development of a toolkit for decision support, focusing on analyzing the dynamics of community adoption of container stores. As a proof of concept, we illustrated how theoretical approaches such as diffusion of innovation theory, theory of planned behavior, and preferential attachment model can be practically integrated into an agent-based model. The results highlight the model's potential to capture the influence of store attributes, location accessibility, and community network structures on sustainable consumer behaviors across varying scenarios in a simulated environment. Our findings align with research such as that by Pakravan and MacCarty (2021), who suggest that higher adoption rates can be achieved through a combination of durable technologies, targeted information campaigns, and the empowerment of key social groups, indicating potential for tailored interventions in community activation.

While our results demonstrate clear relationships between variables and their influence on adoption rates within the model, the findings currently lack grounding in empirical reality. Integrating real-world data would enhance the model's ability to account for the unique characteristics of different social groups. At this stage, validation against real-world observations is necessary to accurately interpret the results and evaluate their robustness and resilience to real-life influences. Nevertheless, based on prior studies that have employed combinations of theories and frameworks similar to our approach, we anticipate that cross-validation with real-world data will support and reinforce the findings generated by the model.

While the model provides a starting point, it is by no means exhaustive and offers room for enhancements to capture the nuanced interplay of behavioral, environmental, and social factors. One area for improvement is the *representation of networks*. Currently, broader social networks are implemented as random structures, but future iterations should incorporate a more elaborated local network design, that reflects the actual social structures of the region in question. The local network, which we see as a separate entity of analysis can be further refined by adopting a structure similar to the preferential attachment model but maintaining strong geographic focus. This would allow for the inclusion of neighborhood effects, especially if sociological research or empirical data suggests that such effects play a significant role in the specific region being modeled. By integrating these enhancements, the model can offer a more nuanced and contextually informed understanding of how local and broader social networks influence community adoption dynamics.

On the continuum between “KISS” (Axelrod, 1997) and “KIDS” (Edmonds and Moss, 2004), our approach leans toward the “KIDS” side, as the model emphasizes integrating descriptive richness through theoretical frameworks such as the diffusion

of innovation theory and theory of planned behavior, aiming to capture the complexity of real-world adoption processes before introducing simplifications. Nonetheless, some aspects of the formal implementation, particularly the use of additive and equally weighted structures, reflect simplifying assumptions introduced for tractability rather than empirical accuracy, which may not reflect actual decision-making behavior. Since the structure of decision-making equations strongly influences simulation outcomes, future work should aim for empirical calibration. Furthermore, there is still potential to enhance the models complexity by incorporating additional theories and grounding it further in real-world data. Particularly relevant are theories that have been explored in the context of agent-based modeling for sustainability. For example, incorporating *social identity approach* (Reicher et al., 2010; Scholz et al., 2023), can provide a richer understanding of group dynamics by emphasizing how individuals' identification with social groups influences their behaviors. This addition would allow for a deeper understanding of how social groups and their norms interact with other drivers of adoption, enhancing the realism and explanatory power of our Agent based model.

In addition, to improve the model, future developments could incorporate more complex decision making, e.g., deciding when to use the container instead of the supermarket. Advantages of the container compared to a supermarket are, for example, the 24/7 opening hours, whereas the offered goods are more favorable in a supermarket. This could lead to both containers and supermarkets being used. If the reduction of CO₂ emissions is considered a priority, this could make sense in some cases, e.g., if someone passes a supermarket on a route he is already taking. In order to achieve this, an integration of realistic daily routines for agents, workplaces and leisure activities with route planning would be useful. Furthermore, an additional assessment of the environmental impact of container use, e.g., CO₂ emissions of different transportation options, would provide deeper insights and allow for an evaluation of trips, e.g., between two communities, where there is a necessity to use private vehicles for transport. This could enable better planning of targeted interventions to adapt behavior.

Conceptualizing supermarkets and container stores as agents with their own properties, opens further realms of conceptualization: exploration of how non-human agents interact with one another and with human agents. The model thus lays the groundwork for an approach to studying human-object interactions (Giaccardi et al., 2016; Harvey et al., 2019), inspired by ethnology and anthropology. This perspective can further enhance the model's ability to simulate complex, real-world scenarios. Extending the model to a larger area with real points of interests such as shopping centers, workplaces and leisure activities would further increase realism.

Data availability statement

The full dataset presented in this article is not readily available due to restrictions, however, model transparency is ensured by sharing the ODD protocol. Requests for more information should be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the patients/ participants or patients/participants' legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

AK: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. YB: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. PF: Conceptualization, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. SF: Conceptualization, Methodology, Supervision, Visualization, Project administration, Writing – original draft, Writing – review & editing. MG: Software, Writing – review & editing. AJ: Writing – original draft, Writing – review & editing. JB: Conceptualization, Supervision, Funding acquisition, Writing – review & editing. IT: Conceptualization, Supervision, Funding acquisition, Writing – review & editing.

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Supplementary material

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