Improving access to retail from a consumer and business perspective.
A model-driven exploration of alternative retail distribution concepts.

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Part 1

Preface

Dedication

I dedicate this thesis to my wife, Anne-Luise,

whose unwavering support and affection give me the strength to live up to my dreams.

Florian Cramer

Acknowledgements

I would like to express my sincere gratitude to Prof. Dr. Christian Fikar for his outstanding support and encouragement as my supervisor. I am also deeply thankful to Prof. Dr. Hanno Friedrich, Prof. Dr. Gerald Reiner, and Prof. Dr. Sandra Transchel for their invaluable guidance throughout my doctoral studies.

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Abstract

The access to goods and markets is of vital importance for consumers and manufacturers alike. Particularly, access to food plays an important role in societal welfare. Yet, traditional brick-and-mortar retail stores have a limited capability to facilitate access due to space and location restrictions. While in recent years a number of alternative distribution channels have emerged, further research is required to understand when, how, and if these channels should be used. This dissertation explores this gap by examining emerging distribution channels that address issues related to the lack of access from a consumer perspective and the perspective of micro, small, and medium enterprises (MSME). In particular, the dissertation focuses on the exploration of two emerging retail distribution concepts: crowd logistics (CL) and mobile retail. This work contributes to academic literature in these areas by exploring them in the context of product diffusion and market access. In addition, the work highlights the need for a holistic perspective when considering emerging distribution concepts through the portrayal of underlying complexities and dynamics using CL as an example. To this end, the dissertation presents three scientific articles, two focusing on CL and one on mobile retail. Using agent-based and discrete-event simulation as well as machine learning, model-driven decision support systems (DSS) are developed and used to conduct scenario analyses. In addition, a novel methodological framework (the 'scoping systems thinking review') for the analysis and exposition of system elements and connections is developed. The analysis of the different scenarios indicates that the geospatial setting is an important aspect when considering the sustainability of different distribution concepts. For example, the analysis of different CL scenarios indicates that rural areas can potentially gain more market access (due to the lower retail density) through CL but also require more extensive operations than urban areas, where relatively small systems can improve retail access. Considering mobile retail, particularly the variance in attractiveness between different stores can leverage its potential to improve a product's market penetration, i.e., the share of customers that adopt the product. The scoping systems thinking review for CL further illustrates that CL delivery systems can be considered complex and dynamic systems. Overall, the dissertation illustrates that model-driven DSS can play an important role in better understanding alternative retail distribution concepts. The results and discussions presented in this thesis contribute valuable insights for future works on alternative retail distribution concepts, highlighting exciting and relevant research opportunities in areas such as operations research, operations management, and supply chain management.

Part 2

Framework paper

1 Introduction

This introductory chapter lays out the foundation of the cumulative dissertation. The framework paper illustrates the background and motivation for this work, describes the underlying problem, and clarifies how the thesis contributes to solving the problem. In addition, the chapter outlines related streams of literature and the employed methodology and summarizes the three manuscripts that the dissertation comprises.

1.1 Motivation

The importance of micro, small, and medium enterprises (MSME) for the transition towards more sustainable food systems is widely acknowledged. After all, MSMEs play a crucial part in global food production (FAO, 2024a). Furthermore, MSMEs can be drivers of sustainability (Coke-Hamilton, 2023), e.g., through sustainable food innovations, such as innovations in cellular agriculture (Stephens et al., 2018, 2019). Related innovations can range from incremental changes, e.g., locally or organically sourced derivatives, to radical innovation, such as liquid foods. It must be noted, though, that the impact of MSMEs can vary between emerging and advanced economies, often showing larger productivity gaps in emerging ones (Madgavkar et al., 2024). To facilitate growth for MSMEs and, subsequently, the innovative power behind them, market access is essential.

Yet, MSMEs can be limited in their customer reach and access to markets. While local produce can be more attractive to customers (Winterstein and Habisch, 2021), retail may only offer a limited amount of locally sourced products on their shelves. In the physical space, retail store shelf space is limited, and listing well-established brands and products entails lower risks for the retailer. Uncertainty and perishability are major themes driving decision-making in retail operations (Mou et al., 2018). Particularly in the food industry, where demand uncertainty and product perishability can play a crucial role in inventory management, this can lead to tensions and trade-offs regarding sustainability (Riesenegger and Hübner, 2022). In contrast, in an online retailing setting, products can lack visibility due to potential choice overload caused by virtually infinite shelf space (Long et al., 2025; Sethuraman et al., 2022; Turri and Watson, 2023). Additionally, in online retailing, certain areas can be faced with inequalities regarding service, i.e., remote areas are charged higher delivery fees or not serviced at all (Newing et al., 2022), limiting its suitability for distributing local produce.

Similarly, logistics operations in these local supply chains may be costly due to lack of scale and challenging because of the geospatial customer dispersion (Mittal et al., 2004; Lorentz et al., 2012), i.e., there are fewer large population centers, and the population is more scattered. While in metropolitan areas, business phenomena such as quick commerce (Buldeo Rai et al., 2023), i.e., retail deliveries within minutes, present many citizens with ample opportunity to satisfy their food needs, people can be left behind in rural areas and smaller cities. High spatial dispersion, low population densities, and infrastructural weaknesses can contribute to the lack of attractiveness for retailers and traditional logistics service providers (LSPs) to consider these areas (Newing et al., 2022). Recent events, such as the COVID-19 pandemic, illustrate the prevailing lack of equitable access to retail services, particularly regarding vulnerable population groups (Altuntas Vural et al., 2024). In this way, the quality of life for people with limited mobility, such as elderly or deprived people, can be limited based on the lack of access to suitable retail options (Edwards et al., 2018; Glickman et al., 2021; Kharel et al., 2024; Kirkup et al., 2004).

Additionally, while there is a growing number of innovations related to retail accessibility, many of them are neither widespread nor well-tested (Ratchford et al., 2023). Thus, it remains unclear how alternative distribution concepts can contribute to solving the underlying challenges with accessibility. Consequently, decision- and policymakers may struggle with deciding how and what initiatives to support. This is exemplified by the variety of alternative distribution concepts that have gained attention in recent years. Examples include drone delivery systems (Chen et al., 2021; Perera et al., 2020), mobile parcel lockers (Kötschau et al., 2023; Peppel et al., 2024; Schwerdfeger and Boysen, 2020), autonomous/unstaffed stores (Ahmed et al., 2023; Benoit et al., 2024), mobile stores (Cao and Qi, 2023; Wishon and Villalobos, 2016a), and crowd logistics (Gläser et al., 2021; Mittal et al., 2021).

This work focuses on two of the above-mentioned concepts, namely mobile stores and crowd-logistics (CL). CL entails the utilization of private unused logistics capacities (Carbone et al., 2017), and mobile retail involves using mobile stores, i.e., stores that can switch locations, either by themselves (vehicle) or through external means (trailer). Examples for mobile retail can be found at farmers' markets, in the form of peddlers and next to stationary retail stores, selling complimentary goods. While research indicates that these two concepts may hold great potential for a sustainable distribution of goods (Ballare and Lin, 2020; Hsiao et al., 2019), more research is needed to equip decision-makers and policymakers with adequate tools to consider how, when, and if they should support their usage (Kasprzak et al., 2022; Li et al., 2019; Pourrahmani and Jaller, 2021; Wishon and Villalobos, 2016a).

To address this gap, the work at hand develops and utilizes model-driven decision-support systems (DSS) for evaluating the use of CL and mobile stores, particularly emphasizing their use to increase market reach and facilitate product diffusion. To this end, the work employs simulation modeling and machine learning to explore how existing market structures in the physical space (stores and marketplaces) compare to deliveries with CL and on-site shopping at mobile stores in different scenarios. DSS build on computer technology to investigate different scenarios (Power and Sharda, 2007), which can help to explore and test diverse settings that otherwise would be infeasible in a real-world exploration due to time, cost, or moral constraints. This dissertation develops and uses model-driven DSS to conduct scenario analyses for CL and mobile retail. In addition, taking CL as an example, the work builds on conceptual modeling to further illustrate how decision-makers and policymakers must also consider underlying dynamic complexities to foster sustainable operations (in the sense of the triple bottom line, i.e., considering the economic, ecological, and social dimensions) of such alternative distribution channels. Consequently, this work focuses on providing decision support to reduce the uncertainties associated with these concepts, not only regarding their potential to strengthen MSMEs and reduce disparity in access but also related to how underlying dynamic aspects can shape and impact sustainability.

1.2 Aims of the dissertation

This dissertation aims to explore and facilitate decision-support that can address issues related to the lack of access from a consumer and MSME perspective, focusing on alternative retail distribution concepts. From the consumer perspective, retail access, particularly to food, is an important aspect of the quality of life for the local population. Limited product choice, reduced access to nutritious and healthy products, as well as long travel distances or travel time to stores, can severely impact consumers (Coveney and O'Dwyer, 2009; Giles-Corti et al., 2016; Pitt et al., 2017; Schwartz et al., 2019). Particularly vulnerable population groups can strongly depend on local retail infrastructure, e.g., due to a lack of mobility or digital literacy. From an MSME perspective, power asymmetries between MSMEs and retailers, as well as larger competitors, can constitute significant barriers to their business activities (Clapp, 2021; Herzberg et al., 2022; Hingley, 2005; Hirsch et al., 2021). At the same time, operating their own distribution channels can be costly and less effective as retail chains not only offer a larger customer base but also synergies for product sales, such as cross-selling effects with other products. Additional factors, such as limited LSP service options, can impose additional challenges (Kump and Fikar, 2021; Paciarotti and Torregiani, 2021). From these two perspectives, 'traditional' retail distribution concepts, including brick-and-mortar stores and deliveries through LSPs, may offer insufficient support to address respective challenges with access to goods and markets. Hence, the thesis addresses two pressing socio-economic matters: (1) How can alternative distribution concepts improve access to food on the retail level, and (2) how can they contribute to better connecting local MSMEs with customers?

In particular, the work focuses on how innovative distribution concepts such as mobile stores and crowd logistics (CL) can contribute to alleviating a lack of access. The dissertation addresses how important access is to the development of MSMEs in terms of the diffusion of new products and market reach and whether mobile stores can alleviate a lack thereof. Furthermore, it explores whether CL could serve as a substitute for LSPs and traditional retail operations. The importance of viewing supply chains in light of the underlying dynamic properties has been highlighted in academic literature (Gammelgaard, 2023; Wieland, 2021). Therefore, focusing on CL as an example, the dissertation also illustrates how underlying dynamic properties can severely influence how these new distribution concepts can affect sustainability. Overall, the aim of this work is to contribute to the discussion on whether, how, when, and to what extent alternative distribution concepts can improve retail access from a socio-economic perspective.

2 Background and related work

The following section provides background and connects related streams of literature relevant to the aims of this dissertation. Specifically, (i) it highlights the importance of distribution processes for the sustainability of food systems, (ii) portrays the relevance of models for DSS, (iii) illustrates the importance of decision support for emerging distribution concepts, and (iv) elucidates the status quo of scientific literature pertaining to CL and mobile retail. The section concludes by synthesizing the different streams of literature, embedding this work within its scientific context.

2.1 Background on the role of distribution in food systems in terms of sustainability

Several works have illustrated the importance of distribution processes in food systems for global sustainability. For example, estimations on the environmental impact extrapolate that up to one-third of anthropogenic greenhouse gas emissions stem from global food systems (Crippa et al., 2021; Poore and Nemecek, 2018), with distribution processes playing a major part in increasing greenhouse gas emissions (Li et al., 2022). Economically speaking, the value of the global food market is projected to be around 9.1 trillion USD by 2024 (Oyedijo and Akenroye, 2024), and from a societal perspective, global food chains not only employ over 1.23 billion people, but also play a critical role in the quality of life, predominantly for vulnerable population groups who suffer from a lack of food security (i.e., a sufficient access to nutritious and healthy foods) (FAO, 2024b). As the interface between producers and consumers, retail distribution plays an important role in providing access to food. For example, in the agri-food industry, alternative distribution channels, including direct sales, play a crucial role in reaching customers (Paciarotti and Torregiani, 2021).

To successfully establish sustainable and equitable distribution channels, retailers must face a number of challenges and market barriers involving different stakeholders, including logistics service providers and the customers (Sallnäs and Björklund, 2023). To ensure the success of new sustainable logistics solutions for retail distribution, decision-makers need to develop a holistic understanding of underlying mechanics' dynamics (Altuntaş Vural and Aktepe, 2022). This requires further research and the development of DSS that can assist in making informed decisions. Amongst others, this includes facilitating a better understanding of how emerging distribution concepts should be operated and what (unanticipated) side-effects may result from their use (Altuntaş Vural and Aktepe, 2022; Claro et al., 2018).

2.2 Models as the basis for decision support systems

As Power and Sharda (2007) in their review of model-driven DSS highlight, DSS build on using simulation, decision analysis, and optimization methods. They delineate model-driven DSS from computer support based on their accessibility for non-specialists, and their purpose to be used repeatedly for one specific decision situation. They further argue that model-driven DSS should contain easy-to-understand models of a decision problem to facilitate their usefulness to decision-makers. In a review of DSS for sustainable logistics, Qaiser et al. (2017) highlight that DSS for logistics processes, particularly related to social aspects of sustainability, offer room for further exploration. As a special form of DSS, spatial DSS combine spatial data and models, such as geographic information systems (GIS), with decision models to evaluate scenarios with spatial properties (Keenan and Jankowski, 2019; Pick et al., 2017). Keenan and Jankowski (2019), reviewing the development of the field of spatial DSS over three decades starting in the mid-eighties, note that spatial DSS are less recognized by the DSS research community. The work at hand integrates spatial components in two of the three manuscripts presented, thus facilitating further discussions on the integration of spatial components in DSS.

For the simulation of complex systems, agent-based simulation modeling (ABS), discrete-event simulation modeling (DES), and system dynamics (SD) modeling are frequently used modeling techniques (dos Santos et al., 2022; Greasley and Owen, 2018; Macal, 2016; Robinson, 2005; Shepherd, 2014). Looking at a combination of at least two of the abovementioned modeling techniques, so-called hybrid simulation, the review by Brailsford et al. (2019) showcases that these modeling techniques are often used in research to experiment with different solutions for decision problems. For example, a review by Kiesling et al. (2012) shows that ABS is frequently and successfully used for the simulation of product diffusion. The review by Greasley and Owen (2018) shows that several works have used DES to model human behavior. While the authors note that using DES to model human behavior can be challenging due to data collection and validation, they conclude that it is a feasible approach to obtain more accurate model results. Regarding SD, Forrester (1994) points out that the first step in the modeling process, the description of the system can be greatly enhanced through the use of systems thinking. These techniques can be particularly useful to increase the accessibility of DSS for non-experts, as called for by Power and Sharda (2007).

In addition to the capability to emulate complex environments, computer-aided simulation offers the advantage that it can be combined with business analytics tools, such as machine learning techniques (ML). Integrating ML can enhance simulation by providing additional options for analysis and modeling. For example, simulation can be used to generate data that then can be analyzed through ML. Similarly, ML models can be used to control elements within a simulation, such as agent behavior. Works such as Shashaani and Vahdat (2023), Sobottka et al. (2019) and Wang et al. (2022) highlight that ML can be combined with simulation to either train or improve ML models or to create surrogate models that reduce the amount of time required for simulations. Consequently, model-based DSS can incorporate a variety of different techniques to help decision-makers make more informed choices.

2.3 The need for decision support for innovations in physical retail distribution

Various researchers have illustrated the importance of decision support for innovation in (physical) retail distribution. Breugelmans et al. (2023) use a multi-method approach, combining the analysis of secondary data with insights from interviews to illustrate that a better understanding of internal and external factors is important to facilitate decision-making and successful implementations of new ways (for example, new retail formats) to serve customers in the physical space. They highlight elucidating conditions affecting retailers' success as a critical inquiry for future research. Similarly, Guissoni et al. (2021) show that a better understanding of how different distribution channels can vary in efficiency in diverse contexts is necessary to evaluate retail channel configurations by employing an econometric model. Sorescu et al. (2011), using a narrative review, point out that further research is needed to better understand new retail business models. They highlight that particularly retail format, activities, and governance are key to helping retailers think strategically, thereby demonstrating the importance of DSS. Reinartz et al. (2011), in a review of literature and business cases, draw attention to the fact that, particularly in established markets, a retailer's access to data does not indicate that these data can be leveraged as the transition to actionable insights can be challenging. Furthermore, works such as Melkonyan et al. (2020), who combine SD with multi-criteria decision analysis, showcase how decision support can help to better understand the sustainability potential of different distribution concepts in local food networks.

2.4 Status quo of crowd logistics and mobile retail

Research on CL has steadily grown over the past decade (Alnaggar et al., 2021; Gläser et al., 2021; Sina Mohri et al., 2023). Explored areas include optimization and network planning (Archetti et al., 2016; He et al., 2020; Kızıl and Yıldız, 2023; Voigt and Kuhn, 2022; Yıldız, 2021), pricing mechanisms (Ermagun and Stathopoulos, 2018; Rechavi and Toch, 2022; Wu and Cheng, 2022), user behavior (Buldeo Rai et al., 2021; Le and Ukkusuri, 2019; Nguyen et al., 2023b,a; Punel and Stathopoulos, 2017; Wicaksono et al., 2022), business models (Buldeo Rai et al., 2018; Devari et al., 2017; Kafle et al., 2017; Mittal et al., 2021), and case studies (Li et al., 2019; Paloheimo et al., 2016). However, no previous work has considered how different levels of participation affect delivery performance. Moreover, calls for a more holistic, systemic view and awareness (Castillo et al., 2022; Samad et al., 2023) of CL and a better understanding of environmental and social trade-offs (Li et al., 2019; Pourrahmani and Jaller, 2021; Qi et al., 2018; Wang and Yuen, 2023) remain largely unanswered, as most works primarily focus on the economic perspective.

At the same time, research on mobile retail is limited in its research focus. Recent efforts (Dulin et al., 2022; Ellsworth et al., 2015; Horning et al., 2021; Hsiao et al., 2018, 2019; Kasprzak et al., 2022; Leone et al., 2017, 2019; Lyerly et al., 2020; Vermont et al., 2022; Weissman et al., 2020; Widener et al., 2012) have primarily concentrated on the question of whether mobile retail in the form of so-called mobile produce markets can serve as an effective food desert intervention. Only few works (Cao and Qi, 2023; Robinson et al., 2016; Wishon and Villalobos, 2016b,c) have considered the topic from an operational perspective. Cao and Qi (2023) use spatial queueing systems to model on-demand mobile stores. Their study highlights the potential of mobile retail to improve service quality through location flexibility. The authors further point out that operations in mobile retail require further exploration. Robinson et al. (2016) use a case study approach, including field observations, analyzing the operations of two mobile stores in Syracuse, United States. While they observe that mobile stores can alleviate issues with access, they note that operational, political, and economic barriers may limit their potential. The authors also highlight that future work needs to address questions regarding the scope and purpose of the operations of mobile stores. Wishon and Villalobos (2016c) study a knapsack problem to optimize assortment decisions for mobile stores, which they solve using a genetic algorithm. Their examination of a sample case in Phoenix, United States, illustrates that operations research can significantly contribute to improving the operational efficiency of mobile stores. This is further substantiated by follow-up work (Wishon and Villalobos, 2016b), in which they further examine a knapsack problem and a vehicle routing problem.

While the studies on mobile stores as a food intervention indicate a fit for the distribution of established products (primarily fruits and vegetables), previous works have not yet explored the potential of mobile retail to contribute to the distribution of new and innovative foods.

2.5 Synthesis

As demonstrated through the review of related work, despite a growing interest in alternative distribution concepts, further research is needed to understand their role in providing sustainable and equitable (food) retail access. This includes examining their necessary scope, their suitability compared to other retail formats, and their societal and environmental impacts.

Particularly research on market access and product diffusion requires further attention. Research on mobile retailing is still emerging, primarily focusing on the potential to improve access to fresh food. However, its potential for facilitating the diffusion of new products has yet to be explored. Regarding CL, many works explore how networks and matching algorithms can be optimized. However, the impact of varying participation levels on retail coverage has yet to be examined. Additionally, while previous work acknowledges the complexity of CL delivery systems, their interrelated subsystems have not been analyzed holistically.

Addressing these gaps is critical to providing adequate decision support for managerial decision-makers and policymakers, thereby helping them to better understand whether, how, and when these distribution concepts can be beneficial. Furthermore, exploring these gaps can clarify key questions for future research, guiding efforts to assess the role of CL and mobile retailing in the transition toward sustainable and equitable food distribution systems. This includes refining questions about when CL and mobile retailing can provide promising performance and in what scenarios other retail formats are preferable.

3 Contributions

As laid out in the previous sections, retail access can be a cornerstone for determining the quality of life for the local population and the survival of MSMEs. Both market access and product diffusion play an important part in this matter. As further illustrated, several emerging distribution concepts may alleviate prevailing issues with distribution processes in the physical space. The underlying problem concerning decision-makers and policymakers is that too little is known about how these emerging distribution concepts can affect social, economic, and environmental sustainability. This thesis contributes to addressing this gap by examining two innovative distribution concepts using conceptual and simulation modeling.

Focusing on CL and mobile retail as examples, the problem at hand is understanding to what extent they could contribute to expanding market reach or facilitating product diffusion. Although CL has received growing attention within the scientific community, no research has yet considered how participation levels may influence its potential to address access to food. This is of particular importance as decision support in this matter could help in deciding on the required scope of operations. Consequently, the first study addresses this gap. Regarding mobile stores, the third study presented in this thesis is the first to consider how they could influence the product diffusion process. With store mobility as the core feature of mobile retail, these stores offer the possibility to flexibly extend local shelf space, which otherwise may be unavailable in the physical space. From the perspective of long-term impact, it also remains unclear how these concepts need to be implemented to avoid negative externalities. This thesis alleviates this uncertainty by proposing a new methodology to illustrate and explore the underlying dynamic properties. Using CL as an example, the second study proposes the combination of a scoping literature review and systems thinking to identify key feedback loops that decide how a concept can contribute to sustainable development.

3.1 Overview over the thesis contents

This cumulative thesis comprises three manuscripts in a journal article format. Table 2.1 gives an overview of the works contained within this thesis. In all cases, the doctoral candidate is the first and corresponding author. The doctoral candidate was responsible for the conceptualization, writing of the manuscript, revision, visualization, methodology development, software development, and analysis. The three articles are presented sequentially, as illustrated in Table 2.1. The underlying research objectives, related research questions, and the employed method are summarized in Table 2.2.

Table 2.1: *Scientific publications that constitute the body of this thesis*

Nr.	Title / Status	Authors	Role	In
1	**Investigating crowd logistics platform operations for local food distribution** *Published* (DOI: IJRDM-10-2022-0400)	Florian Cramer & Christian Fikar	First and corresponding author	International Journal of Retail & Distribution Management*
2	**Modeling sustainable operations in crowd logistics delivery networks: A scoping systems thinking review** *Published* (DOI: 10.1016/j .samod.2025.100039)	Florian Cramer & Christian Fikar	First and corresponding author	Sustainability Analytics and Modeling**
3	**Rethinking accessibility: Catalyzing early-stage diffusion of grocery innovations using mobile pop-up stores** *Working paper*	Florian Cramer & Christian Fikar	First and corresponding author	TBD

* SCIMAGO Business and International Management Q1, H-Index: 101, 5-year Impact Factor: 5.5, CiteScore (2023): 8.6, VHB-JOURQUAL4 Ranking: C, AJG (2024) Ranking: 2

** The first volume of the journal was published in 2021. Thus, most metrics are not yet available at the time of writing. The journal is published in collaboration with the International Federation of Operational Research Societies (IFORS). VHB-JOURQUAL4 Ranking: B

From a methodological standpoint, the three papers focus on model-based approaches, such as simulation modeling and conceptual modeling. This is reflected through the use of ABS, DES, ML, and the development

Table 2.2: *Overview of objectives, questions and methodologies for the research contained in this thesis*

Paper	Research objective	Resulting research question(s)	Employed method(s)
(1) **Investigating crowd logistics platform operations for local food distribution**	Evaluate the feasibility of using crowd logistics (CL) to expand the market reach of MSMEs, considering the trade-offs between food quality and vehicle kilometers traveled in the distribution process. Determine how participation levels impact local producers' market reach.	How does the scope of CL activities impact market reach for local food producers? How does CL impact food quality and transport distance for local food distribution?	• Agent-based simulation • Discrete-event simulation
(2) **Modeling sustainable operations in crowd logistics delivery networks: A scoping systems thinking review**	Identify and analyze the dynamic elements within CL delivery systems, exploring their interactions and impacts on both the environment and society. Additionally, it highlights potential areas for future research, particularly relating to the identified underlying causal loop structures.	What are the critical dynamic elements within CL delivery systems, how are they linked, and how do the different elements interact?	• Scoping systems thinking review, *combining:* – Scoping literature review – Systems thinking (Causal Loop Diagrams)
(3) **Rethinking accessibility: Catalyzing early-stage diffusion of grocery innovations using mobile pop-up stores**	Examine whether mobile retail solutions, such as mobile pop-up stores, can serve as viable alternatives to traditional grocery stores to stimulate early-stage product adoption and diffusion. Explore how different customer dispersion patterns and product rejection shape the product diffusion process in light of product availability.	How do store mobility, location selection, and product rejection affect the initial stages of the product diffusion process?	• Agent-based simulation • Machine learning

of causal loop diagrams (CLDs; for analytical modeling and as a precursor to SD). The focus on model-based decision support was chosen due to the innate dynamic properties within food supply chains. Operations within food supply chains are subject to fluctuating customer demand and product loss and are highly competitive. Thus, piloting and testing new business models can not only be costly and consume a significant amount of time but they can also be associated with a significant level of uncertainty.

3.2 The potential of crowd logistics to increase access to local produce

The first paper, ***'Investigating crowd logistics platform operations for local food distribution'*** (Cramer and Fikar, 2023), explores CL regarding its suitability for the transport of food products, focusing on the potential to increase the reach of local producers. Moreover, the study investigates how the level of participation, i.e., the share of the local population that participates as occasional couriers (OC), can affect access to local produce. While previous studies have considered determinants of the willingness to participate, to the best of the authors' knowledge, no previous study has elaborated on how different participation levels affect CL's delivery capabilities.

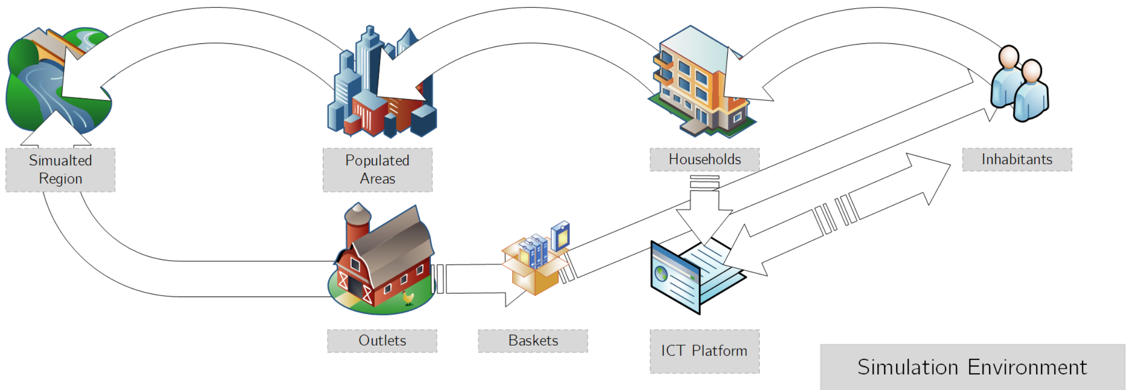

Figure 2.1: *Structure of the simulation environment of the developed decision support system, source: Cramer and Fikar (2023)*

To account for the underlying dynamics in consumer behavior, the study combines ABS with DES to facilitate an understanding of how participant levels influence CL potential in an urban and rural setting. Using farmers' markets and farm shops as sources for the deliveries, the paper also investigates the impact on food quality (using the keeping quality model by Tijskens and Polderdijk (1996)) and changes in travel distance. Figures 2.1 and 2.2 show the structure of the developed DSS used for the exploration. The simulation environment consists of the simulated region, which comprises populated areas with individual inhabitants living in households as well as retail outlets of local producers, such as farmers' markets and farm stores. The processes at outlets and the information and communication technology (ICT) platform are governed through DES, whereas inhabitants and households build on ABS.

For the investigation, two regions from Germany are used as sample cases to investigate rural (Upper Franconia) and urban (Munich municipality) areas. Figure 2.3 portrays the developed scenarios for the analysis: (a) a scenario without any CL activity; (b) a scenario where only shoppers at retail outlets may participate in CL activities; and (c) a scenario where anyone may participate in CL activities, e.g., shoppers as well as people on their way back from work.

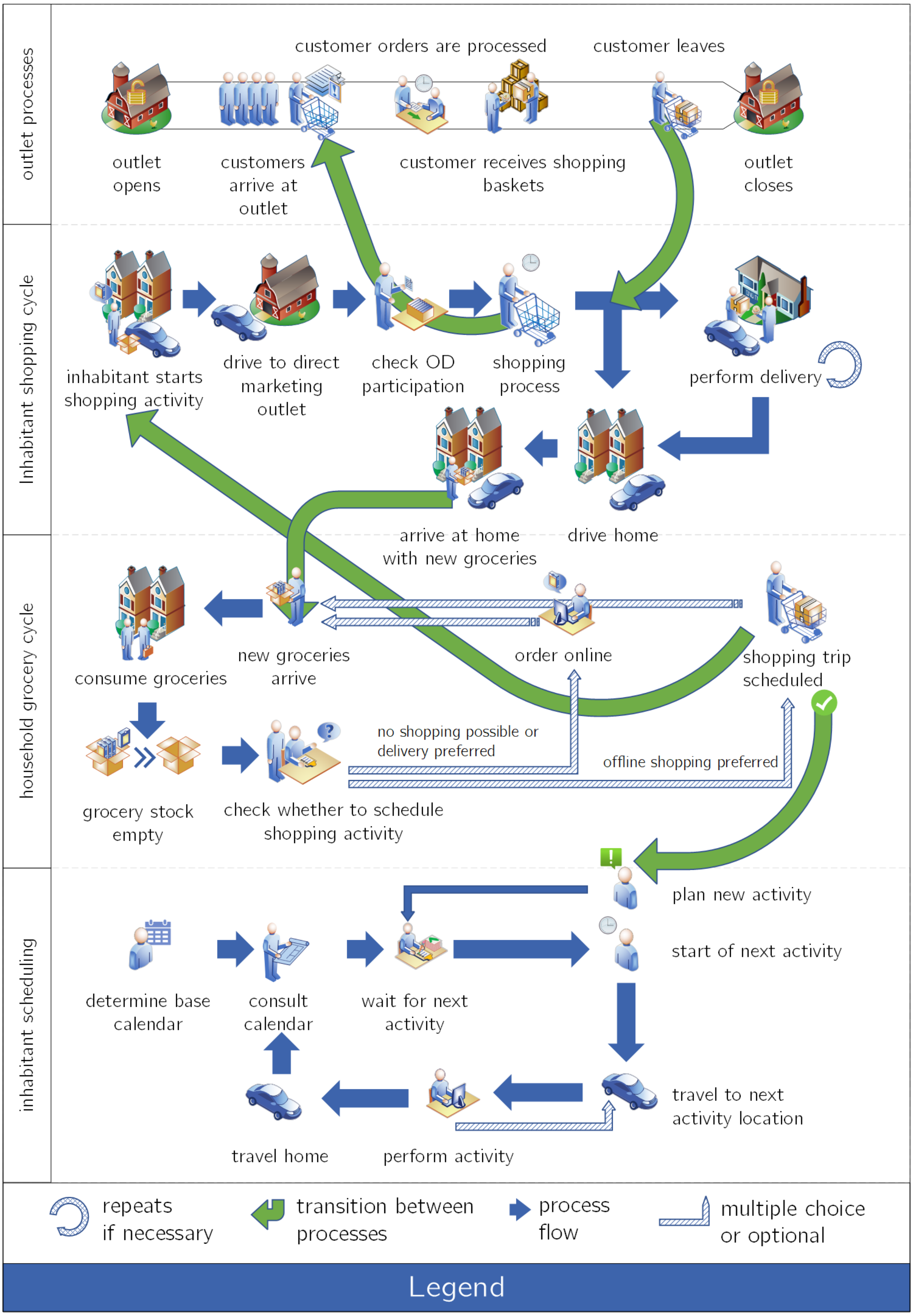

Figure 2.2: *Modeled agent actions and flows for the developed decision support system, source: Cramer and Fikar (2023)*

The results highlight that CL holds significant potential to increase product access at the expense of minor food quality losses. However, as illustrated in Figure 2.4, it also finds differences between rural and urban population

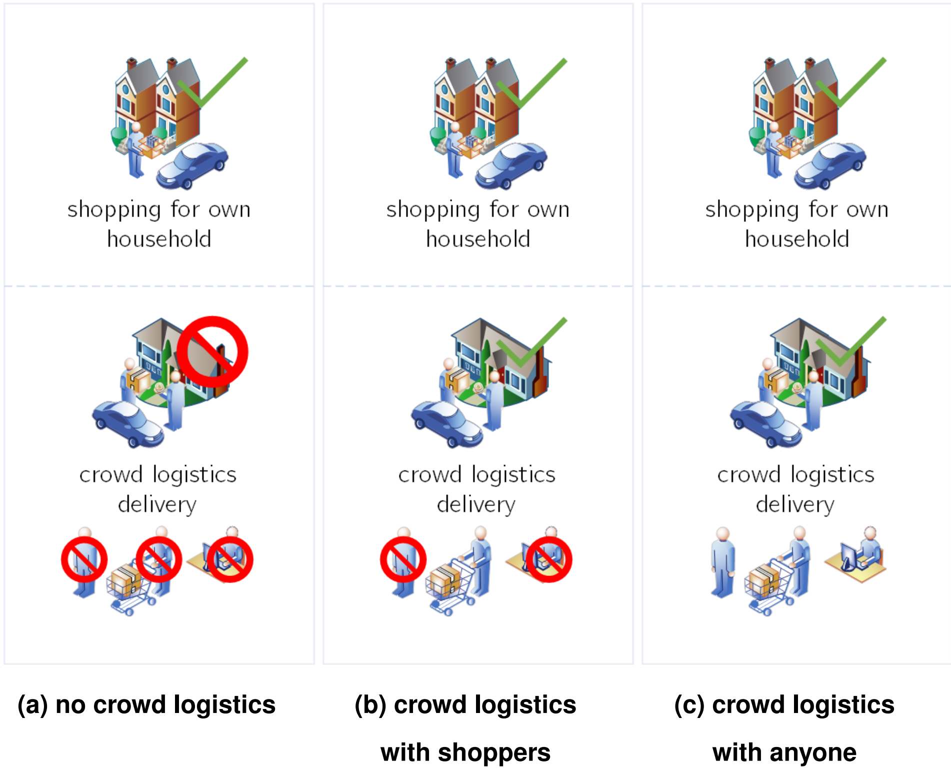

Figure 2.3: *The crowd logistics scenarios explored for the investigation, based on Cramer and Fikar (2023)*

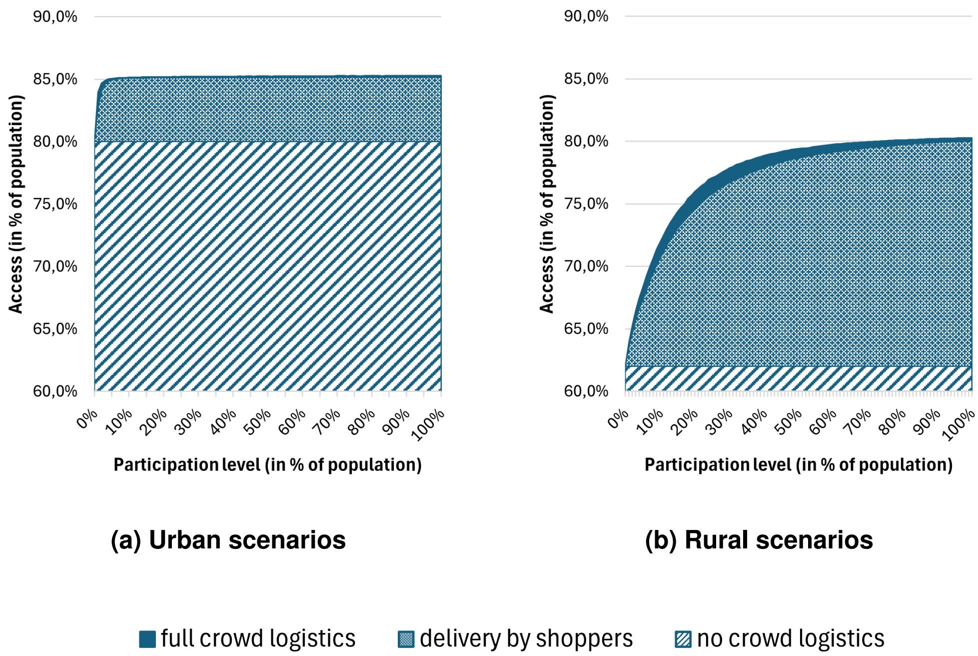

Figure 2.4: *The scope of operations has different effects on the share of population that can be served in rural and urban scenarios, based on Cramer and Fikar (2023)*

scenarios. While using CL in the urban scenarios can add around five percent in access, the rural scenarios can reach up to 18 percent additional population. As the figure shows, urban scenarios reach the point of diminishing returns quickly. Additionally, the difference between scenarios considering only shoppers and those that include considering all inhabitants as a potential OC is relatively small in the urban setting. In contrast, the rural setting exhibits a more pronounced difference between scenarios and a slower, more gradual decline in returns. While the research indicates that CL holds a greater potential for increasing retail access in rural areas, in urban areas, fewer participants are required. As such, the study provides important insights into the required scope of CL delivery systems in different geospatial contexts.

The study also considers the effects of changing preferences for deliveries, preference for local produce, and the impact of convenient store opening times. While varying the preference for local produce does shift the scale of customers and participants, no other significant changes were observed. Testing the effects of a difference in opening time convenience (24/7 availability versus real-world opening times of farm stores and farmers' markets) indicates that the higher the temporal availability, the less the CL system depends on couriers that are not shoppers. This is a highly relevant finding for policymakers when discussing legal frameworks that determine opening times, as the study suggests that less restrictive opening times require fewer 'extra' couriers. It is also an interesting finding for operators of smallholder retail outlets such as farm shops and farmers' markets, as it suggests that providing more convenient opening times and including on-site shoppers could increase customer reach, thereby informing decisions on additional distribution channels.

The analysis further implies that delivery preference plays an important role in the dimensioning of CL systems. A counterintuitive finding of the study is that delivery preference can affect coverage positively at high participation levels while having a negative impact on low ones. The negative impact of low participation levels can be attributed to a lower number of customers that travel to the stores themselves, thus requiring more delivery drivers to cater to the same number of customers. Interestingly, delivery preference also has different effects on competition between OCs in an urban and rural setting. The higher geospatial spread in a rural setting leads to higher competition amongst couriers when the preference for deliveries increases.

In conclusion, the paper highlights several important insights into the design, scope, and setting of CL delivery systems for local food distribution. Amongst others, geospatial customer dispersion and existing retail infrastructure play an important role in CL's viability and required scale. Moreover, the study shows that rebound effects, such as competition between drivers, can have a major impact on the potential to facilitate access. Furthermore, it shows that with increasing levels of participation, the negative externalities can also increase, thereby highlighting the need to understand turning points in CL. This observation served as a primary motivator for the second paper, which focuses on understanding CL from a holistic perspective.

3.3 Understanding crowd logistics from a systems perspective

Considering the identified potential in the first paper, as well as the fact that CL initiatives are still relatively scarce in practice, the second article, entitled ***'Modeling Sustainable operations in crowd logistics delivery networks: A scoping systems thinking review'*** (Cramer and Fikar, 2025a), provides a more holistic understanding of CL delivery systems. To this end, the article develops a new methodological framework grounded in a scoping literature review and systems thinking. Using scientific literature as the basis for identifying core structures in CL, the article maps CL as a dynamic, wicked system. Figure 2.5 illustrates the iterative approach to building a holistic understanding of CL delivery systems.

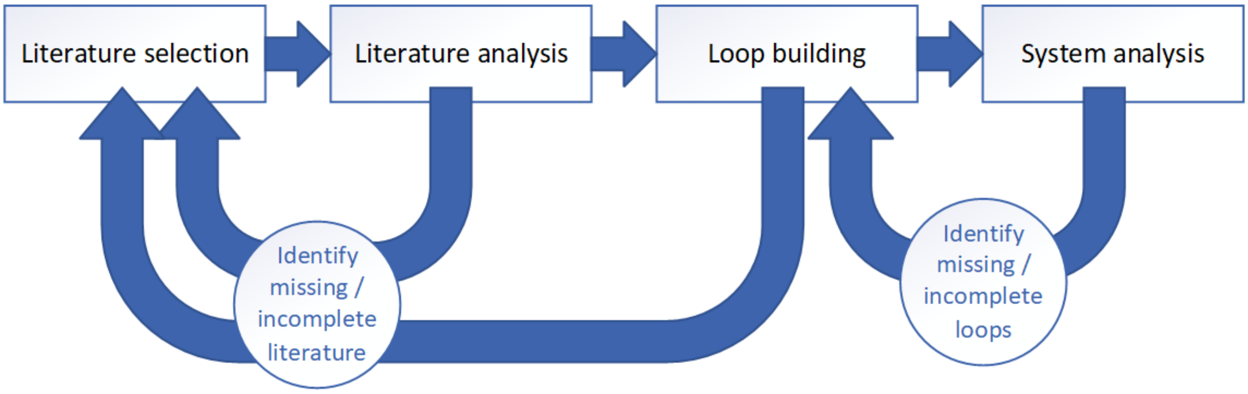

Figure 2.5: *The scoping systems thinking review methodological framework, based on Cramer and Fikar (2025a)*

The study builds on several calls for a more holistic and dynamic understanding of CL delivery systems (Carbone et al., 2017; Castillo et al., 2022; Frehe et al., 2017; Gläser et al., 2021; Li et al., 2019; Pourrahmani and Jaller, 2021; Qi et al., 2018; Samad et al., 2023; Ta et al., 2023). Building on the procedure suggested by Thomé et al. (2016) for literature reviews in operations management, the paper selection for the literature review followed a six-step process: First, potential papers were identified based on a defined search string and inclusion and exclusion criteria. The initial results were screened through a check of keywords and titles, followed by a cursory reading of abstracts. The remaining articles were used for a forward and backward search, adding relevant citing and cited works to the selection. After that, articles were selected based on a full reading of the articles. At a later stage, the selection was updated to accommodate missing papers addressing gaps identified through the loop modeling process and system analysis. Through coding of the literature, relevant concepts and structures for the modeling process were identified.

In total, 63 causal relations were identified within the CL literature, and 23 additional causal links were substantiated in the wider context of the sharing economy literature. The resulting loop structures comprise a total of eight reinforcing loop structures (marked with an “R”), i.e., loops that facilitate same-direction reactions (e.g., an increase follows an increase, a decrease follows a decrease), and 18 balancing loop structures (marked with a “B”), i.e., opposite-direction reactions (e.g., a decrease is followed by an increase). Within these structures, three major sides were identified: The customers’ side, the couriers’ side, and the platforms’ side. Figure 2.6 portrays all identified loop structures, highlighting how CL delivery systems can be understood as wicked systems, i.e., as complex and dynamic systems involving unintended side effects, diverging goals, and interconnected sub-systems. The figure illustrates how the three major sides involved in CL delivery systems, the customers, the couriers, and the platform, interact and influence each other.

The analysis of the loop structures shows that operating sustainable CL delivery systems is not a trivial task. Amongst others, the paper highlights the need and difficulty of integrating traditional logistics service providers with CL. It further outlines that user pools, i.e., customers and couriers, are a limiting factor for system growth. For example, the analysis highlights that user pools may be susceptible to depletion. Consequently, user retention

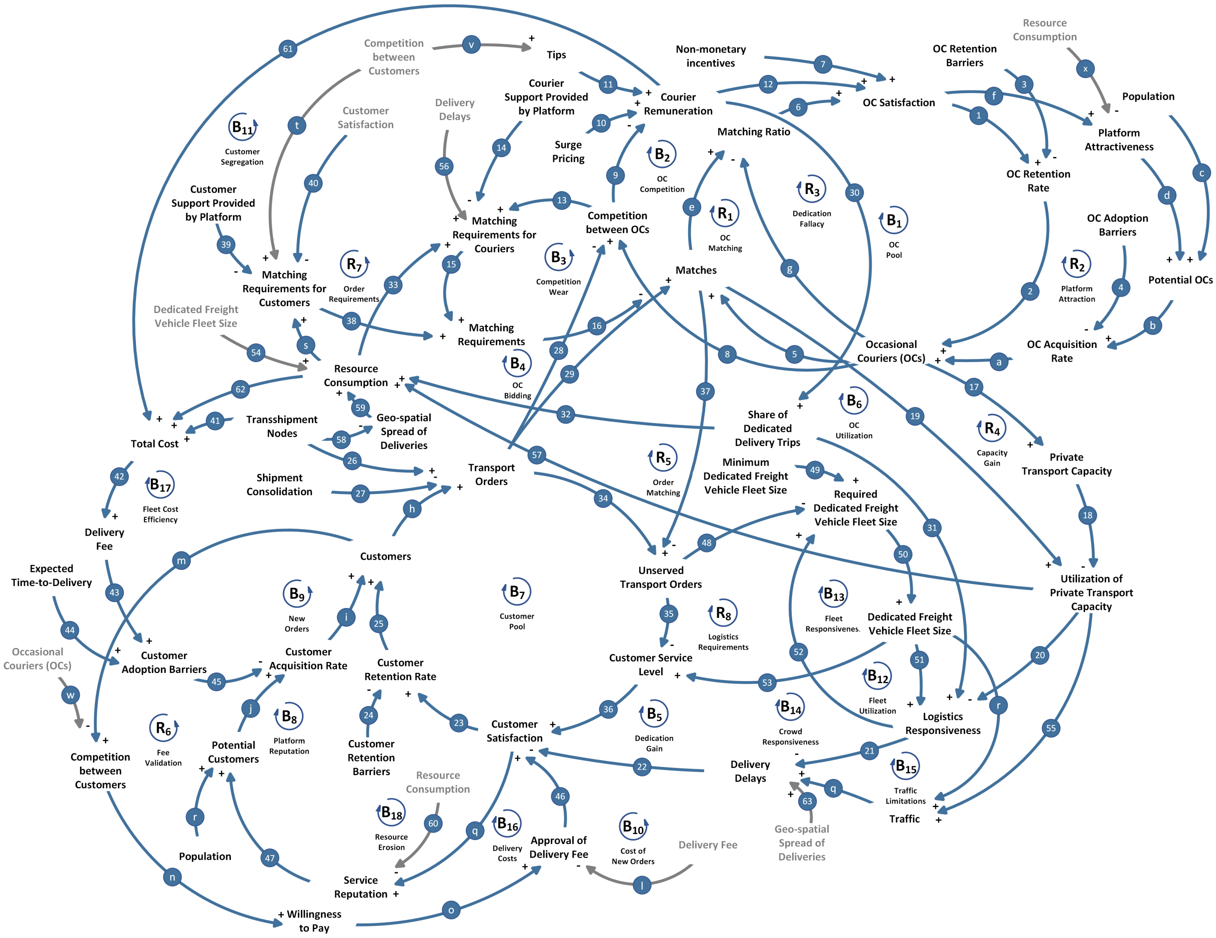

Figure 2.6: *Causal loop diagram of crowd logistics delivery systems, source: Cramer and Fikar (2025a)*

plays a major role in achieving sustainable CL delivery systems. The analysis indicates that commonly used incentivization strategies, such as surge pricing and tipping, could cause such a development if they are not implemented with care.

The study also emphasizes the potential impacts of CL systems from a societal perspective. While CL could lead to better resource use by increasing the load factors for private vehicles, incentivizing its use in the form of dedicated trips, i.e., not as detours to existing trips but rather as extra trips, may lead to rebound effects and increase traffic load. Furthermore, incentivizing dedicated trips can lead to creating full-time instead of occasional drivers. Considering that these couriers operate on a freelance basis, they may face several disadvantages, such as a lack of union options, lack of insurance, and income fluctuations.

The results highlight that alternative distribution concepts, such as CL, must be viewed from a holistic perspective to achieve sustainable operations. The proposed methodological framework, the scoping systems thinking review, can help build an initial understanding of underlying system structures and dynamic dependencies. The identified dynamic structures and identified opportunities for future research can serve as stepping stones for further exploration of CL. Relatedly, Table 2.3 provides an overview of several research questions emanating from the work. Three particularly promising areas for future work comprise explorations on how operations can and should be scaled, discussions on how efficiency and effectiveness can be balanced, e.g., how optimization efforts impact societal and environmental developments, and analyses focusing on contextual elements, i.e., how cultural idiosyncrasies and area of application affect the sustainability of CL delivery systems. Additionally, the developed causal loop diagrams can provide valuable decision support, helping decision-makers and policymakers to understand better how their choices may influence, evolve, or counteract intended sustainability goals.

Table 2.3: *Examples for future research opportunities concerning crowd logistics delivery systems, based on Cramer and Fikar (2025a)*

Topic	Possible research questions
Operations scaling	*How can customers be motivated to use CL?*
	How can customer participation be leveraged to facilitate the growth of the courier base and vice versa?
	How can a lack in customer base be compensated?
	Do ridesharing and crowd logistics platforms compete over the same user pools?
	What are the long-term effects of monetary control mechanisms on operations stability and growth?
	What capabilities contribute the most to maintaining momentum in CL initiatives?
Optimization vs. Effectiveness	*What are the long-term effects of monetary control mechanisms on CL's sustainability potential?*
	What dynamic differences issue the greatest challenge for an extension of LSPs through the integration of CL?
	How can a 'healthy' share of dedicated trips for a specific CL initiative be determined?
	To what extent does current practice create social disparity and segregation?
	How do remuneration control mechanisms affect the couriers' quality of life?
	Is the customers' or the couriers' side more strongly affected by adverse social impacts caused by CL?
	What are the infrastructural prerequisites to facilitate the sustainable use of CL for deliveries?
	What are the interdependencies between sustainable use of CL and societal developments?
Contextuality	*What potential does crowd logistics hold during public emergencies?*
	How do societal challenges, such as an aging population and a decreasing number of people with driver's licenses, affect CL?
	How does cultural context impact CL sustainability potential?

3.4 The potential of mobile retail to facilitate product diffusion

The third article, ***'Rethinking accessibility: Catalyzing early-stage diffusion of grocery innovations using mobile retail solutions'*** (Cramer and Fikar, 2025b), explores mobile retail with respect to its potential to assist in early product diffusion. The study compares the achieved market penetration, i.e., the share of the population that adopted the product, and total sales in varying scenarios. Specifically, mobile stores are compared to selecting promising stores for listing new products and picking at random from existing retail locations. These two selection scenarios for stationary stores were chosen to reflect a centralized and a decentralized planning approach: (1) The selection by a central planning authority, e.g., a retailer, choosing the most promising stores first, and (2) a decentralized approach, in which each retailer can choose whether to list a product or not by themselves (which was simulated through a random selection of store locations). In addition to varying the number of stores, the work also explores mixing different stores and the effect of product rejection. For the exploration, ABS is used to simulate customer adoption behavior and ML is used to identify promising locations.

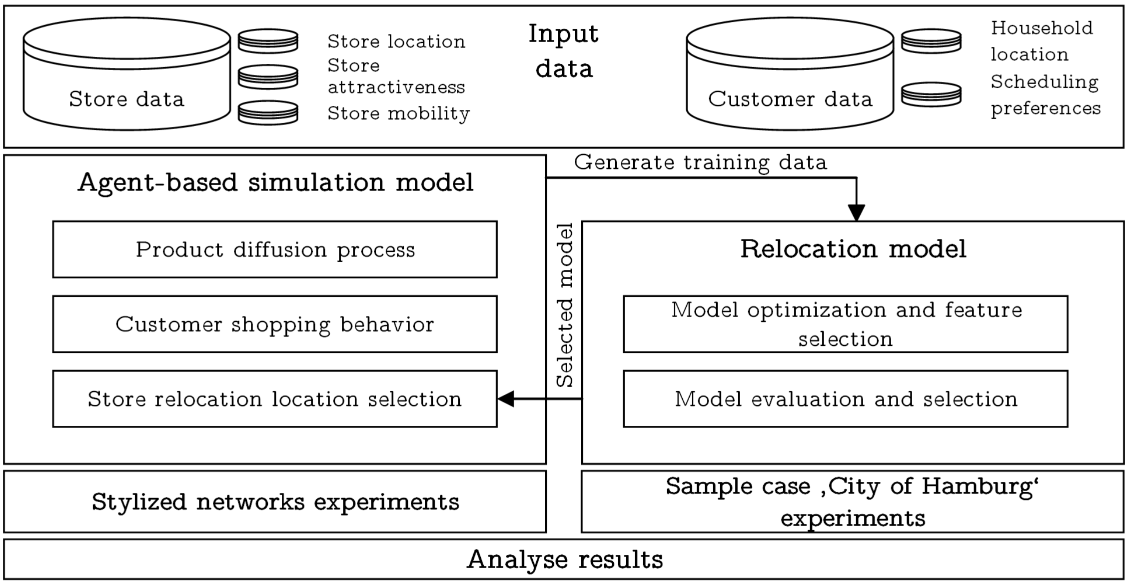

Figure 2.7: *Structure of the developed decision support system combining agent-based simulation and machine learning for the location selection process, source: Cramer and Fikar (2025b)*

Figure 2.7 illustrates the methodological framework and structure of the DSS developed for the exploration. The DSS uses ML (neural networks) to estimate location potential based on the sales history for each location. For stationary stores, the location is set at the beginning of the simulation, whereas for mobile stores the potential for each location is re-evaluated each period (with the restriction that stores cannot visit locations consecutively, as this could lead to a stationary rather than a mobile store setting). ABS is used to model the product diffusion process based on individual agent behavior, building on the ideas of the Bass (1969) diffusion model, thereby incorporating the effects of advertisement and word of mouth, as illustrated through Figure 2.8. The figure illustrates the product adoption process, which is divided into different phases: Starting with an unaware potential customer, the customer learns of the new product either through advertisement or from his or her peers through word-of-mouth. Once the customer is aware he or she looks for an option to buy and try the product. Once the customer is able to buy the product, the product is evaluated. Either the product is adopted or rejected, i.e., the customer is either willing to use the product and to buy it again, or not. When a customer decides to adopt the product, the product then is bought regularly. Thus, the effect of negative word-of-mouth is represented implicitly through the customers who reject the product, thereby blocking communication paths in the social network. This approach was chosen to minimize conflicts with parameterization and complexity, ensuring a more robust and interpretable model.

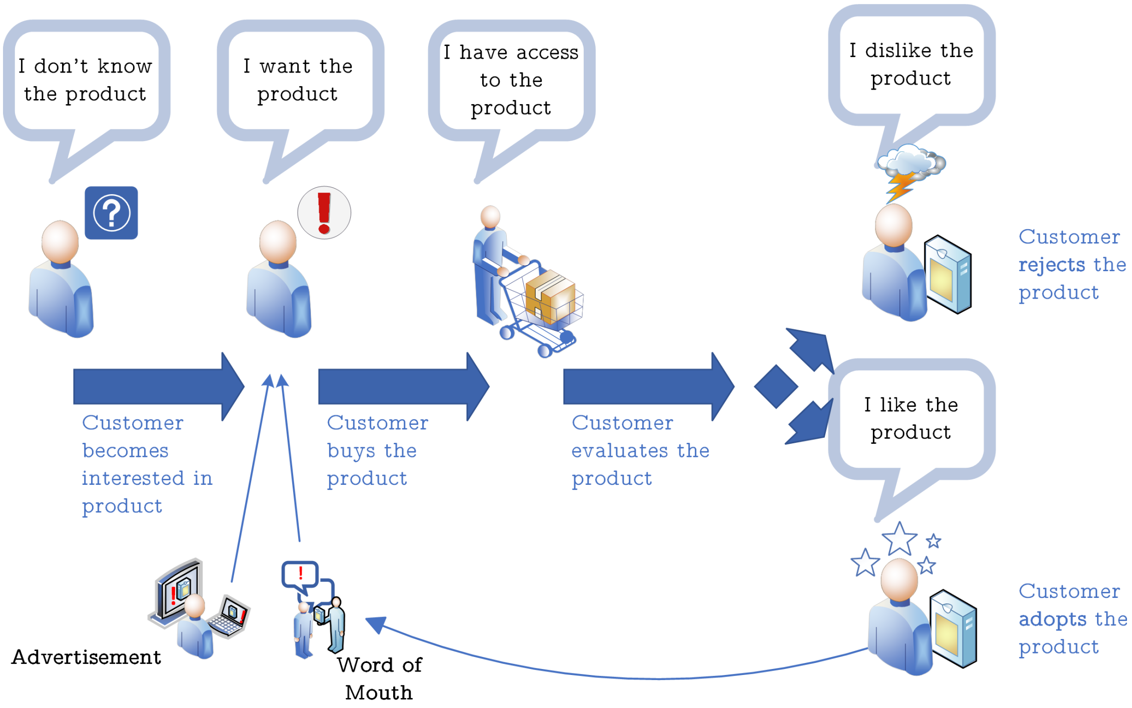

Figure 2.8: *Each agent in the simulation has their own adoption process which can be triggered through advertisement or word-of-mouth, source: Cramer and Fikar (2025b)*

The study explores both real-world geographical settings and stylized geospatial configurations to account for potential issues with generalization. For the real-world sample case, the City of Hamburg, Germany, was chosen, as it is frequently used as a test market and harbors a large number of food-related start-ups and MSMEs. For the stylized setting, dispersion patterns by Gehring and Homberger (2001), DIMACS (2021), and Uchoa et al. (2017) were explored. Figure 2.9 portrays the different dispersion patterns mapped to a 500 by 500 Cartesian coordinate system. For the real-world case, the store locations of a major retail chain were used, whereas for the stylized experiments, ten stores were located in space, using distance clustering, so that each covers ten percent of the population. For the exploration, it was assumed that the mobile stores are located in the parking lots of these store locations.

While the analysis shows that mobile stores cannot compete with selecting particularly promising stores in all scenarios, it elucidates that there are settings where mobile stores are superior in terms of market penetration, e.g., in areas with small clusters and a high store attractiveness heterogeneity. Figure 2.10 illustrates the performance for the sample case. Considering that many retail stores struggle with shelf space limitations, the results indicate that mobile stores can be an adequate solution for 'incubating' new products, i.e., facilitating early product diffusion before moving successful products onto the shelves of stationary stores.

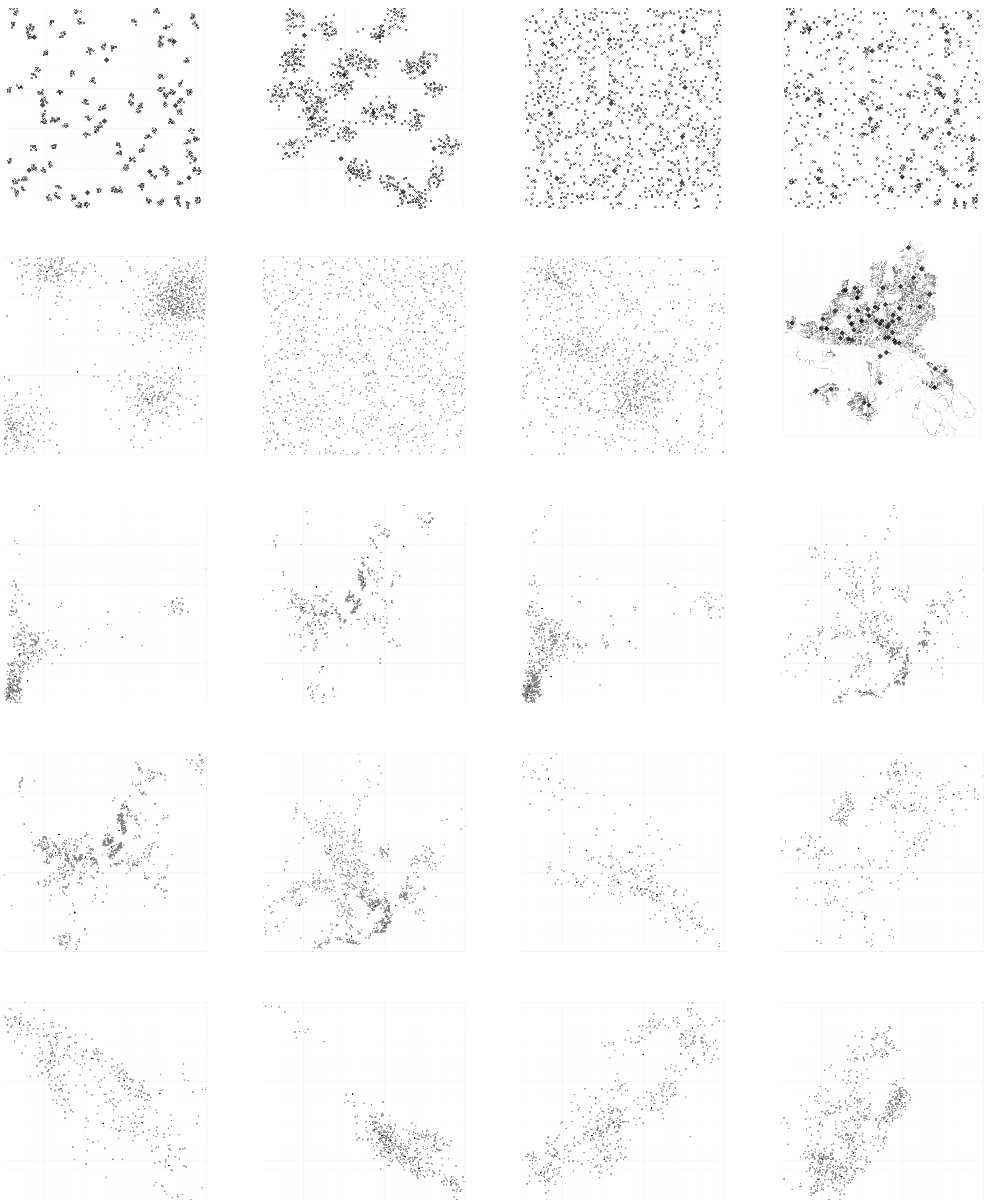

Figure 2.9: *Geographical dispersion patterns considered in the evaluation of the potential of mobile retail in terms of market penetration and total sales, based on Cramer and Fikar (2025b)*

As illustrated, in a real-world setting, selecting promising stores can become impossible due to shelf space limitations. Therefore, it is more likely that the performance of stationary stores would be closer to that of a random selection procedure. The comparison between mobile stores and randomly selected stationary stores showed higher market penetration for mobile stores for all explored settings. Moreover, mobile stores also showed

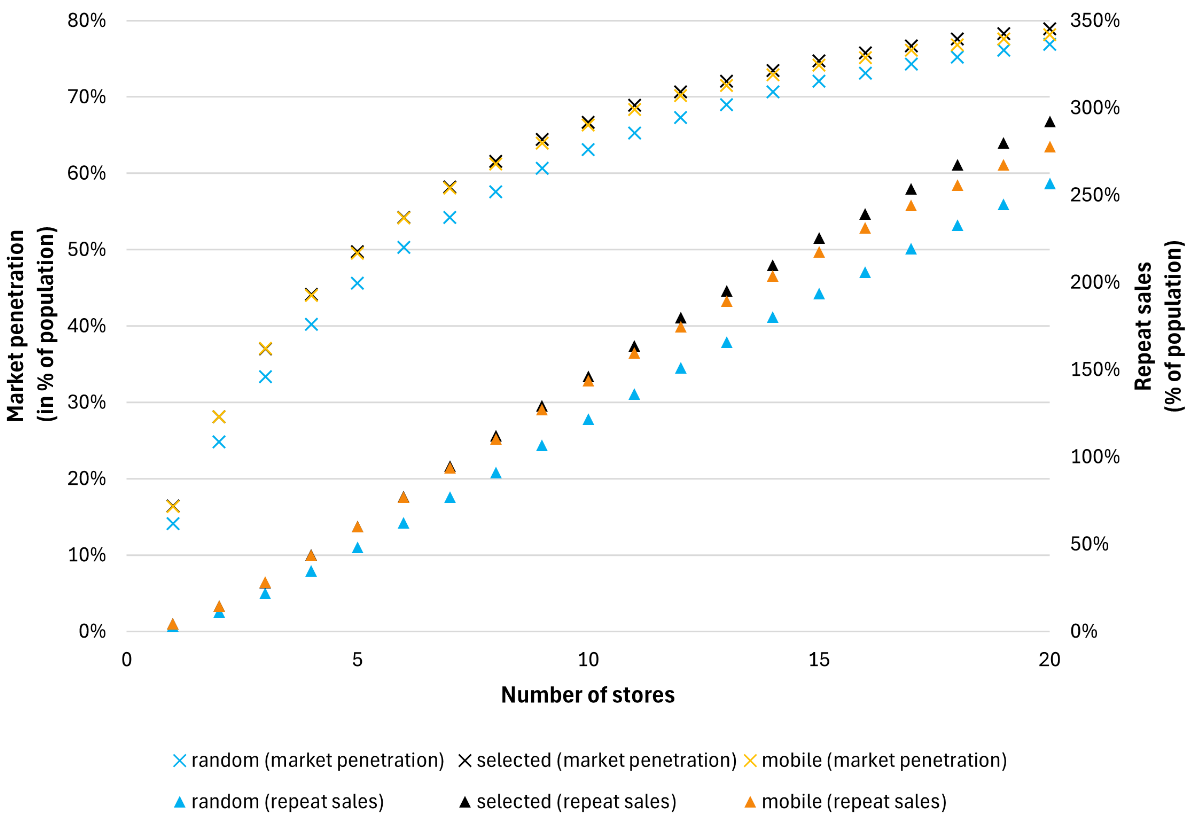

Figure 2.10: *Development of market penetration and repeat sales with increasing store numbers, based on Cramer and Fikar (2025b)*

Table 2.4: *Development of market penetration (in %) subject to dispersion setting and store heterogeneity for the selection of one single store, based on Cramer and Fikar (2025b)*

No store attractiveness heterogeneity (cv=0)												
	Small clusters			*Large clusters*			*Random dispersion*			*Random clustering*		
week	random	selected	mobile	random	selected	mobile	random	selected	mobile	random	selected	mobile
1	0.30	0.33	0.31	0.30	0.32	0.35	0.29	0.37	0.34	0.28	0.32	0.32
2	0.92	0.92	0.92	0.89	1.03	1.03	0.93	1.02	1.02	0.90	0.98	0.97
3	1.89	1.95	1.94	1.90	2.13	2.15	1.90	2.09	2.05	1.86	2.07	2.04
4	3.34	3.40	3.38	3.28	3.72	3.64	3.27	3.65	3.64	3.27	3.62	3.57
5	5.07	5.17	5.23	5.02	5.70	5.57	5.06	5.49	5.50	5.02	5.53	5.52
6	7.21	7.29	7.33	7.10	8.07	7.91	7.16	7.69	7.81	7.07	7.77	7.72
7	9.65	9.75	9.71	9.44	10.70	10.56	9.62	10.26	10.30	9.56	10.33	10.35
8	12.29	12.44	12.36	12.15	13.61	13.47	12.20	13.18	13.19	12.17	13.32	13.16
9	15.18	15.40	15.19	14.99	16.85	16.72	15.08	16.35	16.33	14.96	16.38	16.30
10	18.2.	18.51	18.35	18.12	20.36	20.17	18.09	19.73	19.65	17.98	19.67	19.49
11	21.48	21.67	21.59	21.37	24.00	23.81	21.26	23.11	23.14	21.17	23.16	22.89
12	24.77	25.07	24.93	24.80	27.76	27.67	24.66	26.69	26.79	24.51	26.76	26.48
13	28.33	28.56	28.45	28.29	31.75	31.49	28.17	30.46	30.49	27.99	30.52	30.19

Low store attractiveness heterogeneity (cv=0.25)												
	Small clusters			*Large clusters*			*Random dispersion*			*Random clustering*		
week	random	selected	mobile	random	selected	mobile	random	selected	mobile	random	selected	mobile
1	0.28	0.32	0.31	0.30	0.30	0.38	0.29	0.34	0.31	0.33	0.33	0.33
2	0.85	0.94	0.92	0.89	0.98	1.07	0.89	1.00	0.93	0.89	0.98	1.02
3	1.80	1.98	1.90	1.84	2.03	2.16	1.90	2.05	1.96	1.94	2.12	2.12
4	3.27	3.42	3.30	3.26	3.64	3.68	3.24	3.53	3.46	3.36	3.69	3.61
5	4.97	5.21	5.10	5.09	5.54	5.74	5.03	5.43	5.29	5.11	5.55	5.56
6	7.07	7.36	7.29	7.18	7.89	8.05	7.06	7.65	7.45	7.18	7.72	7.77
7	9.39	9.69	9.74	9.56	10.59	10.86	9.35	10.11	9.98	9.52	10.22	10.18
8	11.98	12.33	12.33	12.17	13.53	13.72	11.98	12.86	12.75	12.00	13.06	13.03
9	14.76	15.11	15.20	15.06	16.70	17.04	14.79	15.86	15.76	14.87	16.08	16.14
10	17.64	18.19	18.28	18.10	20.15	20.48	17.76	19.08	18.98	17.90	19.34	19.38
11	20.78	21.27	21.56	21.24	23.80	24.02	20.87	22.47	22.42	21.18	22.67	22.79
12	24.03	24.53	24.96	24.68	27.57	27.71	24.18	26.05	26.01	24.52	26.17	26.38
13	27.40	27.88	28.44	28.18	31.43	31.59	27.69	29.66	29.73	27.92	29.77	30.08

Medium store attractiveness heterogeneity (cv=0.5)												
	Small clusters			*Large clusters*			*Random dispersion*			*Random clustering*		
week	random	selected	mobile	random	selected	mobile	random	selected	mobile	random	selected	mobile
1	0.29	0.30	0.33	0.26	0.36	0.34	0.28	0.32	0.30	0.28	0.32	0.33
2	0.79	0.92	0.95	0.89	1.02	0.99	0.84	0.95	0.94	0.87	0.99	0.97
3	1.74	1.94	1.95	1.82	2.15	2.10	1.85	2.00	1.99	1.82	2.07	1.98
4	3.09	3.41	3.42	3.13	3.66	3.66	3.20	3.36	3.50	3.21	3.61	3.49
5	4.79	5.22	5.26	4.85	5.52	5.58	4.94	5.23	5.36	4.83	5.53	5.37
6	6.80	7.34	7.46	6.82	7.77	7.79	6.93	7.34	7.50	6.84	7.64	7.54
7	9.05	9.49	9.84	9.11	10.26	10.40	9.15	9.79	10.03	9.05	10.10	10.09
8	11.44	12.07	12.45	11.63	13.00	13.17	11.57	12.45	12.89	11.43	12.73	12.76
9	14.10	14.97	15.31	14.37	15.94	16.31	14.31	15.31	15.79	14.12	15.70	15.76
10	16.88	17.87	18.41	17.26	19.13	19.61	17.11	18.33	19.03	16.94	18.74	18.96
11	19.87	20.90	21.62	20.27	22.49	23.11	20.09	21.47	22.36	19.84	22.04	22.36
12	22.83	24.07	25.08	23.47	26.02	26.65	23.20	24.80	25.78	22.79	25.43	25.83
13	25.93	27.30	28.47	26.73	29.58	30.34	26.31	28.24	29.29	25.97	28.83	29.45

High store attractiveness heterogeneity (cv=0.75)												
	Small clusters			*Large clusters*			*Random dispersion*			*Random clustering*		
week	random	selected	mobile	random	selected	mobile	random	selected	mobile	random	selected	mobile
1	0.28	0.30	0.31	0.32	0.32	0.35	0.31	0.30	0.30	0.30	0.29	0.30
2	0.89	0.90	0.91	0.91	0.97	0.99	0.86	0.95	0.96	0.89	0.95	0.94
3	1.79	1.89	1.93	1.91	2.05	2.05	1.81	1.96	2.02	1.84	2.00	2.01
4	3.15	3.32	3.39	3.21	3.48	3.57	3.13	3.39	3.49	3.18	3.48	3.42
5	4.80	5.08	5.21	4.89	5.29	5.46	4.81	5.09	5.42	4.81	5.28	5.29
6	6.67	7.04	7.31	6.84	7.42	7.71	6.64	7.11	7.56	6.60	7.21	7.48
7	8.74	9.27	9.75	8.93	9.78	10.32	8.71	9.37	10.00	8.60	9.47	9.97
8	11.01	11.65	12.30	11.25	12.34	13.14	11.02	11.82	12.70	10.83	11.91	12.61
9	13.43	14.20	15.07	13.66	15.10	16.11	13.45	14.45	15.57	13.18	14.53	15.58
10	15.94	16.84	18.03	16.16	17.87	19.32	15.99	17.23	18.54	15.73	17.21	18.71
11	18.59	19.63	21.18	18.90	20.85	22.70	18.61	20.02	21.89	18.42	19.95	21.91
12	21.23	22.49	24.39	21.56	23.83	26.25	21.33	22.96	25.23	21.15	22.91	25.26
13	23.88	25.28	27.73	24.35	26.89	29.80	24.07	25.93	28.61	23.78	25.87	28.69

higher repeat sales for almost all settings. Considering the difference in market penetration, particularly at low to medium store numbers, mobile stores can also create a temporal offset, i.e., a head start in terms of product diffusion, which can be measured in days that the selection of random stores needed to catch up to the same level of market penetration.

The analysis of the extent of variations in store attractiveness further illustrates the potential of mobile stores for product diffusion. With an increasing variation of store attractiveness between stores, mobile stores started delivering higher market penetration than choosing selected stationary stores. As Table 2.4 highlights, particularly dispersion patterns based on a clustered dispersion structure can lead to a better performance of mobile stores in terms of market penetration. Starting at a medium heterogeneity in store attractiveness, mobile stores outperform stationary ones in most cases for clustered customer dispersion settings. While the study shows that an increasing heterogeneity in store attractiveness can impede market penetration, the analysis indicates mobile stores can address this issue better than stationary stores, particularly in settings with high heterogeneity and small clusters. Regarding repeat sales, the variations did not indicate any significant changes.

The study offers several important insights regarding the use of alternative distribution concepts for product diffusion. For example, the study highlights the importance of the underlying geospatial customer and retail dispersion structures. Therefore, when deciding when or to what extent to use alternative retail distribution concepts, such as mobile retail, understanding the target area is crucial. While the study indicates that when all stores are perceived as similar in attractiveness and customers live in metropolitan areas, i.e., mega-cluster structures, mobile stores are less effective than selected stationary stores, the built environment of such areas (densely populated urban areas) likely can impose barriers that mitigate the difference. For example, establishing new stationary stores within urban areas can be expensive, and stores within city centers cannot easily extend their size to accommodate more shelf space. In rural areas, on the other hand, customer structures are dispersed, making the diffusion process more scattered. Mobile stores can address issues in both settings due to their high location flexibility. However, this flexibility comes at the cost of repeat sales, as frequent relocations can drastically limit a store's temporal availability.

4 Discussion

Research on CL and mobile stores varies in focus and progress when considering their potential as alternative distribution concepts to improve (food) retail access. Therefore, this thesis contributes to different aspects of the distribution process for either concept. Regarding mobile retail, the study (Cramer and Fikar, 2025b) within this dissertation focuses on mobile retail's potential to serve as a platform to facilitate product diffusion. Considering that mobile stores are a cost-efficient and flexible distribution concept that requires relatively little long-term commitment, mobile stores could be interesting channel choices for MSMEs and retailers to expand local networks. For example, local MSMEs could operate a mobile store collaboratively to enhance access to locally sourced produce. Moreover, considering that in a real-world scenario, the selection of the most promising stores is not always feasible or possible, the study indicates that mobile stores could be well suited to facilitate early-stage product diffusion. It must be noted though that the study does not consider the effect of ephemerality (increased attractiveness due to limited-time availability), which constitutes a major factor for the attractiveness of pop-up stores (Zogaj et al., 2019), or co-location (locating a retail store in the vicinity of another, thus increasing the attractiveness of the area) (Chen et al., 2020; Nilsson and Smirnov, 2016), which may leverage sales for both the mobile store as well as adjacent retail stores. Therefore, considering the observations made in Cramer and Fikar (2025a) for CL, further research from a holistic perspective is required to better understand how mobile stores can contribute to product diffusion in a sustainable manner.

While research on mobile stores has addressed their potential to facilitate access to (food) retail options, CL lacks in this perspective. Previous research efforts in CL have given little consideration to essential questions concerning the evaluation of CL for increasing accessibility to retail. The explorations of the required scope of such systems in this thesis can serve as a stepping stone for future research efforts and the implementation of CL in practice. For example, the analysis presented in Cramer and Fikar (2023), showcases that particularly rural areas could benefit from the use of CL. Considering that rural areas, with their more dispersed customer and store structures, are more challenging for people with limited mobility, investments in infrastructure and the integration of LSPs with CL in these areas could prove to be beneficial for customers, MSMEs, retailers, and logistics providers. This contrasts with current developments, as established CL initiatives primarily operate in urban areas, where customers and OCs are less dispersed and available in greater numbers. The analysis in Cramer and Fikar (2023) further highlights that acquiring desirable couriers, e.g., those that can cover unattractive routes, is more important than simply growing the courier pool. This finding highlights an important point pertaining to the potential of alternative distribution concepts: the impact of geospatial customer dispersion.

The analyses of the different CL (Cramer and Fikar, 2023) and mobile store (Cramer and Fikar, 2025b) scenarios clearly highlight the importance of geospatial aspects for the choice and design of alternative distribution concepts, thereby offering insights beyond their context, and aligning with previous research, such as Rechavi and Toch (2022) or Yang et al. (2024). For example, the potential of mobile stores to increase market penetration correlates with customer dispersion and store heterogeneity. The results presented in Cramer and Fikar (2025b) indicate that depending on the customer dispersion, either mobile or selected stationary stores lead to the highest market penetration, whereas a random selection of stationary stores yields the lowest for most scenarios. In addition, the experiments showed that with increasing heterogeneity in store attractiveness, mobile stores show a strongly increased performance, particularly for clustered customer dispersion settings. The comparison of CL scenarios (Cramer and Fikar, 2023) further highlights the difference between urban and rural scenarios. In an urban context, the potential of CL to increase access is limited due to the already high level of retail accessibility; however, relatively small numbers of OCs can provide some improvement. In a rural context, CL can boost access much higher while also needing a larger scope of operations. Therefore, the thesis illustrates that geospatial context is key when contemplating alternative distribution concepts.

When considering the role of temporal availability, the results presented in (Cramer and Fikar, 2023) regarding the effect of convenient opening times indicate that when opening times limitations are eliminated, building on shoppers as OCs shows the same potential as including everyone as a potential courier. Several other works, such as Dayarian and Savelsbergh (2020), Dayarian and Pazour (2022), and de Maio et al. (2024) have also highlighted the potential of using shoppers as OCs. Given that CL can also happen on a small scale between family members, friends, and neighbors, as examined by Devari et al. (2017), investments in assisting infrastructure (e.g., meeting places and parcel lockers) could also improve initiatives building on social capital.

This is illustrated through CL activities during the COVID-19 pandemic, where neighbors, family, and friends placed shopping bags containing food or medical supplies in front of infected people's doorsteps to ensure their well-being. While taking along groceries for neighbors, friends, and family already takes place in practice, coordinated efforts via public CL platforms could benefit local stakeholders.

Yet, taking into account the results from the analysis of CL on a systems level, it must be noted that alternative distribution concepts, such as CL systems, may come with disadvantages and difficulties for local communities. The identified potential fallacies and negative side effects (Cramer and Fikar, 2025a) clearly highlight that a discussion beyond economic and customer service aspects is important when evaluating the sustainability of alternative distribution concepts. For instance, the analyses indicate that user control mechanisms like surge pricing and tipping could wear out the user pool in the long term and may lead to adaptive user behavior that circumvents managerial efforts. They also illustrate that CL also has the potential to cause or exacerbate social segregation on both the customers' as well as the couriers' sides. Several identified loop structures illustrate that CL delivery systems involve a number of mechanisms that can cause rebound effects. For example, increasing the number of OCs to facilitate fast deliveries may cause increased traffic, thereby increasing delivery delays. Increasing the share of dedicated delivery trips may increase the number of available OCs but also lead to an increase in resource consumption as drivers no longer take parcels along the way but instead drive dedicated routes.

In line with previous works (Carbone et al., 2017; Devari et al., 2017; Li et al., 2019; Pourrahmani and Jaller, 2021; Qi et al., 2018; Wang and Yuen, 2023), the paper (Cramer and Fikar, 2025a) highlights the importance of understanding that CL delivery systems are wicked systems and thus require a holistic perspective, considering not only economic but also environmental and societal aspects. Therefore, the scope and design of CL initiatives, as well as the required integration with LSPs, need careful consideration. The presented CLDs can inform fellow researchers for future research and modeling of CL delivery systems in this regard. While CL was used as an example to illustrate the complexity of sustainably improving retail access, this complexity extends to all distribution concepts. Therefore, this thesis highlights the need for holistic approaches when considering the sustainability of distribution concepts. The introduced casual loop diagrams provide an easy-to-understand visual decision support that can guide decision-makers- and policymakers in this process.

The results and analyses presented as part of this dissertation further illustrate several pathways for future research. With research on mobile retail still in its infancy, the work shows that further research, particularly from an operational perspective, is necessary. From an operations research perspective, further development of optimization methods for routing, scheduling, inventory management, assortment and shelf space management, and location choice is necessary. For example, in light of the presented findings, further research is necessary to determine when products should be moved from mobile shelves to stationary ones and vice versa. Furthermore, given the many possibilities to choose store size and design, further research needs to investigate trade-offs between store size and configuration and its ties to costs and emissions.

When moving to CL, the dissertation clearly highlights that future research efforts need to consider CL from a holistic perspective. This includes further elaboration on how CL affects its users and the environment and what managing strategies can increase its sustainability. Thus, one primary concern that needs to be addressed to enable a transition to sustainable implementations is the trade-offs between optimization and effectiveness.

Beyond this focus, further research should also address contextual challenges for CL, such as the impact of an aging population or a decreasing number of driver's license holders. Future works can also investigate how the adoption of CL can be facilitated and how competition affects the user pools in the long term.

On a more general level, the dissertation highlights the need for more holistic perspectives and DSS to guide research, assist managers, and empower policymakers. While the thesis underscores the need for further research, it also highlights the potential of alternative distribution concepts to improve sustainability, presenting them as an exciting opportunity for scholars in operations and supply chain management.

5 Concluding remarks

The aim of this thesis is to contribute to a better understanding of how alternative retail distribution channels can facilitate market (MSMEs) and product (customers) access. Focusing on CL and mobile retail, the dissertation considers how CL can influence market access and how mobile stores may shape the product diffusion process. Additionally, the thesis contemplates the implications of integrating these two perspectives into a systems perspective, thereby considering alternative distribution channels as dynamic and complex systems.

Through the development of model-driven DSS and the analysis of various scenarios, the thesis addresses the required scope of CL delivery systems and the potential of mobile retail to facilitate product diffusion. The analysis of the proposed scenarios indicates that both concepts can serve as viable alternatives to traditional retail stores. It also shows, however, that a holistic understanding of distribution channels is necessary to better understand unanticipated side effects, such as negative externalities. As the discussion in the previous section highlights, different questions related to retail access (e.g., whether to facilitate product adoption or general availability) can require different solutions. It also shows that spatiotemporal aspects can play a major role when addressing these questions. Depending on the geographical and infrastructural setting, the respective scale and scope of operations may vary significantly. This illustrates an important point: There are no one-size-fits-all solutions when considering how to improve retail access for both the customers and the MSMEs. Individual distribution channels may even work best when combined with other distribution channels into synergetic, complementary systems. Needless to say, such hybrid systems also increase complexity, making understanding how to manage them sustainably even harder.

Therefore, this thesis emphasizes that understanding retail distribution channels from a holistic perspective is key to acting sustainably. It takes a step forward toward a better systemic understanding of alternative retail distribution channels. Furthermore, this work is among the first to examine CL from a holistic perspective, illustrating how CL delivery systems can be viewed as wicked systems. The presented CLDs expose the complexity of sustainably managing alternative distribution channels, such as CL. Thus, the thesis highlights the need for holistic perspectives when considering how alternative distribution channels can address potential issues with retail access. The methodological framework developed, the scoping systems thinking review, offers an innovative and useful tool to examine dynamic dependencies and system relationships. While further empirical research is needed to substantiate the results and insights presented in this thesis, the decision support developed, in the form of scenario analyses and causal loop diagrams, provides a foundation for more sustainable real-world implementations.

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Part 3

Scientific articles

1 Article 1

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Investigating crowd logistics platform operations for local food distribution

Purpose: Short food supply chains have the potential to facilitate the transition to more sustainable food systems. Related distribution processes, however, can be challenging for smallholder and family farmers. To extend the market reach of farmers without the need for extensive investments, crowd logistics can be used. The purpose of this paper is to explore the benefits and trade-offs of implementing crowd logistics platforms in short food supply chains.

Design/Methodology/Approach: A decision support system based on agent-based and discrete event simulation modelling is developed, which closely approximates the behaviour of customers and distribution processes at outlets. Different scenarios are explored to evaluate the potential of crowd logistics in rural and urban settings using the example of regions from Bavaria, Germany.

Findings: Results show that crowd logistics can be used to increase the reach of farmers in short food supply chains at the cost of minor food quality losses. Moreover, a difference between urban and rural settings is noted: An urban scenario requires less investment in the driver base, whereas the rural scenario shows a higher potential to increase market reach.

Originality/value: Platform-based food delivery services are still mostly unexplored in the context of short food supply chains. This research shows that platform services such as crowd logistics can be used to support local agriculture and facilitate the distribution of perishable food items. By introducing a simulation-based decision support system and providing detailed results on various application settings, this research serves as a stepping stone to facilitate successful real-world implementations and encourage further research.

Keywords: Short Food Supply Chains; Alternative Food Networks; Agri-food Chains; Crowd Logistics; Platform Services; Decision Support System; Hybrid Simulation Modelling.

1. Introduction

The topic of sustainable and healthy food has become more important to consumers in the past decade (van Loo *et al.*, 2017; Lusk and McCluskey, 2018). Consumers show an increasing preference for locally sourced food (Winterstein and Habisch, 2021). One aspect that has facilitated the growing interest and put policymakers and companies under pressure to adopt more environmentally sustainable logistics processes is an increase in food supply chain transparency (Berti and Mulligan, 2016).

Modern food supply chains often span over multiple countries and involve distant production to provide consumers with a year-round supply of their preferred diet selection (Macfadyen *et al.*, 2015; Davis *et al.*, 2021). Longer travel distances are linked to increased food kilometres and transport time, thus, a higher level of greenhouse gas emissions and food waste (Duram and Oberholtzer, 2010). Consequently, food retailers are adapting to changing demand for locally sourced food by offering an increasing selection of local produce (Printezis and Grebitus, 2018; Enthoven and van den Broeck, 2021). Due to the lack of a formal definition of what exactly 'local' food is, there is a discrepancy between customer expectation and advertised regionality of fresh produce with frequently used definitions spanning distances from 10 up to 100 miles (Feldmann and Hamm, 2015). Furthermore, the definition of food regionality also depends on the infrastructure and size of a country (Duram and Oberholtzer, 2010). In some cases, the distance may even span up to several hundred miles (Paciarotti and Torregiani, 2021). Even though some retail outlets sell produce from smallholders and medium-sized local producers, the complexity and design of retail supply chains do not always allow to provide consumers with food from the nearest source (Bosona and Gebresenbet, 2011). Hence, smallholder farmers have to organise transportation themselves and are often confined to alternative sales channels such as farmers' markets, farm shops or speciality shops (Garner and Ayala, 2018; Paciarotti and Torregiani, 2021). While these outlets allow small farmers to increase profit and reach, they are often limited due to their location. Modern consumers, however, prefer a convenient shopping experience with a limited willingness to travel long distances for grocery shopping (Grunert and Ramus, 2005; Huang and Oppewal, 2006; Hagberg and Holmberg, 2017).

The concept of crowd logistics (CL), i.e., employing information and communication technology (ICT) platforms to utilise spare logistics capacity, such as the transportation capacity of non-professionals (Carbone *et al.*, 2017), can be used instead to integrate online deliveries into those trips that already take place. Participating drivers can be called occasional drivers (ODs) or crowd shippers (Gatta *et al.*, 2019; Punel *et al.*, 2018). Thus, costs can be saved by employing ODs and using underutilised transportation resources. At the same time, the market reach can be extended. However, this may come at the expense of non-cooled transportation. Privately owned vehicles usually lack sufficient cooling equipment for fresh produce,and, thus, their usage can lead to an increased loss in food quality. Furthermore, the effects are limited due to consumers' limited willingness to make lengthy detours for deliveries (Marcucci *et al.*, 2017).

Other ways to increase this reach and accessibility are home deliveries and shipments to specified reception points (González-Feliu *et al.*, 2012). Various initiatives already integrate online-to-offline shopping processes for locally sourced food with the farmers' market concept (e.g., see Food Assembly (2021*a*); NETs.werk (2021)). Nevertheless, even with the addition of new pickup locations and more flexible opening hours, there are still limitations due to the lack of consumers' willingness to make lengthy trips to purchase food. Moreover, initiatives and companies that are working on these concepts often use their own new locations for outlets, requiring additional investment in infrastructure.

The historically grown locations and opening times of retail outlets, such as farmers' markets and farm shops, within the short food supply chain (SFSC) and the temperature-dependent perishability of food products present additional challenges for implementing CL platforms. To investigate the effects of CL platform activities on SFSC operations, this work builds on a simulation-based decision support system (DSS). This paper evaluates the feasibility of using CL to increase the market reach of micro, small and medium-sized enterprises (MSMEs) and to provide customers with locally sourced food while considering trade-offs related to food quality and vehicle kilometres travelled. The contribution of this paper thus is twofold: (i) It examines food quality and travel-related trade-offs when using CL to increase farmers' reach, and (ii) provides managerial insights for various scenarios based on an online-to-offline CL platform for local produce. In this way, the work also discusses whether respective policy interventions to facilitate the use of CL in SFSCs are advisable.

The remainder of this paper is structured as follows: Section 2 contains a review of related literature and contributions in the areas of SFSC and CL. The research design used in this paper is introduced in Section 3. Section 4 contains a description of the DSS parametrisation, while Section 5 discusses the results of the computational experiments. The paper closes with concluding remarks and identified topics for future research in Section 6.

2. Related Work

In a recent literature review on SFSC logistics, Paciarotti and Torregiani (2021) identify food supply chain structure, locally available structures, vehicle load factors, vehicle type, consumers' trips, and vehicle routes as main parameters affecting SFSCs sustainability. Moreover, the authors note that platform-based food delivery services are still mostly unexplored in the context of SFSC. Furthermore, last-mile transportation for perishable produce in SFSC often lacks in efficiency (Melkonyan *et al.*, 2020). At the same time, the demand for fresh produce, such as fresh fruits and vegetables, is growing due to changes in consumers' dietary needs (Reynolds *et al.*, 2014). Additionally, Enjolras and Aubert (2018) found that while selling through SFSC channels leads to increased social sustainability, it is also associated with lower economic sustainability for farmers.

Direct-to-consumer sales are primarily relevant for MSME agri-food businesses, positively impacting ones located near densely populated areas (Capt and Wavresky, 2014). If such businesses focus solely on direct-to-consumer sales, they can earn significantly less than those pursuing other marketing strategies (Park *et al.*, 2014), potentially limiting the attractiveness of SFSCs from a producer's perspective. At the same time, rural areas suffer from an increasing withdrawal of retail outlets (Nilsson, 2022). Modern retail chains' replacement of traditional retail outlets further exacerbates this problem, which can lead to increased poverty in rural communities (Vermeulen *et al.*, 2008). Facilitating a stronger link between producers and consumers could alleviate some of these problems by increasing food security (i.e., access to fresh food) and providing additional sales channels for MSME agri-food businesses. One possibility to increase this link can be the integration of CL into SFSCs.

CL is an ICT based business model that can potentially alleviate efficiency issues in first- and last-mile logistics (Wang *et al.*, 2016). Past research on the use of CL in food supply chains has mainly focused on on-demand food delivery services (e.g., Fikar *et al.* (2018); Liu *et al.* (2019); Tu *et al.* (2020); Seghezzi and Mangiaracina (2021)), while only a few papers such as Melkonyan *et al.* (2020) and Mittal *et al.* (2021) have explored other food supply chain related distribution.

Melkonyan *et al.* (2020) introduce a toolset to explore the sustainability of last-mile logistics and distribution strategies. In their research, the authors consider both the use of traditional logistics service providers and CL by the example of the Austrian alternative food network NETs.werk. System dynamics simulation and multi-criteria decision analysis are used to evaluate different scenarios. While the paper explores the financial and environmental impacts of CL in an SFSC, the effects on shelf life deterioration or the spatial distribution of the supply chain are, in contrast to this work, not considered. Furthermore, the authors do not consider individual actors' behaviour. However, it is suggested to apply agent-based simulation (ABS) modelling for further research in this area.

The benefits of integrating ABS are shown in Mittal *et al.* (2021). The authors use ABS to model the process of rescuing surplus food from restaurants. The developed model contains restaurant and OD agents, which evaluate their willingness to participate based on utility values. Furthermore, based on survey data, Mittal *et al.* (2021) develop different personas, i.e., consumer archetypes, for the modelling of the OD agents. Their results show that network effects can be crucial to maintain OD and restaurant participation. However, the authors also identify tipping points at the height of OD and restaurant participation, which lead to a system crash. Consequently, close monitoring of participation levels in such systems is advisable.

In regard to the use of shared resources and planning capabilities, Fikar and Leithner (2021) explore collaboration in SFSCs. The authors develop a DSS based on discrete event simulation (DES) modelling, which integrates an adaptive large neighbourhood search metaheuristic to examine the effects of logistics collaboration on SFSC efficiency. According to their findings, collaboration in SFSC can result in a reduction of vehicle kilometres travelled and the number of required transport vehicles. At the same time, they find that collaboration can lead to an increased loss in food quality.

All these papers highlight the great strength of using simulation modelling to investigate SFSCs operations. Particularly, hybrid simulation modelling, i.e., the combination of multiple simulation techniques, can be used to create DSSs which facilitate real-world decision-making processes (Brailsford *et al.*, 2019). The review by Utomo *et al.* (2018) further shows that ABS is quite frequently used for the modelling of agri-food supply chains. However, the review reveals that most papers consider one echelon supply chains, simulating either production planning or investment decisions. In this paper, ABS is combined with DES modelling into a hybrid simulation model. Furthermore, the investigated aspects in this paper are linked to transportation and include sustainability-related aspects such as transportation distance and food quality deterioration. The resulting model is used to propose a DSS to evaluate the use of CL platforms in SFSCs as an alternative to traditional food distribution.

3. Methodology

The DSS presented in this paper was developed to support decision-makers in agri-food supply chains and to investigate the feasibility of CL when exploring alternative ways for the physical distribution of food. More specifically, the system analyses the introduction of an online platform to facilitate CL concepts and evaluates the viability of such concepts in SFSCs. To enable this, the DSS builds upon a hybrid simulation model at its core, which combines elements from DES and ABS, of which the former is used to model distribution processes, whereas the latter models agent behaviour. Business process model notation (BPMN) was used in the first step to structure the problem setting. Based on this representation, the individual agent classes, process flows and transitions were generated. The subsequent part describes the specifics of the developed DSS.

3.1. *Simulation Design*

As shown in Figure 1, the DSS developed in this work uses the following agent classes: simulated regions, populated areas, households, inhabitants, outlets, baskets and ICT platform. The individual agent classes are described in the subsequent subsections.

3.1.1. *Simulated Region*

The agent class 'Simulation Region' models the specifics, e.g., network locations and infrastructure, of the considered study region. Each model region in the simulation comprises population areas and outlets, each with unique geospatial locations. Population areas further contain households, each accommodating a stochastically assigned number of inhabitants. The simulated region comprises a road network generated automatically from OpenStreetMap, based on the selected area. This enables an approximation to real-world calculation of travel durations and further provides the user flexibility to run the DSS in varying study regions. The road network contains a weighted, directed graph with roads as arcs and junctions as vertices. The underlying specifics of traffic and infrastructure are emulated by measuring travel distance within the network in duration rather than length.

3.1.2. *Populated Areas*

Populated areas, i.e., cities or towns, are located on vertices embedded in the road network of the simulated region with specific latitudes and longitudes. Each area contains a number of households that are allocated to it, based on the European Commission (2018) GEOSTAT $1km^2$ population grid. Consequently, highly populated areas within the study regions generate more movement and higher demand than ones with a lower population.

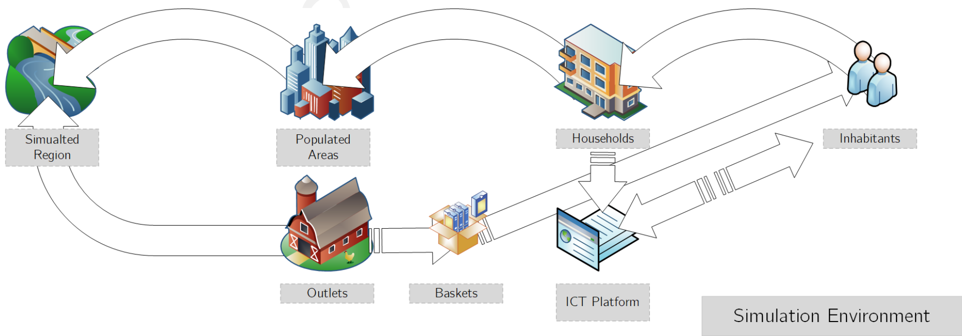


Fig. 1: Agent structure of the simulation environment

3.1.3. *Outlets*

Outlets are locations within the study region where regional food is sold. They have individual schedules and locations. Locations are based on real-world ones of corresponding outlets in the model regions. The number of customers per outlet is determined by the geospatial location of the outlet and the travelling distance of neighbouring households. Opening times may vary in regard to opening days and hours. The outlets' attractiveness to households, therefore not only depends on spatial but also on temporal availability. Arriving customers at outlets are processed sequentially in order of arrival through elements of DES. It is assumed that outlets always have sufficient supply to fulfil all incoming customer requests. The top part of Figure 2 summarises how the processes at outlets interlink with inhabitant and household processes. After initialising the outlet schedule, the outlet opens at the specified opening times and serves arriving customers until no more business hours remain within the simulated time frame.

3.1.4. *Households*

Households are aggregate units of inhabitants, representing families, living communities and single households. The demand and preferences are determined on the household level, whereas the shopping process is located in the inhabitant agents. All characteristics of households, which are located within populated areas, are defined stochastically to enable a heterogeneous representation of real-world processes. The preference for local food of each household is based on the parameter 'preference for regional food'. The preference is evaluated in the form of a Bernoulli distribution on household level. Thus, households that do not prefer local food do not plan any shopping trips to direct marketing outlets. However, inhabitants of such households may still participate as ODs. The household's grocery ordering cycle is depicted in Figure 2. To determine the distance a household is willing to travel to an outlet, a custom distribution based on data provided by members of Food Assembly (2021*b*) is used. Thus, every household has a different maximum distance. This distance is then used to allocate the closest outlet as the preferred shopping outlet. In case there is no outlet within the specified reach, the household can only place orders online. When a household is in a state of requiring grocery shopping, it is checked whether there is a preference for online deliveries. Households may have a preference to shop online, which can be set by defining a parameter called delivery preference. Online orders are managed and processed by a central ICT CL platform which is described in Subsection 3.1.7. When the household does not prefer online deliveries over offline shopping, the household's inhabitants are tasked to schedule a shopping trip to a nearby outlet. If there are markets available within the determined maximum travel distance limit, the inhabitant consults his or her schedule to check whether there is a chance to visit a nearby outlet by checking opening times and available free time slots in his or her schedule. If there is no time slot available or no outlet in the vicinity, the inhabitants notify the household of their unavailability. Otherwise, if the inhabitant can schedule a shopping activity at an outlet, the activity is added to the schedule. As soon as it is time to go shopping, the inhabitant enters the activity cycle for shopping at an outlet. The shopping activity may either be a dedicated shopping trip or a detour to an already scheduled trip. If no inhabitant is able to schedule a shopping activity, the household places an online order.

3.1.5. *Inhabitants*

Each inhabitant represents a single person within the chosen model region. Each inhabitant is allocated to exactly one household. The inhabitants are responsible for executing the shopping process, while the demand and preferences handling are controlled on a household level. ABS is used to model the inhabitant's behaviour through the integration of state charts and events for specific routines. After initialising and evaluating consumer metrics such as employment conditions or willingness to travel to outlets, the inhabitant starts a sequence of activities that is determined by an individual schedule. The bottom part of Figure 2 depicts the processes connected to the inhabitant's scheduling process. Each inhabitant agent has a unique schedule that includes work days and work hours, spare time, and grocery shopping activities. Agents may be employed part-time (up to 30h/week), full-time (40-45h/week), or they may be unemployed. Furthermore, inhabitants can have access to their own means of transportation by accessing the household's resources. Inhabitant activities are processed sequentially. The inhabitant starts at his or her home location and consults the schedule to determine the next activity and its starting point. Upon passing the starting point, the inhabitant performs the activity until the scheduled activity ends. The end of the activity is either determined by the scheduled duration or the passing of a sequence of sub-activities. Activities can involve travelling to a specific location or performing an action such as performing a delivery or working at the current agent location.

3.1.6. *Baskets*

Baskets represent combinations of different perishable products sold at outlets. Upon service, the customer is handed a basket whose perishability properties are determined stochastically at the time of basket creation, thus creating baskets with varying food quality parameters. It is assumed that the basket's contents are at the maximum quality level when loaded for delivery at the outlets. After pick-up by an inhabitant, the quality level is reduced continuously, hence, deterioration continues until the basket is delivered and accepted by the household. Upon arrival at the household, the delivery is evaluated regarding quality conditions and transportation metrics (quality loss during transportation, travel distance, etc.). To model food quality loss, this paper solely focuses on shelf-life requirements for customers and sellers as one of the major aspects of food quality as described by Luning and Marcelis (2020). To this end, the keeping quality model by Tijskens and Polderdijk (1996) was adopted. The keeping quality model allows for a simplified portrayal of product acceptance by integrating acceptance limit and intrinsic properties into a single index. Food quality aspects related to sensory desires, convenience conditions, safety prerequisites, health requirements and authenticity concerns are not included in the model. According to this model, food quality depends on storage temperature and storage length. For the computational experiments in this work, it was assumed that all vehicles have air conditioning set to a temperature of 20°C. The quality estimation was implemented with the help of temperature logs for every basket, which recorded the duration and temperature for each leg of the delivery.

3.1.7. *ICT Platform*

The ICT platform collects all submitted online orders. All orders are assigned on a first come, first served basis. ODs choice of deliveries is based on a greedy approach, picking the delivery with the shortest detour first. Potential routes of ODs are calculated based on a dynamic pickup and delivery problem with outlet opening time windows, solved by employing a heuristic matching algorithm: ODs first check whether their (remaining) routes already include an outlet from which they can pick up a basket for delivery, if not, they check whether there are outlets close to the original route and whether the order destination could be reached within

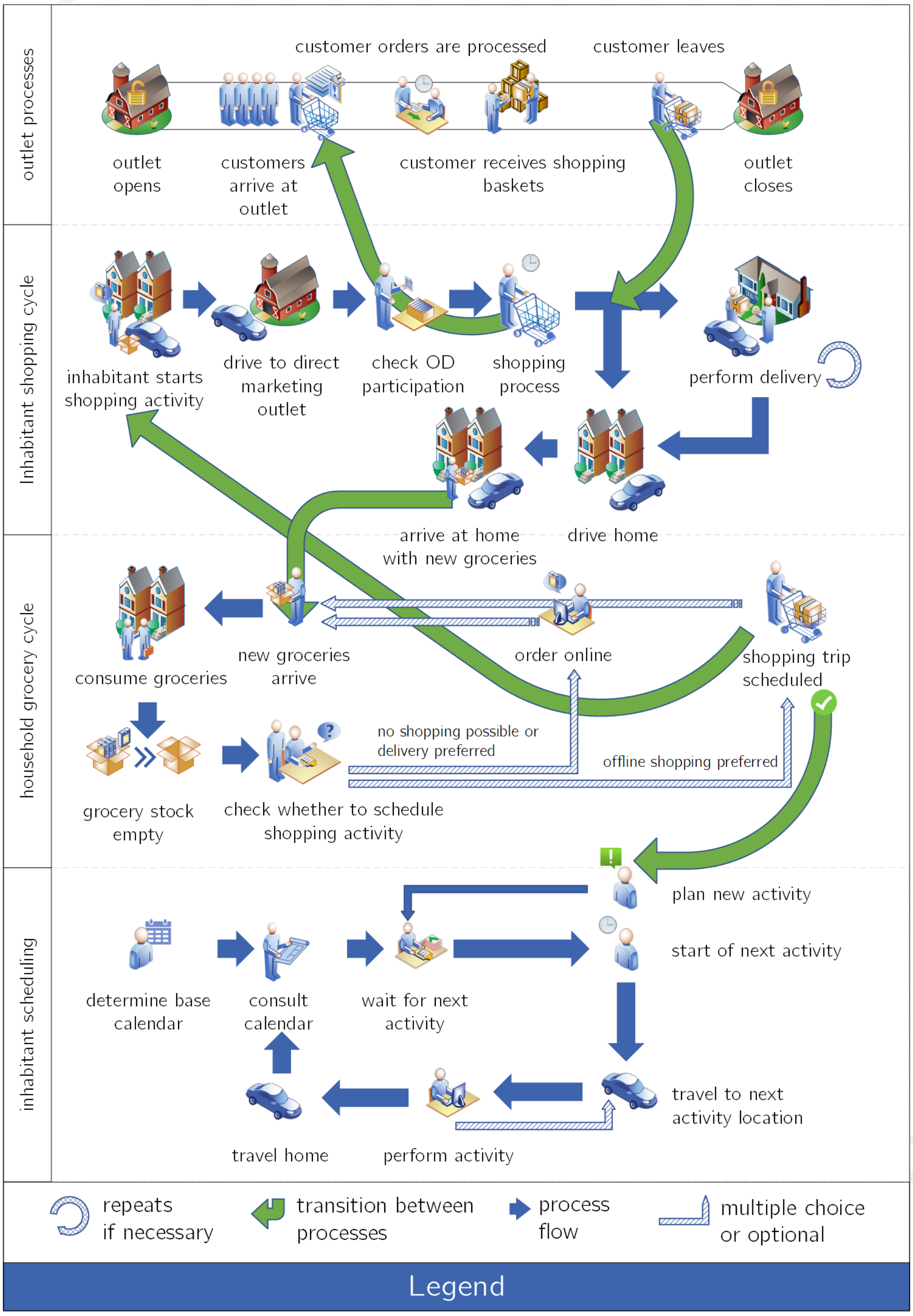


Fig. 2: Interlinked processes at direct marketing outlets, households and inhabitants

their current detour limit. CL orders can be accepted by ODs as long as the OD is not currently travelling. Thus, new deliveries can be accepted every time before heading to a new location. Each shopping basket is delivered to the doorstep of the recipient household. If no inhabitants are at home at the time of delivery, the basket continues to deteriorate until picked up by one of the household inhabitants, resulting in additional food quality loss.

3.2. *Scenario Design*

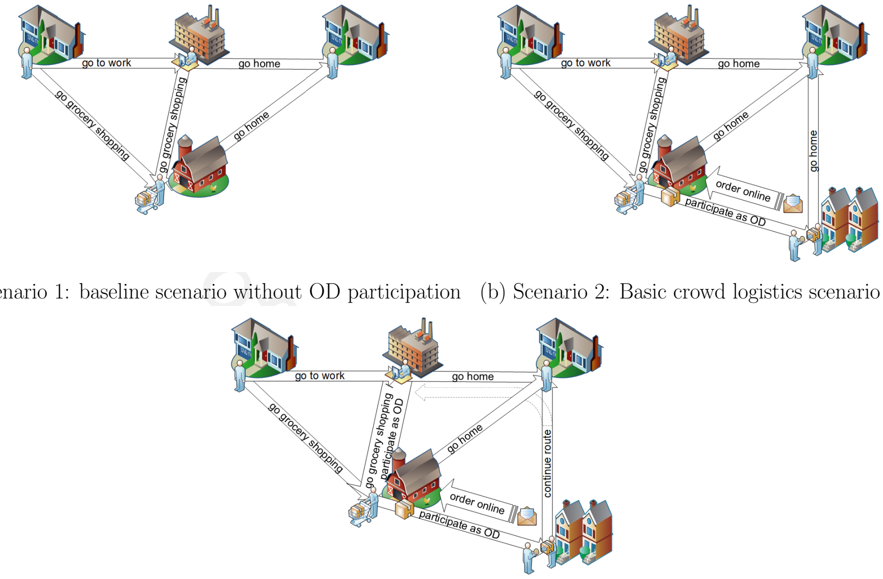
As simulated regions, two areas in Bavaria, Germany, were chosen. As for the time parameter, a two-week period in June was selected due to the broad availability of locally produced fresh food during that period. Upper Franconia was picked as a model region for a rural setting and Munich municipality for an urban one. Demographical data from Upper Franconia and Munich municipality, such as population structure, employment rates, and available data on local alternative food outlets, like farmer's markets and farm shops, was used to approximate a realistic setting for the scenarios.

Simulation population size was calculated based upon the estimated current population living in the model regions (according to the EC (2018) GEOSTAT $1km^2$ population grid) and the average household size (according to LfS (2021)). Areas and their population size were calculated by combining the GEOSTAT data and geospatial data with QGIS (version 3.24). For the computational experiments, the used population size was reduced to reflect that not every single inhabitant has an interest in shopping for locally sourced food. For the shopping outlets, a total of 214 outlets (83 rural / 131 urban) were identified based on data from local authorities, communal websites , and OpenStreetMap data retrieved via the Overpass API.

Figure 3 shows the different scenarios explored in this paper. In total, three scenarios were developed: (3a) a baseline scenario without any OD participation, (3b) a simple crowd logistics scenario, where only shoppers may participate as ODs, and (3c) an advanced crowd logistics scenario, in which shoppers and non-shoppers may participate as ODs. The scenarios are described in detail in the subsequent paragraphs.

Scenario 1: Baseline scenario for alternative food networks

For the baseline scenario (Scenario 1), the status quo of direct marketing outlet processes is assumed as follows: Farmers' markets are held at specified locations and at a specified time interval. Farm stores are opened several time slots per week at fixed locations. For the scenarios, at least a weekly participation was assumed, as outlets that are organised less than weekly are less likely to provide a viable alternative for consumers to replenish their food supplies (La Trobe, 2001). During the opening days, the outlet is open for a specified period in which local producers



(a) Scenario 1: baseline scenario without OD participation (b) Scenario 2: Basic crowd logistics scenario

(c) Scenario 3: Advanced crowd logistics scenario

Fig. 3: Three scenarios were developed for the simulation

may offer their products for sale. No CL platform activities, i.e., no online orders, are possible in this setting.

Scenario 2: Alternative food networks with simple crowd logistics implementation

The second scenario is extending the baseline scenario by adding basic CL activities through the integration of an ICT platform. In this scenario, inhabitants that visit shopping outlets (shoppers) may transport baskets to other households as long as the detour does not exceed the ODs detour willingness threshold. Hence, for Scenario 2, potential ODs can accept deliveries during their visit to an outlet. Inhabitants from households that only shop online are not considered as potential ODs. The values for the detour willingness threshold are based on finding by Le *et al.* (2019) and Le and Ukkusuri (2019). The additional parameter, participation willingness, represents the willingness to consider participation as OD in percent of the total population. The parameter is implemented as a global value that is evaluated in form of a Bernoulli distribution on the inhabitant agent level. In contrast to the baseline scenario, households now have a choice to place online orders when there are no outlets available in their vicinity at the time of demand when there is no time to drive to an outlet during opening hours, or by generally preferring deliveries over collections.

Scenario 3: Alternative food networks with advanced crowd logistics implementation

Scenario 3 complements the CL delivery process by also allowing non-shoppers to participate as ODs, either before or after a scheduled activity. Consequently, Scenario 3 represents a fully-fledged CL scenario. Inhabitants are able to accept delivery requests at any time as long as they are not currently travelling to a new location.

4. Computational Experiments

The DSS was developed with AnyLogic version 8.7.12 with each scenario explored in an urban and a rural setting. For each simulation run and parameter setting, 100 replications were calculated. The detailed results for each setting and replication are available for further investigation at [REDACTED FOR REVIEW]. In total, four test cases (T1, T2, T3, and T4) were developed. Table 1 gives an overview of parameter settings and varied parameters. For each test case, all three CL scenarios (Scenario 1, 2 and 3) and population settings (urban and rural) are explored. The choice of parameter settings for the test cases is motivated by scientific literature:

The number of participants within a CL delivery system is of vital importance for these systems (Arslan *et al.*, 2019). The willingness to participate reflects varying incentivisation of the population and the respective number of available ODs (Fessler *et al.*, 2022). The preference for local produce was included to reflect customers' increasing consideration of regionality as buying criterion, as highlighted by Winterstein and Habisch (2021). Their research further highlights a difference in behaviour between urban and rural inhabitants, which is reflected in the experiments via the population setting. Furthermore, research by Hagberg and Holmberg (2017) shows that a growing number of customers order groceries online. Therefore, the test cases also consider a changing propensity to order online. The review by Kelly *et al.* (2011) illustrates that local produce is also offered via vending machines. The parameter concerning opening times reflects the possibility of installing vending machines or parcel lockers at market locations, thus enabling local produce's all-day availability. Accordingly, the variable parameters for the experiments include the propensity to participate as an OD (participation willingness), the preference for deliveries over outlet visits (delivery preference), the preference for local food, i.e., food from SFSCs, and the opening times of outlets.

A number of agent parameters are assigned stochastically: Employment is based upon official data on employment rates in Germany by BfA (2021), the maximum travel distance to an outlet is determined based on findings on the average willingness to travel to a direct marketing outlet gained by analysing data provided by Food Assembly (2021*b*). Grocery shopping demand is determined based on the average German consumer's shopping frequency by VuMA (2022). Furthermore, car ownership for each household is determined stochastically based on statistics on German's average car ownership by VuMA (2022).

The base value for the preference for local food was set to 38,76%, which ac-

Table 1: Parameter settings for the computational experiments

Test Case	T1	T2	T3	T4
Participation Willingness	0.0, ... , 1.0 in 0.01 steps	0.0, ... , 1.0 in 0.1 steps	0.0, ... , 1.0 in 0.1 steps	0.0, ... , 1.0 in 0.01 steps
Delivery Preference	0.027	0.027, ... , 0,277 in 0.005 steps	0.027	0.027
Preference for Local Food	0.3876	0.3876	0.4, ... , 1.0 in 0.1 steps	0.3876
Outlet Opening Times	regular	regular	regular	always open

cording to a representative study by IfD (2021) was the national average of people (aged 14 and above) that preferred local food in 2021 in Germany. Due to a lack of more detailed data for the study region and the differentiation between urban and rural populations, this national average was used to approximate the preference. As for the delivery preference, a base value of 2,7% was chosen, which according to HDE (2022) corresponds to the share of food sold online 2021 in Germany.

Both population settings, i.e., urban and rural, were explored for all test cases. In test setting T1, the willingness to participate as an OD is varied from 1% to 100% in 1% increments. According to HDE (2022), online food sales increased by 0.7% in 2021 and 0.6% in 2020. It was chosen to project similar growth for 50 years. Thus, for T2, the participation willingness increment is increased to 10%, while delivery preference is varied from 2.7% to 27.7% in 0.5% increments. In the third test setting, T3, the preference for local food is varied from 40% to 100% in 10% increments. The last test setting, T4, is a variation of T1 in which all outlets are set to be open 24 hours per day, seven days per week.

5. Results and Discussion

The computational experiments in this work explore the effects of an increasing participation willingness in different population and scenario settings. Moreover, the effect of rising levels of a preference for deliveries over collections and the preference for regional food on these effects are considered.

5.1. *Impact of increasing levels of participation willingness*

In this subsection, the general effects of increasing levels of participation willingness in the CL scenarios in an urban and a rural population setting are explored. Participation willingness refers to the share of the total population in the observed area that would consider participating as an OD, not the actual share of participants.

Market reach

In general, the increase in participation willingness does not lead to a proportionate increase in ODs. The scenario setting only slightly affects the number of ODs. In the urban setting, the amount of participants is slightly higher for Scenario 3. In the rural setting, Scenario 3 exhibits some competition effects, through which at some point the amount of participants rises slower than in Scenario 2, resulting in an overall lower share of participants than in Scenario 2.

When comparing the increase in the share of customers that can be reached with CL, the rural setting shows much more promise. Figure 4 illustrates that the number of households that can be served only slightly increases in the urban setting for both scenarios. Within the first 10%, there is a sudden rise in served households which then flattens, thereafter showing strongly diminished effectiveness of increasing participation willingness. The rural setting on the other side not only shows a much higher increase in served customers but also a steadier increase with diminishing effectiveness for participation willingness levels of 50% and higher.

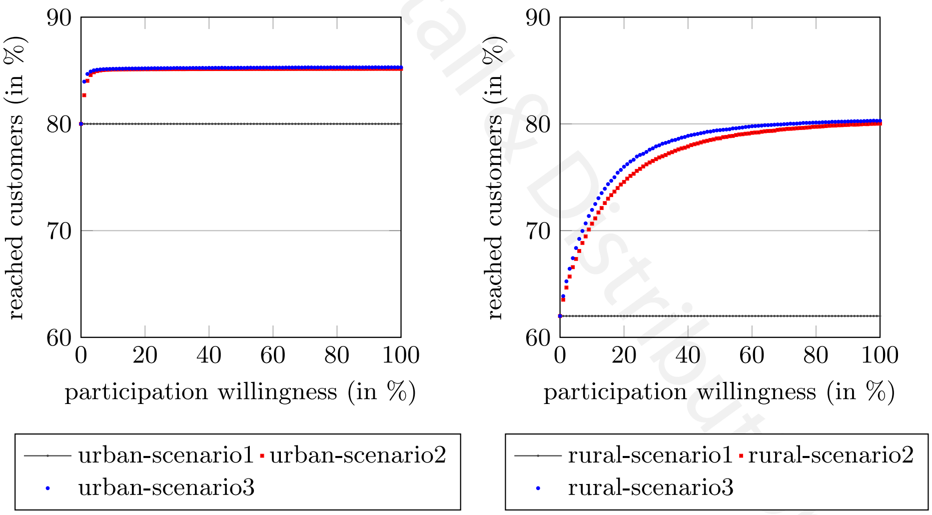


Fig. 4: Change in the amount of potential customers that can be reached with increasing participation willingness compared to Scenario 1

Food quality

Figure 5 illustrates the differences in food quality loss between the urban and the rural setting. For a rural setting, Scenarios 2 and 3 both show a significant but similar increase in food quality loss caused by distribution. In the urban setting, Scenario 2 causes almost double the increase of Scenario 3, while both are less than half of the increase caused in a rural setting. A possible explanation is a comparatively poor infrastructure with longer travel distances in the rural setting. The base level of food quality loss by transportation is relatively low, with a value of less than 1% of total quality in the rural and less than 0.5% in the urban setting.

A comparison of the average increase in total food quality loss shows that Scenario 2 performs better in a rural setting, whereas Scenario 3 performs better in an urban setting. The difference is caused by the longer driving times to outlets in a rural setting and competition effects between potential ODs, which leads to a sub-optimal allocation in Scenario 3 for a rural setting.

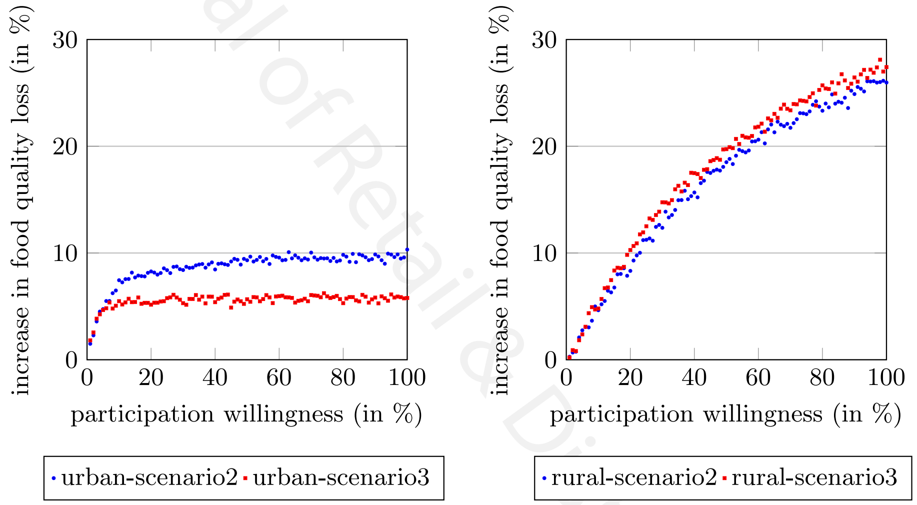


Fig. 5: Increase in the loss of food quality by distribution subject to increasing levels of participation willingness

5.2. *Impact of increasing levels of delivery preference*

For T2, delivery preference is varied to explore its effect on the impact of increasing levels of participation willingness. An increase in delivery preference shows different effects for the rural and the urban population setting. In the urban setting, the number of participants increases for both Scenario 2 and 3. The increase can be attributed to a higher number of potential customers with rising levels of delivery preference and, consequently, lower competition between potential ODs. In contrast, in a rural setting, the number of participants decreases after reaching an optimal level. There is increasing competition in Scenario 2 after about 15% and in Scenario 3 after about 20% of delivery preference. Thus, a higher level of delivery preference ultimately leads to increasing competition between potential ODs in a rural setting. With an increase in orders with rising levels of delivery preference, there is also a rise in orders from undesirable, i.e., inconvenient locations. When the number of potential ODs that can fulfil these inconvenient orders also rises with increasing levels of participation willingness, competition over these orders becomes stronger.

In regard to the share of served customers, it has to be noted that there is an initial drop in the base level of reached customers, which correlates with the increase in delivery preference, caused due to traditional offline shoppers no longer visiting direct marketing outlets. While the base scenario shows a decline in the base level of served customers, the effects of the CL scenarios increase. As highlighted by Figure 6 , the urban setting profits with a slightly higher increase in Scenario 2 and a moderately higher increase in Scenario 3. A similar, however, slightly less pronounced development for the rural setting can be observed in Figure 7. The difference in the impact can be attributed to the fact that in an urban setting, the increase rather originates from an increase in convenience shopping, whereas in the rural setting, there is a higher gap in base supply.

5.3. *Impact of increasing levels of preference for regional food*

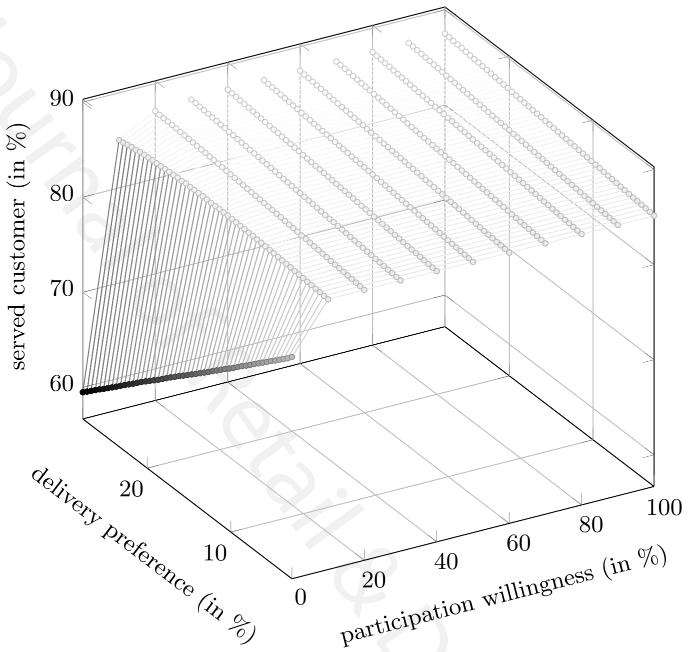
In T3, instead of delivery preference, the preference for local food was varied. However, besides a significant increase in participants, an increasing preference for regional food shows no real impact on the potential of implementing CL platforms.*An increase in the preference for local food only marginally increases the amount of reached customers.

5.4. *Impact of convenient opening times and increasing levels of participation willingness*

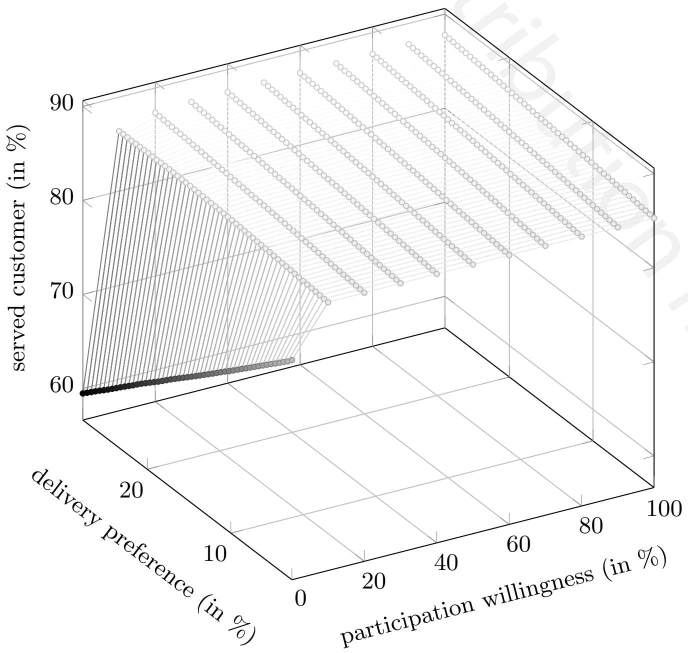
For the exploration of the effect of more convenient outlet opening times, it was assumed that all direct marketing outlets are open 24 hours per day, seven days per week. The change in outlet availability has little impact on participant levels in general, which remained almost unchanged in regard to the change in participation willingness. However, the unlimited opening times lead to a convergence of Scenario 2 and Scenario 3. This convergence is observed for all effects of increasing participant willingness and is caused due to the first come, first served order allocation. Consequently, when opening times are irrelevant, the differentiation between shoppers and non-shoppers no longer makes much of a difference. Comparing Figure 8 with Figure 4 also shows that optimising the outlets' schedules can lead to an increase in the reached customer base compared to the base level.

In the urban setting, the amount of served customers only shows an increase after the initial introduction of ODs and then immediately levels off. As can be witnessed in Figure 8, there is still a significant increase in the rural setting for the first 25%, after which the increase also levels off. Furthermore, the difference between the urban and rural setting in regard to how many customers can be reached now vanishes at high levels of participation willingness.

*For detailed results, the reader is referred to the supplementary material provided in doi: 10.17632/w63fcbf2yd.1.

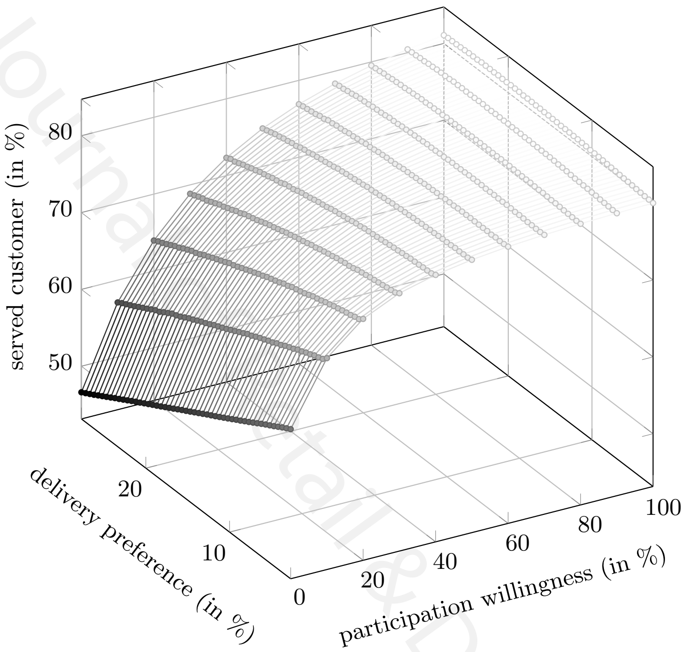


(a) urban scenario 2

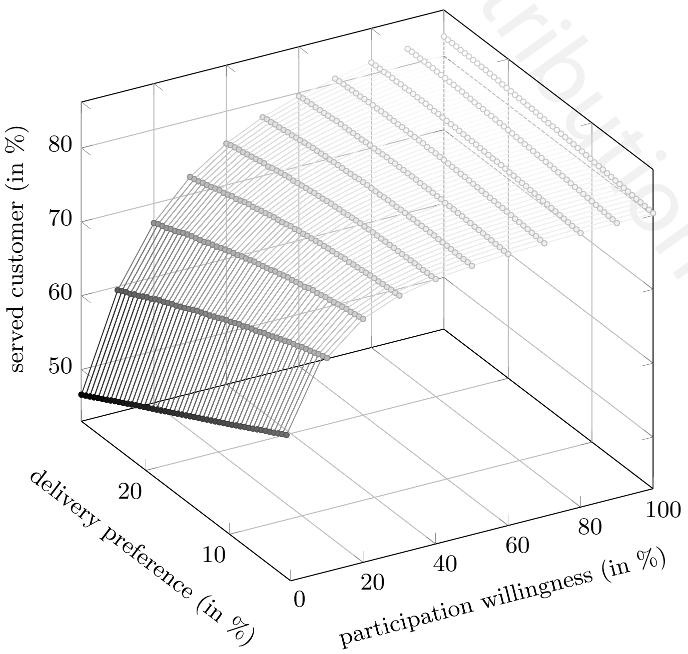


(b) urban scenario 3

Fig. 6: Change in the amount of served customers subject to increasing levels of participation willingness and delivery preference in an urban setting



(a) rural scenario 2



(b) rural scenario 3

Fig. 7: Change in the amount of served customers subject to increasing levels of participation willingness and delivery preference in a rural setting

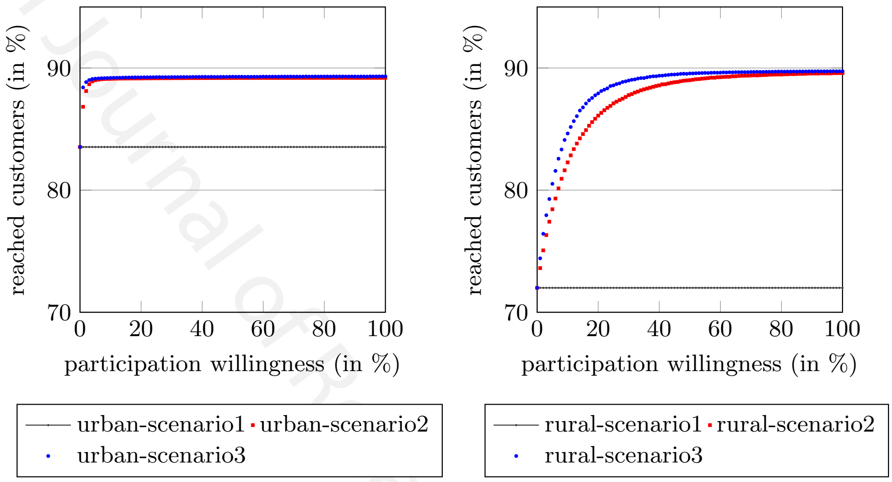


Fig. 8: Change in the amount of potential customers that can be reached with increasing participation willingness for convenient opening times

5.5. *Managerial and policy implications*

The presented case studies highlight several implications of interest to both policymakers and managerial decision-makers. They show that the level of participants does not rise proportionally with an increasing participation willingness, indicating that it is important to identify and target OD profiles that match the underlying properties of the encompassing environment. Thus, the study supports the view advocated by Frehe *et al.* (2017) that a simple mass of random mass does not suffice to facilitate successful implementations of crowd logistics platform business models. Instead, it seems to be more important to reach drivers with favourable attributes, highlighting the need for DSSs to identify key characteristics and success factors in different operating settings.

Consequently, the results suggest, as further noted in Rechavi and Toch (2022), that infrastructural and geospatial properties of the environment should be considered closely. For instance, depending on the infrastructural settings, different driver profiles with regard to trip frequency, trip length, and detour willingness are relevant. From a managerial perspective, this means that incentives for participation should be tailored to driver profiles and infrastructural properties of the environment. From the perspective of policymakers, it shows that subsidising infrastructure, e.g., by providing municipal collection points, should be considered to facilitate real-world implementations of CL platforms in SFSC. Especially in rural areas, retailers increasingly pull out due to a lack of location attractiveness (Nilsson, 2022), leaving back underserved areas. This further exacerbates issues with food access, primarily for deprived households and older adults, which often suffer from limited mobility. CL platforms can be a promising option to counteract this development.

This insight further influences how CL platforms need to be designed. Depending on the region and different driver profiles, the focus of CL platforms may vary between coverage (i.e., food access) and convenience goals. For instance, increasing the preference for deliveries leads to a reduced base coverage for both population settings. However, due to this decrease and the associated increase in potential customers, implementing a CL ICT platform service, especially in an urban setting, becomes more attractive. This indicates that platform attractiveness for urban areas can be promoted with a higher preference for deliveries. Furthermore, while the convenience factor is likely to prevail in urban areas, the research by Devari *et al.* (2017) revealed that social factors should not be omitted.

While this work provides first insights regarding the link between a preference for deliveries and CL platform effectiveness, further research on what attributes are relevant to estimate a good driver fit, depending on the environmental settings, is needed. For instance, it must be noted that the employed modelling of the road network cannot fully reflect urban congestion levels. Therefore, the attractiveness may vary according to rush-hour and off-peak traffic levels.

With a focus on SFSCs, the presented experiments highlight that with an increasing outlet availability, i.e., more convenient opening times, the number of reached customers increases significantly. In a rural scenario, the increase led to a growth of competition between potential ODs with rising levels of participation willingness. The observed competition effects are in line with findings by Chen and Chankov (2017), who also identified the supply-to-demand ratio as a critical factor in this regard. Even with these competition effects, the use of CL platforms shows a great potential to increase market reach for smallholder and family farmers, who often have limited financial capabilities (Paciarotti and Torregiani, 2021) to invest in complex distribution structures. The incurred loss in total food quality is comparatively minor to the potential gain in market reach and, hence, CL platforms can facilitate a better connection between consumers and producers in SFSCs.

This allows for an increase in overall food access, particularly to locally produced food, despite a slight loss in product quality. The increased reach further facilitates the growth of local MSME agri-food businesses, which additionally contributes to the social aspect of sustainability, e.g., by providing job opportunities. Furthermore, the use of CL platform services in SFSCs can particularly raise the availability of locally produced food products for people that do not possess the necessary means of transportation, such as people with deprived backgrounds and older people, generating social benefits for the local population. Thus, it might be interesting for policymakers to consider funding and subsidies for CL initiatives in SFSC that address social issues, such as access to healthy and fresh food as well as the social integration of deprived households and older adults. Consequently, from a policymaker's perspective, it can be more attractive to consider the development of CL platforms for SFSCs in rural settings.

The analysis of the impact of an increasing preference for locally sourced food, however, shows no impact on the CL platform's effectiveness. While from a structural perspective, there is little to no impact on the number of potential ODs, the preference for local food could still be an incentivising factor for OD participation from a behavioural perspective. For instance, Punel *et al.* (2018); Devari *et al.* (2017) and Arslan *et al.* (2019) suggest that environmental and social aspects of sustainability can be motivators for participation as an OD. While the effectiveness of CL concepts in SFSC is unaffected by the population's preference for local food, increasing the preference directly scales the size of the target market. When also introducing more convenient opening times, e.g., by placing parcel lockers for collection near outlets, there is no longer any benefit to considering non-shoppers as potential ODs. Hence, the results support the findings by Dayarian and Savelsbergh (2020) that using in-store customers can be a viable option for performing last-mile deliveries. A focus on shoppers opens the possibility of offering incentives like discounts or coupons when transporting a basket for another customer.

6. Conclusions

In this paper, a DSS to evaluate the feasibility of CL platform services in SFSCs was introduced. To model the DSS, a hybrid simulation approach using elements from DES and ABS was employed. The DSS was used to evaluate the viability of employing CL in SFSCs in different scenarios and population settings. For the computational experiments, the impact of increasing the population's willingness to participate as ODs was explored using the example of two study regions in Bavaria, Germany. Furthermore, the influence of an increasing preference for deliveries over collections and for regional food was analysed.

The performed computational experiments reveal several implications for possible implementation and the viability of CL concepts in SFSCs. While there are trade-offs in the form of an increase in the average travel distance per shopping basket and a loss in food quality by distribution, there are substantial benefits in terms of an increase in sales and the customer base that can be covered. In general, diminishing returns in terms of effectiveness are observed at higher levels of participation willingness. About 10-20% of participation willingness are sufficient in an urban setting, while the rural setting shows strongly diminishing returns for levels of participation willingness from 50% upwards. Consequently, efficient CL systems in SFSC are possible without maximising participation incentivisation. On the contrary, especially when also considering non-shoppers as potential ODs, too high levels of participation can even lead to an increase in competition. In general, the difference between considering shoppers as potential ODs and further including non-shoppers is negligible in many cases. Therefore, for the implementation of CL concepts in SFSC, consumers who already shop at outlets should be primarily targeted as potential ODs.

Additionally, the effectiveness of employing a CL concept in a SFSC highly depends on the underlying infrastructure. Hence, incentives should be tailored to driver profiles, which consider the geospatial and infrastructural properties of the encompassing environment. With the status quo of a relatively low share of online deliveries for food items, the concept is less effective in areas with strong infrastructure, i.e., urban areas, than in less developed ones, i.e., rural areas. However, the effectiveness is highly correlated to increasing levels of preference for deliveries over collections, thus, urban areas are likely to become more attractive for CL in SFSCs in the future should delivery preference continue rising. Furthermore, the average quality loss by distribution, the increase in average basket travels distance, and the overall shopping-related vehicle kilometres travelled are slightly higher than in the urban setting. Nonetheless, to increase the reach of smallholder farmers, CL concepts in SFSCs in a rural setting are preferable.

Various topics for future research originate from this work, including the examination of possible participation incentives, case studies and field trials as well as the analysis of ways to improve benefits and reduce trade-offs for possible implementations of CL concepts in SFSCs. Moreover, concrete conceptualisations for real-world implementations considering the associated complexities for MSME agri-food businesses are also lacking and, thus, require additional exploration. This further includes the development of efficient order allocation optimisation procedures to decrease travel distances and food quality losses further and to increase participation attractiveness of CL implementations in SFSCs. Furthermore, examining the impact of various consumer behaviour in the form of different personas can yield further insights into managerial and policy implications.

Declarations

Conflict of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data Deposition Information

The datasets generated by the simulation model and analysed during the current study are available at the Mendeley Data repository, doi: 10.17632/w63fcbf2yd.1.

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2 Article 2

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Modeling sustainable crowd logistics delivery networks: A scoping systems thinking review

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ABSTRACT

Traditional logistics systems face numerous challenges, such as driver shortages, low load factors, and increasingly high barriers to urban distribution. One concept that can mitigate many of these issues is crowd logistics, i.e., the utilization of unused private transport capacities. Despite the advertised benefits of crowd logistics, such as cost, mileage, and emissions reductions, real-world implementations are rare. Many initiatives have been short-lived, and there is a general lack of integration with traditional logistics service providers. Yet, underlying system behavior and intricate interlinkage of crowd logistics system components remain mostly unexplored. Consequently, this research uses a scoping literature review approach combined with elements from systems thinking to explore the causal dependencies and future research opportunities with respect to crowd logistics system behavior for deliveries. Through the review of scientific literature, causal loop diagrams are developed and analyzed concerning the dynamics and potentially prevalent system archetype structures to facilitate insights into crowd logistics systems. Our work shows that combining a scoping literature review with a systems thinking approach can yield valuable insights into system structures and future research opportunities. We identify critical system interlinkages and dynamics, offering a foundation for future quantitative modeling and decision-making in sustainable operations. Furthermore, the work outlines future research directions, such as novel application areas or further elucidating the effects of control mechanisms.

1. Introduction

Traditional logistics companies suffer from a variety of problems, such as driver shortages (Ji-Hyland and Allen, 2022; Wang et al., 2022), load factor balancing (Ni and Wang, 2021), and urban travel restrictions (Hu et al., 2022b). In addition, while customers may have been willing to wait for deliveries for a few days in the past, nowadays, customer expectations concerning time-to-delivery have become a significant factor in creating customer value (Gawor and Hoberg, 2019; Zhong et al., 2022). At the same time, sustainability issues are gaining increasing importance. Some resulting pressure for companies stems from new policies, e.g., to regulate carbon dioxide emissions of vehicles (Lurkin et al., 2021; Xu and Xu, 2022), or restrictions caused by urban traffic regulations (Holguín-Veras et al., 2020). Moreover, an increasing number of customers is demanding more sustainable operations (Ignat and Chankov, 2020). Due to the resulting growth in the number of dimensions companies compete in, innovative and more efficient delivery methods are becoming crucial (Winkelhaus and Grosse, 2020). Some innovations in this area are technical, such as drones or mobile parcel lockers, while other innovations are based on developing business models. Examples of the latter are the rise of platform services (Jovanovic et al., 2021), the sharing economy (Hamari et al., 2016) and the ecosystem economy (Jacobides, 2019).

With regard to logistics services, the development of platform services has opened new ventures to use dormant transport capacities: The concept of crowd logistics (CL) is advocated to have the potential to leverage underutilized capacity to facilitate more sustainable (Carbone et al., 2017; Punel et al., 2018), flexible (Frehe et al., 2017) and efficient (Buldeo Rai et al., 2018; Devari et al., 2017) logistics systems. Carbone et al. (2017) define CL as an umbrella term for crowdsourced logistics services. Crowdsourcing is outsourcing a specified task to "[...] a group of individuals whose characteristics of number, heterogeneity, and knowledge will be determined by the requirements of the crowdsourcing initiative". (Estellés-Arolas and González-Ladrón-de Guevara, 2012, p. 194). In CL delivery systems, these participants serve as occasional couriers (OCs). Using underused logistics capacities, such as private vehicles, opens up the possibility of increasing resource utilization and operational flexibility as well as lowering costs. Hence, CL can potentially alleviate some of the prevalent issues, e.g., driver

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shortages, in traditional logistics systems. At the same time, increasing vehicle utilization may be contrary to the goals of cities and larger jurisdictions (Fransen et al., 2023), thus posing additional challenges from a governance and legal perspective. Furthermore, incentivizing a higher private vehicle utilization may come with additional challenges, such as a more difficult tracking of Scope 3 emissions.

Practice shows that in addition to large retail players, such as Amazon Inc. (2024) and Walmart Inc. (2024), specialized companies focused on providing CL services, like Maplebear Inc. (2024, Instacart) in the US or Shopopop (2024) in France, are trying to leverage the potential of CL to facilitate fast customer deliveries. As such, a better understanding of CL delivery systems can play a part in reaching the United Nations (2023) sustainable development goals (SDG), particularly SDG9 (industry, innovation, and infrastructure), SDG11 (sustainable cities and communities), and SDG12 (sustainable consumption and production patterns) by providing a lever to reduce urban traffic, resource use or even facilitating community building. While research in CL has increased in recent years, system behavior, i.e., the impact and influence of system elements on each other, and the integration with traditional logistics are still poorly understood (Frehe et al., 2017; Gläser et al., 2021; Le et al., 2019). Most research takes a static perspective, i.e., they ignore that CL systems can be considered as wicked, complex systems, thus ignoring CL systems' dynamics and changes over time. Yet, understanding the dynamics can help to achieve these systems' long-term viability, stability, and positive impact on society and the environment.

There have been several calls for additional CL research, highlighting the importance of understanding CL from a dynamic perspective. For example, Rougès and Montreuil (2014) and Frehe et al. (2017) highlight that understanding how to maintain momentum, i.e., balancing the correct ratio of OCs and customers to keep operations running, is one of the most critical factors for the success of CL initiatives. In this regard, Gläser et al. (2021) propose to research how the required number of OCs can be reached and what capacity of OCs is needed, and Samad et al. (2023) state that more work is needed to understand system behavior and the integration of CL systems with the traditional logistics service providers (LSPs), i.e., logistics operations that use dedicated freight vehicle fleets and permanently employed drivers. He et al. (2022) further point out that in comparison to shared mobility, i.e., crowd-sourced transportation of people, CL has received relatively less attention. In addition, Savelsbergh and Ulmer (2022) highlight that the uncertainty in demand and delivery capacity is a determining factor to differentiate CL from traditional deliveries. Research by Castillo et al. (2022b) further substantiates that understanding the stability of CL delivery systems needs additional exploration, especially regarding the formulation of adequate driver recruitment and retention strategies. Ta et al. (2023) elaborate that successful utilization of crowd-sourced logistics systems depends on understanding underlying aspects such as customer service implications, economics, and operational challenges. All these works show that the dynamics within CL delivery systems need further exploration, especially regarding how to maintain system stability and growth.

The research in this paper contributes to filling this gap by highlighting dynamic elements in CL systems and identifying potential areas for future research by exploring the causal structures of CL concepts. To enable this, an understanding of what the different elements of the system under study are and how they are linked and interact is required. Taking this into account, our research contributes to advancing theory in three ways: Firstly, we introduce a framework to guide researchers and practitioners by identifying core elements and linkages within CL delivery systems, facilitating a better understanding of dynamic complexities. Secondly, we analyze the identified system structure and infer how CL delivery systems can impact both the environment and society. Thirdly, we identify future research opportunities that can enable leveraging the positive effects of CL and limit negative externalities. To guide our research, we thus propose the following research question:

"What are the critical dynamic elements within CL delivery systems, how are they linked, and how do the different elements interact?"

To explore this question, we combine a scoping literature review and a systems thinking approach.

The remainder of our paper is structured as follows: First, we provide a brief background on research related to sustainability in CL. The subsequent section explains the literature review procedure and the rationale for the systems thinking approach, followed by a presentation of the results from the review of related literature and identified causal relations, as well as a detailed analysis of the determined causal loop structures. Afterward, we analyze the recognized structures and highlight future research opportunities. The paper concludes with a summary of the learnings from using a scoping systems thinking review approach and the key takeaways from our analysis.

2. Background

While research has elucidated many aspects related to the operations of CL delivery systems, their impact on the environment and society remains uncertain. Many researchers have called for research that emphasizes the societal and environmental impact of CL delivery systems. For example, Carbone et al. (2017) urge that both the individual participant and the initiatives must be considered when examining the sustainability impact of CL. Pourrahmani and Jaller (2021) suggest taking a closer look at the OC's labor rights and burden of costs. Devari et al. (2017) have pointed out that more research is needed to determine the rebound effects, i.e., trade-offs, which lead to a net negative impact on sustainability. Qi et al. (2018) have proposed exploring social indicators, e.g., the effect on the unemployment rate or social trust building, as key metrics to evaluate CL performance. Likewise, Li et al. (2019) suggest addressing how CL impacts social and environmental factors. Wang and Yuen (2023) ask what the optimal level of environmental and social value created by individuals can be. Areas such as the impact on traffic and quality of life remain unexplored, and still little is known about how operations affect OCs from a social perspective and how, e.g., the involved physical labor and the fact that OCs are not reimbursed for insurance or repairs affect their well-being (Pourrahmani and Jaller, 2021). Likewise, understanding how CL can affect the environment also needs to be clarified. While compared to LSPs, using CL has the potential to save VMT and thus reduce externalities (Ballare and Lin, 2020), the environmental impact of CL greatly hinges on whether trips are dedicated or not (Buldeo Rai et al., 2018; de Oliveira Leite Nascimento et al., 2023). One way to reduce the impact is limiting mode choice, e.g., by focusing on public transportation (de Oliveira Leite Nascimento et al., 2023). As the next sections will show, a significant number of dynamic dependencies are involved within CL, thus illustrating why determining CL's exact environmental and social impact is challenging.

3. Methodology

Rather than a systematic literature review, such as the review by Samad et al. (2023) or Sina Mohri et al. (2023) that reviews the status quo of CL delivery systems and provides bibliometric details, our paper combines a scoping literature review approach with systems thinking to analyze dependencies and feedback structures between system components and overall system behavior. In this case, the literature review serves as a basis to identify core links and to provide an initial understanding of CL systems. Fig. 1 summarizes the approach visually. Building on the identified links, systems thinking is used to construct a visual framework that depicts the dynamic connections and underlying system structure. We refer to this approach as a scoping systems thinking review.

The scoping literature review is a methodology that differs from the systematic literature review in that it focuses on mapping the body of literature rather than summing up the best research available to answer a particular research question (Pham et al., 2014). Munn et al. (2018) note that scoping literature reviews are particularly suited to elucidate key concepts and characteristics related to a chosen concept. While this methodology has received little attention in the Operations Research literature, research by Pham et al. (2014) identified 344 studies in various fields, such as healthcare and software engineering, that used this method. Considering our aim to identify system structures and to understand better how CL delivery systems can be addressed as wicked systems, we chose to pursue a scoping literature review over a systematic literature review.

The scoping systems thinking review in this work is used to identify gaps, propose opportunities for further research, and analyze the overall system structure. To this end, we construct causal loop diagrams (CLDs) based on the elements and links identified through the scoping review that can be used as a guiding framework. As for the general structure of the literature review, we build on the procedure suggested by Thomé et al. (2016) for literature reviews in the field of Operations Management.

3.1. Literature review procedure

To understand the state of the art, we used Web of Science, Scopus, and Google Scholar to identify relevant literature. For the initial search, the search string *("crowd* AND ("logistic*" OR "ship*" OR "delivery* OR "transport*")) OR ("cargo" AND "hitch*)* was used to search titles, abstracts, and keywords. The search was limited to results until July 2023, and later updated to include papers published until the end of 2023, starting with the paper by Rougès and Montreuil (2014), which provided an initial understanding of the value creation processes of CL platforms. We included academic articles and conference proceedings. White papers were only considered in exceptional cases when subsequent research was built on the work. Literature reviews were only considered if they synthesized new findings rather than summarizing the status quo.

After a preliminary search, we decided to exclude highly contextual aspects from our review, such as specific courier and customer behavior and their impact on externalities. Studies by Le and Ukkusuri (2019) and Ta et al. (2023) show industry-specific customer preferences, and Ta et al. (2018) have highlighted that cultural differences can impact customer and OC behavior in CL delivery systems. We argue that these aspects can be neglected since this scoping study aims to take a holistic, systemic perspective.

The search resulted in 1.491 findings on Web of Science, 7.020 findings on Google Scholar, and 3.095 results in Scopus. From these results, 237 papers were selected based on the title, keywords, and a cursory reading of the abstracts. The keyword "transport network companies", which stems from the literature on shared mobility, was disregarded after the initial screening. After a full screening of the abstracts, 111 of these papers were discarded. A total of 139 additional papers were identified based on a forward and backward search, i.e., identifying further relevant literature by a cascading search of references and articles that cited the identified papers as suggested by Thomé et al. (2016). After a cursory reading of the remaining papers, 220 papers were discarded. We used the remaining 45 articles to review the literature and to analyze the causal relationships. We updated and extended our review to 49 articles in January 2024 to include articles until the end of 2023. The results are presented in the subsequent section.

3.2. Rationale for a systems thinking approach

The underlying assumption of the systems thinking approach is that a system is more than the sum of its parts (Ackoff, 1994). Systems thinking helps to understand the underlying complex structure of systems and how their parts interact. These interactions are also described

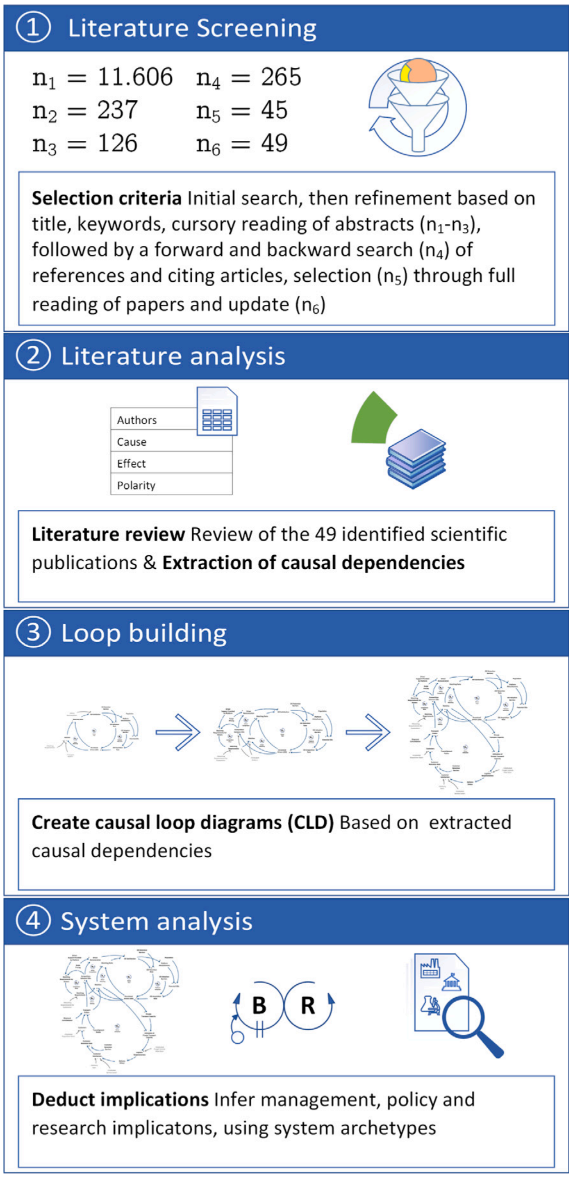

Fig. 1. Overview of the scoping systems thinking review methodology employed in this paper.

as a system's feedback (Sterman, 2004). As such, systems thinking takes a holistic approach to understanding systems of any kind, from social over biological to mechanical systems (Meadows, 2008). Systems thinking is particularly suited to facilitate multidisciplinary research and enable a better understanding of how a system can contribute to sustainability (Blatti et al., 2019). To facilitate a system's understanding, the systems thinking approach employs various tools, including both soft and hard Operations Research methodologies. One tool that graphically depicts system dependencies is the causal loop diagram (CLD), which visually shows the interrelation of causes and effects as well as feedback structures within a system. Fig. 2 shows the structure of a CLD based on an example by Sterman (2004).

In a CLD, system elements are connected, influencing other elements by positive (+) connections, which lead to similar changes in the connected element, or negative (-) connections, i.e., connections whose change results in counteracting behavior. The example in Fig. 2 shows how road construction is connected to current highway capacity and

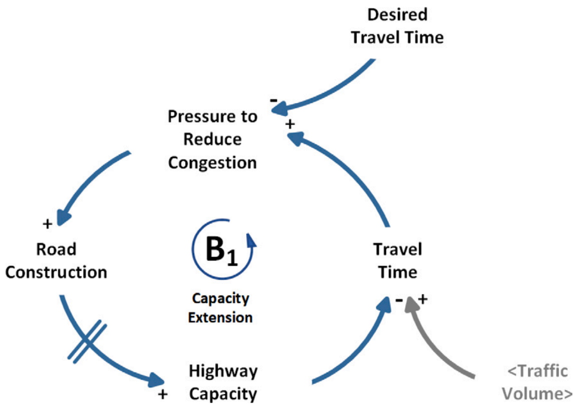

Fig. 2. A CLD example, based on Sterman (2004).

external factors, such as the desired travel time and traffic volume (marked with <> and a gray color-coding as a shadow variable, i.e., a variable that originates in other parts of the system). An increase in highway capacity reduces (-) the travel time, which then leads to a subsequent decrease in the pressure to reduce congestion and, consequently, road construction. The reduced efforts in road construction then, after time (delay, marked with ||), lead to a subsequent decrease in highway capacity, leading to higher travel times. Increasing traffic volume reinforces (+), i.e., increases, the travel time.

Whether the loop exerts a reinforcing or balancing behavior can be determined by ‘walking around the loop,’ i.e., starting at any point in the loop and following the loop connections in one direction until one has arrived back at the starting point. Every time one encounters a negative connection, one changes the direction one views while continuing to walk. If one arrives at the destination facing the same direction, the loop is a Reinforcing Loop (+). If one arrives facing the opposite direction one has started with, it is a Balancing Loop (-). The loops within the system are marked with a loop identifier in the form of a circular arrow and the letter ’*B*’ for a Balancing and ’*R*’ for a Reinforcing Loop. The example in Fig. 2 has one negative polarity link within the loop, thus making it a *B* Loop. For further information, we refer to Sterman (2004).

As is customary in developing CLDs (Daellenbach et al., 2012), we pursued an iterative approach to building the CLDs. Previous studies, such as Rebs et al. (2019) and Kump and Fikar (2021), show that combining a literature review with a systems thinking approach can facilitate a deeper understanding and yield valuable insights for practitioners and researchers alike. The iterative process of building the CLDs further enhances the critical discussion within the literature review process. Furthermore, using CLDs allows us to consider system archetypes to explore possible system behavior.

4. Results

Based on the review presented in the previous section, the following section synthesizes the systemic structure of CL delivery systems. To this end, the identified findings and connections were repeatedly decomposed and re-composed. Fig. 3 shows a CLD depicting all identified loop structures. The CLDs are described consecutively in this section to show how different loops build on core structures. For example, the OC’s side is depicted starting in Fig. 4, which is then extended in Fig. 5. While all CLDs are linked, we chose to introduce different parts of the system step by step to facilitate a better (gradual) understanding of the underlying complexities related to the different sides involved.

Building on the previous section, links are labeled with numbers, indicating their corresponding link ID, referenced in Table 1, illustrating which link structure has been identified in which reference. Throughout the section, we mark the respective causal dependencies with reference numbers enclosed in less-than and greater-than signs (e.g., $\langle 1, 2, 3\rangle$). The sequence of the numbers is aligned with the description of loop structures within the CLDs shown in Figs. 4 to 8; the corresponding paper references can be found in Table 1. Links deduced by the authors are not numbered but labeled with a letter. These links were not found within the body of reviewed literature but were deduced during the iterative modeling process. As Table 3 in Appendix A illustrates, these presumed links are supported within the broader context of the sharing economy literature. The subsequent descriptions of loops describe the link under a ceteris paribus assumption to illustrate the loop mechanism. An overview of all loop structures can further be found in Appendix B, Appendix C and Appendix D.

4.1. *Dynamics on the couriers’ side*

Ten major loops (six balancing, four reinforcing) are connected to the OCs depicted in two CLDs, namely Fig. 4, and 5, which build on each other.

4.1.1. *Courier pool and platform attraction*

A major criterion in maintaining CL operations is the available OC pool that can be used to match transport orders. Fig. 4 depicts how the B_1 *OC Pool* interacts with R_2 *Platform Attraction* and R_1 *OC Matching*. The level of available OCs depends on the inflow of new ones, i.e., the OC acquisition rate $\langle a\rangle$, and the capacity to retain existing ones, i.e., the OC retention rate $\langle 2\rangle$. Both rates are subject to various barriers, which may vary depending on cultural and geographical settings. The total amount of OCs is subject to the number of available potential OCs that can be acquired $\langle b\rangle$.

At the same time, the number of potential OCs depends on the population size $\langle c\rangle$ and the platform’s attractiveness $\langle d\rangle$. An increase in OCs results in more matches $\langle 5\rangle$, increasing OC satisfaction $\langle e, 6\rangle$, thus further improving platform attractiveness $\langle f\rangle$. In this way, the R_2 *Platform Attraction* loop can either boost or exacerbate the availability of OCs.

The loop structures on the OCs’ side are balanced through the B_1 *OC Pool* loop. The more OCs are available, the less likely is the chance for an OC to get a match $\langle g\rangle$. The reduction leads to less OC satisfaction $\langle 6\rangle$, thus limiting OC retention $\langle 1\rangle$ and reducing total OC levels $\langle 2\rangle$.

4.1.2. *Courier competition*

While OC remuneration impacts OC satisfaction $\langle 12\rangle$, remuneration is influenced by the competition between different OCs $\langle 9\rangle$. As the left-hand side of Fig. 4 highlights, the level of competition is determined by the ratio of OCs to transport orders $\langle 8, 28\rangle$. The lower the ratio of transport orders per OC, the higher the competition between OCs becomes. The higher competition then leads to lower remuneration $\langle 9\rangle$, decreasing the OCs’ satisfaction $\langle 12\rangle$, which, in turn, leads to lower retention rates $\langle 1\rangle$, thus forming the B_2 *OC Competition* loop. At the same time, increasing competition between OCs can lead to higher matching requirements for OCs $\langle 13\rangle$, e.g., due to greater difficulty in balancing courier utilization and an increase in organizational complexity with an increasing number of variables that need to be considered. This results in higher overall matching requirements $\langle 15\rangle$, thus potentially reducing the number of matches $\langle 16\rangle$. The reduction of matches leads to a reduction in OC satisfaction $\langle e, 6\rangle$, ultimately decreasing the retention rate $\langle 1\rangle$, thus wearing out the OC level $\langle 2\rangle$. The reduced number of OCs then leads to less competition $\langle 8\rangle$, thus concluding the B_3 *Competition Wear* loop.

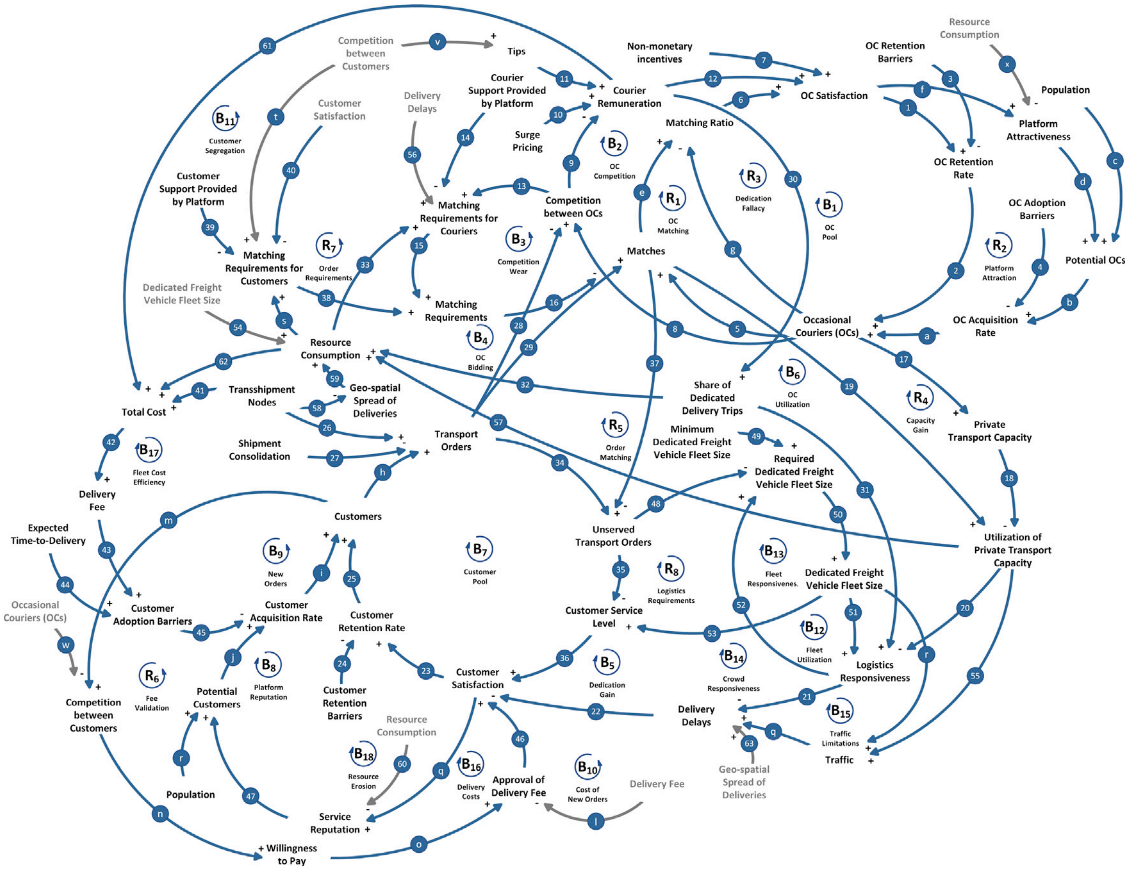

Fig. 3. Crowd logistics delivery systems can be considered as wicked systems.

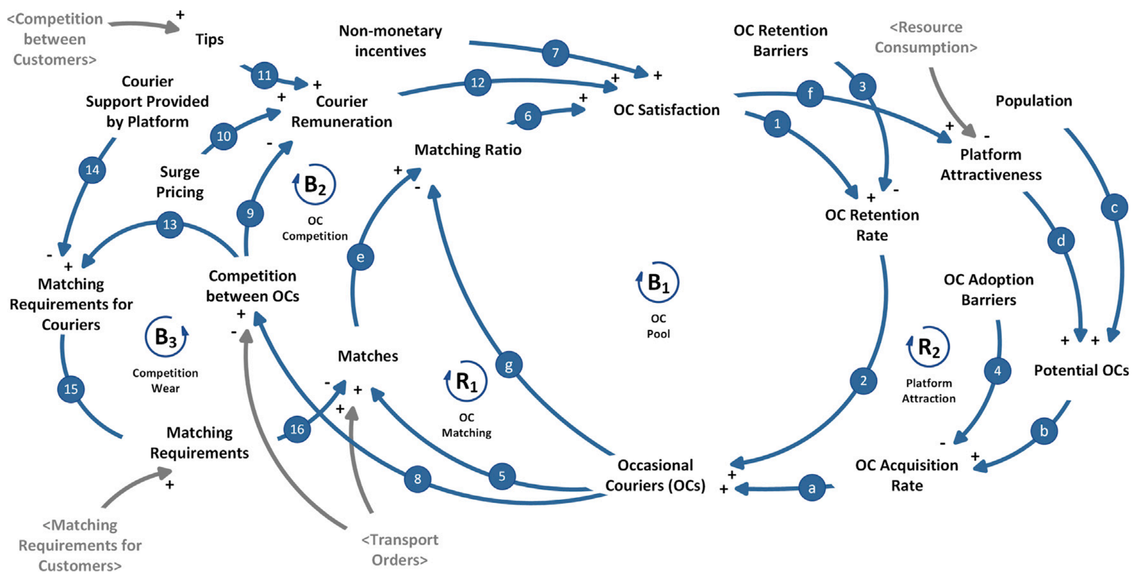

Fig. 4. Competition balances the level of occasional couriers.

Table 1
Identified causal links with respective reference.

ID	Reference(s)
1	Asdecker and Zirkelbach (2020), Xu et al. (2020)
2	Dai and Liu (2020), Castillo et al. (2022b)
3	Castillo et al. (2022b), Fessler et al. (2022)
4	Archetti et al. (2016), Fessler et al. (2022), Ermagun and Stathopoulos (2018)
5	Le et al. (2019), Yıldız (2021)
6	Taylor (2018), Xiao et al. (2023), Mittal et al. (2021)
7	Devari et al. (2017), Pourrahmani and Jaller (2021), Wang and Yuen (2023), Nguyen et al. (2023b), Mittal et al. (2021)
8	Chen and Chankov (2017), Cramer and Fikar (2024), Xiao et al. (2023), Castillo et al. (2022b)
9	Rechavi and Toch (2022)
10	Castillo et al. (2018), Qi et al. (2018)
11	Castillo et al. (2022b)
12	Shen and Lin (2020), Castillo et al. (2022a), Nguyen et al. (2023b,a), Xu et al. (2020)
13	Le et al. (2019), Cramer and Fikar (2024), Rechavi and Toch (2022)
14	Carbone et al. (2017), Zhang et al. (2019), Asdecker and Zirkelbach (2020), Li et al. (2019)
15	Alharbi et al. (2022)
16	Arslan et al. (2019), Zhang et al. (2019)
17	Archetti et al. (2016), Castillo et al. (2022a), Dayarian and Savelsbergh (2020)
18	Dayarian and Savelsbergh (2020), Yıldız (2021), Azcuy et al. (2021)
19	Behrend et al. (2019), Dayarian and Savelsbergh (2020), Guo et al. (2019)
20	Rougès and Montreuil (2014), Huang and Ardiansyah (2019), Castillo et al. (2022b), Dayarian and Savelsbergh (2020), Arslan et al. (2019)
21	Chen and Chankov (2017), Castillo et al. (2022b)
22	Huang and Ardiansyah (2019), Wicaksono et al. (2022)
23	Frehe et al. (2017), Mittal et al. (2021)
24	Le et al. (2019), Nguyen et al. (2023a), Mittal et al. (2021)
25	Frehe et al. (2017), Le et al. (2019)
26	Yıldız (2021), Zhang et al. (2023), Voigt and Kuhn (2022)
27	Dayarian and Savelsbergh (2020)
28	Chen and Chankov (2017), Mittal et al. (2021), Taylor (2018), Ghaderi et al. (2022), Cramer and Fikar (2024)
29	Castillo et al. (2018), Dayarian and Savelsbergh (2020)
30	Taylor (2018), Qi et al. (2018)
31	Archetti et al. (2016), Arslan et al. (2019), Ghaderi et al. (2022), Behrend et al. (2019), Chen and Chankov (2017)
32	Buldeo Rai et al. (2018), de Oliveira Leite Nascimento et al. (2023), Qi et al. (2018)
33	Fessler et al. (2022), de Oliveira Leite Nascimento et al. (2023)
34	Chen and Chankov (2017), Azcuy et al. (2021), Taylor (2018)
35	Chen and Chankov (2017), Xiao et al. (2023), de Oliveira Leite Nascimento et al. (2023)
36	Taylor (2018)
37	Chen and Chankov (2017), Guo et al. (2019), Voigt and Kuhn (2022), Zhang et al. (2019), Behrend et al. (2019)
38	Dayarian and Savelsbergh (2020), Ji et al. (2020), Li et al. (2019)
39	Carbone et al. (2017), Li et al. (2019)
40	Buldeo Rai et al. (2018), Alharbi et al. (2022), Ermagun and Stathopoulos (2018)
41	Macrina et al. (2020), Ballare and Lin (2020), Ghaderi et al. (2022), Ermagun and Stathopoulos (2018)
42	Ghaderi et al. (2022)
43	Lan et al. (2022), Wicaksono et al. (2022)
44	Rougès and Montreuil (2014), Wicaksono et al. (2022), Le et al. (2019)
45	Le et al. (2019)
46	Li et al. (2019), Rechavi and Toch (2022)
47	de Oliveira Leite Nascimento et al. (2023)
48	Carbone et al. (2017), Azcuy et al. (2021)
49	Devari et al. (2017), Dayarian and Savelsbergh (2020), Castillo et al. (2022a), Bin et al. (2020)
50	Rougès and Montreuil (2014), Azcuy et al. (2021), Devari et al. (2017)
51	Castillo et al. (2018), Chen and Chankov (2017), Kızıl and Yıldız (2023), Castillo et al. (2022b), Arslan et al. (2019)
52	Devari et al. (2017), de Oliveira Leite Nascimento et al. (2023), Kızıl and Yıldız (2023)
53	Chen and Chankov (2017), Castillo et al. (2022a), Ballare and Lin (2020)
54	Castillo et al. (2018, 2022a), Qi et al. (2018)
55	McKinnon (2016), Fessler et al. (2022)
56	Fessler et al. (2022), de Oliveira Leite Nascimento et al. (2023), Azcuy et al. (2021)
57	Qi et al. (2018)
58	Ghaderi et al. (2022), Voigt and Kuhn (2022)
59	Azcuy et al. (2021), Voigt and Kuhn (2022), Ghaderi et al. (2022)
60	Wicaksono et al. (2022)
61	Castillo et al. (2022b)
62	Guo et al. (2019), Huang and Ardiansyah (2019), Ballare and Lin (2020), Pourrahmani and Jaller (2021)
63	Kızıl and Yıldız (2023)

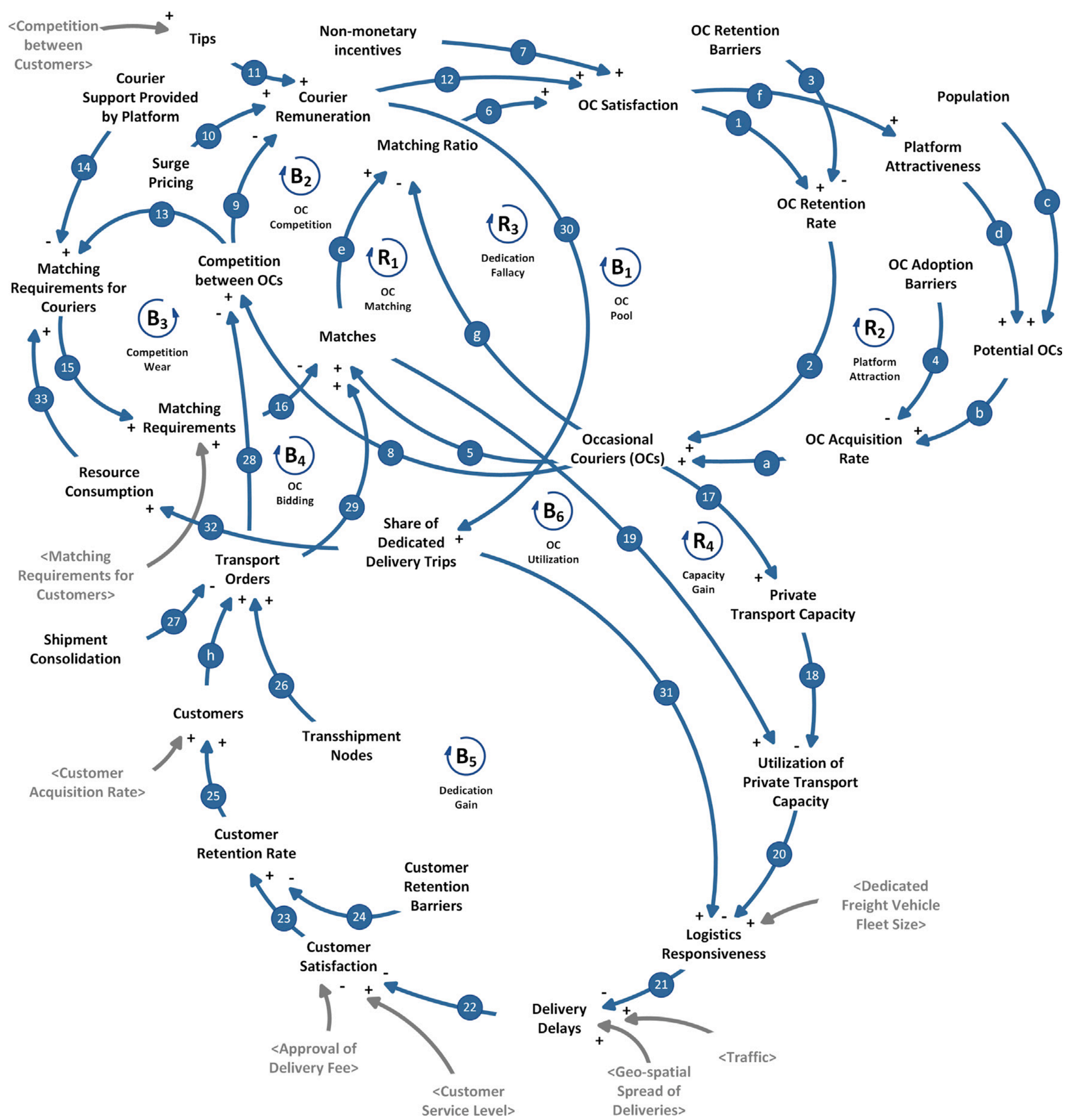

Fig. 5. Buildup of the courier pool and the impact of competition.

4.1.3. *Courier utilization and trip dedication*

Using private transport capacities is an important factor contributing to how flexible and responsive CL delivery systems can fulfill transport orders. The bottom half of Fig. 5 shows how B_1 *OC Pool* and R_1 *OC Matching* facilitate OC utilization. A defining aspect within CL delivery systems is the share of dedicated trips.

Related to the share of dedicated deliveries, an R and a B loop affect dynamics on the OCs' side. The B_5 *Dedication Gain* loop balances the share of dedicated delivery trips by controlling the number of customers, while the R_3 *Dedication Fallacy* loop reinforces it by affecting matching requirements. In both loops, an increase in competition leads to lower remuneration ⟨9⟩. The lower remuneration reduces the attractiveness of making dedicated trips ⟨30⟩. In the B_5 *Dedication Gain* loop, this leads to a loss of logistics responsiveness ⟨31⟩. The loss is followed by increasing delivery delays ⟨21⟩, further reducing customer satisfaction ⟨22⟩. Eventually, the drop in customer satisfaction is followed by a decrease in customer numbers ⟨23, 25⟩, thus reducing transport orders ⟨h⟩ and consecutively matches ⟨29⟩. In the R_3 *Dedication Fallacy* loop, the reduction in dedicated delivery trips leads to less resource consumption ⟨32⟩, lowering matching requirements ⟨33, 15⟩ and consequently increasing matches ⟨16⟩. The change in matches then leads to a respective change in OC levels.

4.2. *Dynamics on the customers' side*

Customers' dynamics are determined by eight major loops (five balancing, three reinforcing). Fig. 6 depicts how the B_7 *Customer Pool* connects to associated loops.

4.2.1. *Customer pool and matching*

Fig. 6 shows that, as is the case with the OC level, the customer level depends on acquisition ⟨i⟩ and retention ⟨25⟩. An increase in the customer level leads to more transport orders ⟨h⟩. By using shipment

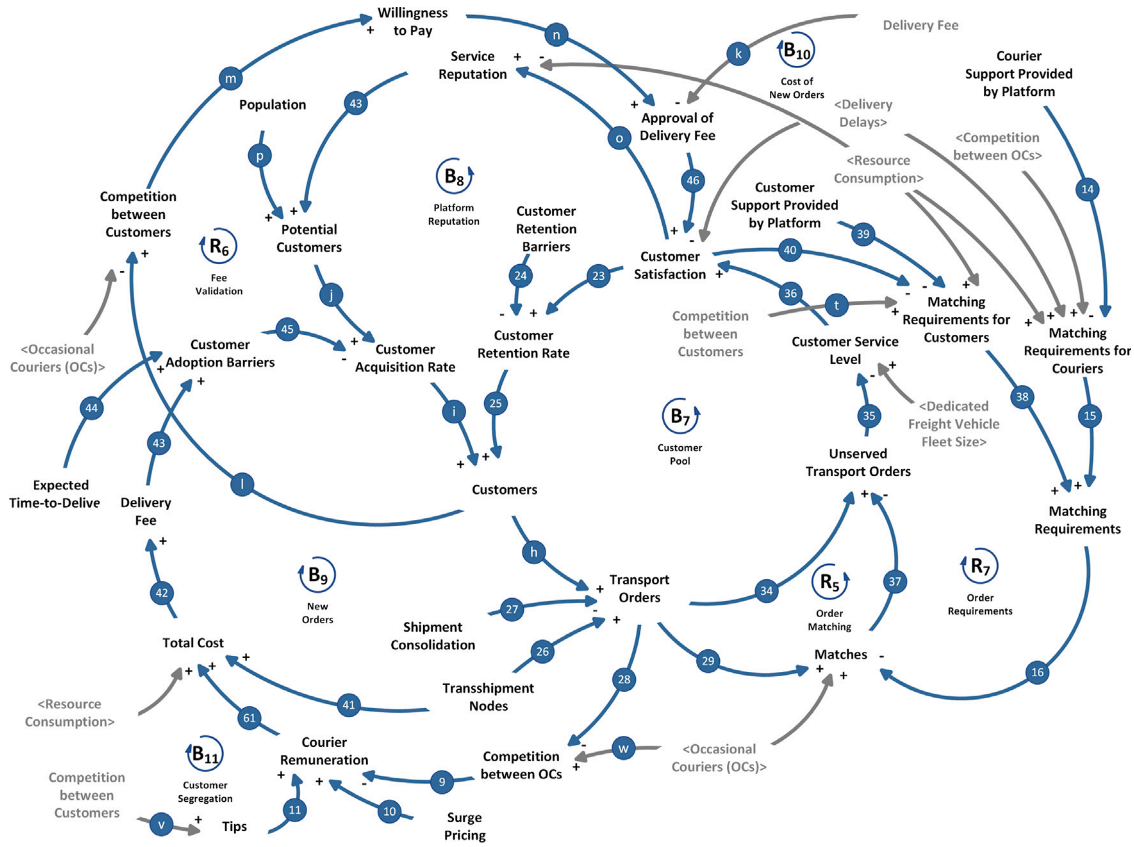

Fig. 6. The acquisition of new customers can impact adoption and retention barriers.

consolidation and additional transshipment locations, CL platform operators can partially control the number of generated transport orders resulting from the number of customers ⟨26, 27⟩. An increase in transport orders leads to more matching possibilities ⟨29⟩. If the number of OCs is insufficient, it also increases the number of unserved transport orders ⟨34, 37⟩, thus decreasing customer service levels ⟨35⟩. When customer service level decreases, customer satisfaction also drops ⟨36⟩, which, in turn, decreases customer retention ⟨23⟩. In this way, the R_5 *Order Matching* loop balances the B_7 *Customer Pool* loop through the ratio of successful matches to transport orders. A dedicated vehicle fleet can compensate for the lack of OCs and thus increase customer service level ⟨53⟩.

4.2.2. Platform reputation and fee validation

As Fig. 6 shows, the B_7 *Customer Pool* loop connects to the R_7 *Order Requirements* on the right-hand side and loop structures related to generating orders and competition between customers on the left-hand side. A major factor involved in acquiring new customers is R_8 *Platform Reputation*. A high service reputation increases the pool of potential customers ⟨47⟩, thus leading to higher customer acquisition ⟨i⟩.

At the same time, competition between customers leads to reinforcing the acceptance of higher fees through the R_6 *Fee Validation* loop. When customer numbers rise, so does competition between the customers ⟨l⟩. The increasing competition facilitates a higher willingness to pay ⟨m⟩, which encourages the approval of delivery fees ⟨n⟩. Concurrently, the higher competition also impacts tipping behavior ⟨v⟩, which allows customers to directly impact OC choices by increasing courier remuneration ⟨11⟩. A higher approval of the delivery fees leads to higher customer satisfaction, which boosts the customer retention rate ⟨23⟩. However, the approval of the delivery fee is mitigated by the actual delivery fee; thus, R_6 *Fee Validation* is influenced by B_2 *OC Competition* and the competition between customers.

4.3. Dynamics on the platforms' side and operations management

Another important element in CL delivery systems is fleet management. The underlying dynamics are depicted first in Fig. 7, then extended through Fig. 8, portraying the loops connected to the platform's side and associated aspects of operations management. With a total of nine *B* loops and three *R* loops, the Figure shows a prevalence of *B* loop structures.

4.3.1. Logistics requirements and traffic limitations

As can be observed in Fig. 7, the R_7 *Order Requirements* loop serves as a basis for the R_8 *Logistics Requirements* loop. Subject to the number of matches, the required size of the dedicated freight vehicle fleet changes accordingly: With increasing matches, the utilization of private transport capacities rises ⟨17⟩, causing a drop in logistics responsiveness ⟨20⟩ as less free capacity remains. This leads to the B_{14} *Crowd Responsiveness* loop, in which the loss of logistics responsiveness is followed by an increase in delivery delay ⟨21⟩, leading to decreased customer satisfaction ⟨22⟩. It further results in the R_8 *Logistics Requirements* loop: To compensate for the loss in responsiveness, the required dedicated vehicle fleet must grow ⟨52⟩. This increases the actual fleet size of dedicated delivery vehicles ⟨50⟩, which consecutively leads to higher customer service levels ⟨53⟩. A higher customer service level increases customer satisfaction ⟨36⟩, lowers customer matching requirements ⟨40⟩, and facilitates more matches ⟨38, 28⟩, thus concluding the R_8 *Logistics Requirements* loop.

The management of B_{13} *Fleet Responsiveness* and R_8 *Logistics Requirements* puts a strain on the underlying infrastructure, which is balanced through the B_{15} *Traffic Limitations* loop. With an increasing utilization, traffic increases ⟨55⟩. The increase in traffic leads to delivery delays

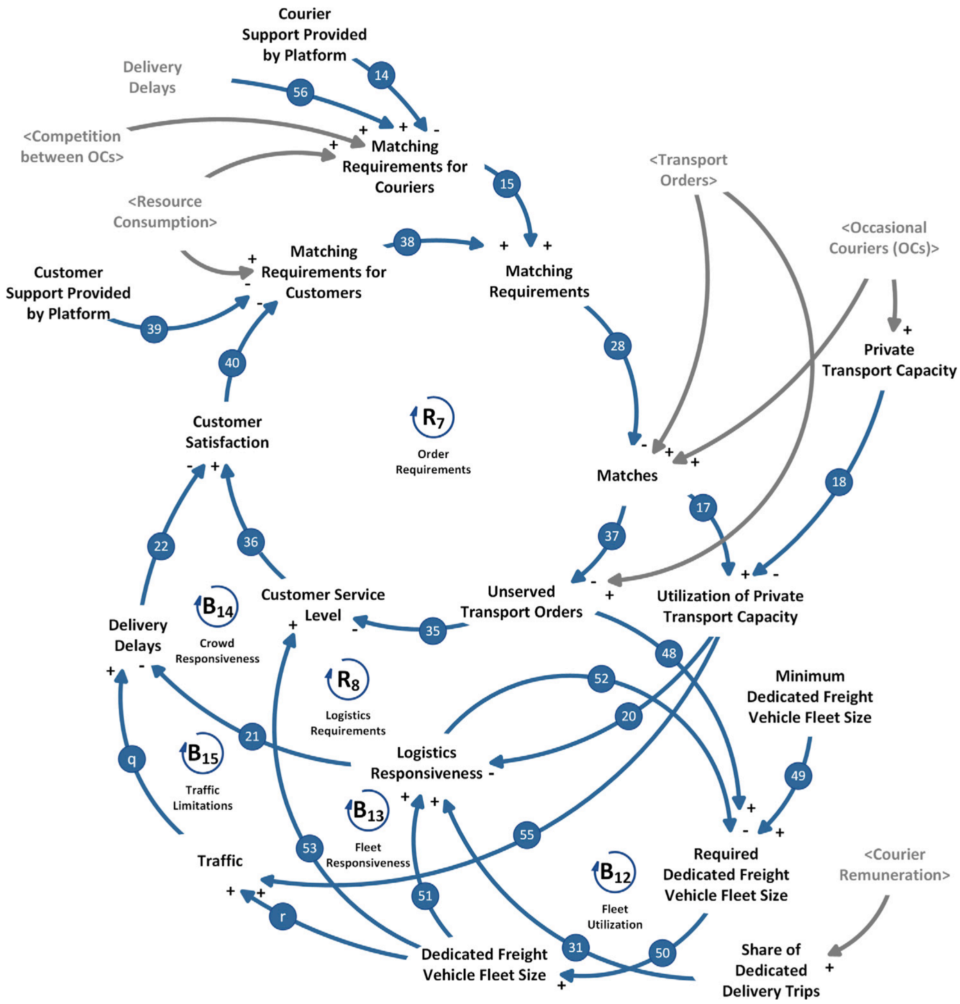

Fig. 7. Fleet management in crowd logistics delivery systems involves the interplay between dedicated freight vehicle fleet and the private transport capacity supplied by occasional couriers as well as their impact on the used infrastructure.

⟨q⟩, compromising customer satisfaction ⟨22⟩. The lower customer satisfaction subsequently increases matching barriers ⟨40, 38⟩. At the same time, the delivery delays also increase matching barriers from the OC's perspective ⟨56, 15⟩. Thus, the effect of the B_{15} *Traffic Limitations* loop effectively encircles matching requirements from both sides.

4.3.2. Fleet cost efficiency and eroding resources

The bottom left area of Fig. 8 extends Fig. 7 through the inclusion of the B_{17} *Fleet Cost Efficiency*, B_{16} *Delivery Costs* and the B_{18} *Resource Erosion* loop structures. *Fleet Cost Efficiency* in CL delivery systems primarily hinges on fixed infrastructure costs and the OCs: The total costs increase with the OCs' remuneration ⟨k⟩, the number of transshipment warehouses ⟨41⟩, and the resource consumption ⟨62⟩, which is affected by the dedicated freight vehicle fleet size ⟨54⟩. Increasing total costs results in higher customer delivery fees ⟨42⟩, thus increasing customer adoption barriers ⟨43⟩. This ultimately leads to a reduction in the number of unserved transport orders ⟨45, i, h, 34⟩, followed by downsizing the required amount of dedicated freight vehicles ⟨48⟩, leading to a decrease in the size of the freight vehicle fleet ⟨50⟩ and a lower resource consumption ⟨54⟩. The B_{17} *Fleet Cost Efficiency* loop balances excess fleet capacity to account for the loss of transport orders.

Changes in fleet composition and utilization also impact resource use, thus causing B_{18} *Resource Erosion*. Higher utilization and a larger required fleet consume resources through the acquisition of new assets and operations. When resource consumption rises, the service's reputation declines ⟨60⟩. This decline limits the number of customers ⟨47, j, i⟩. This causes fewer transport orders to be issued ⟨h⟩, thus reducing the number of matches ⟨29⟩. The lower matches then lead to lower utilization of private transport capacities ⟨48⟩, facilitating logistics responsiveness ⟨20⟩. As a consequence, fewer dedicated freight vehicles are required ⟨52⟩, thus balancing resource consumption ⟨50, 54⟩.

5. Discussion

As the results show, combining a scoping literature review with systems thinking can help to understand CL delivery systems as wicked systems. It is important to highlight that the 'wickedness' in such systems does not originate in their structure alone but in the dynamic properties, which can lead to unanticipated effects and behavior. The subsequent subsections discuss the implications of our study and provide potential future research directions of interest.

5.1. Implications for system scaling and stability

The underlying dynamics in CL delivery systems can pose major challenges for managers and policymakers. The following subsection discusses the implications of our work regarding system design, scaling, and management.

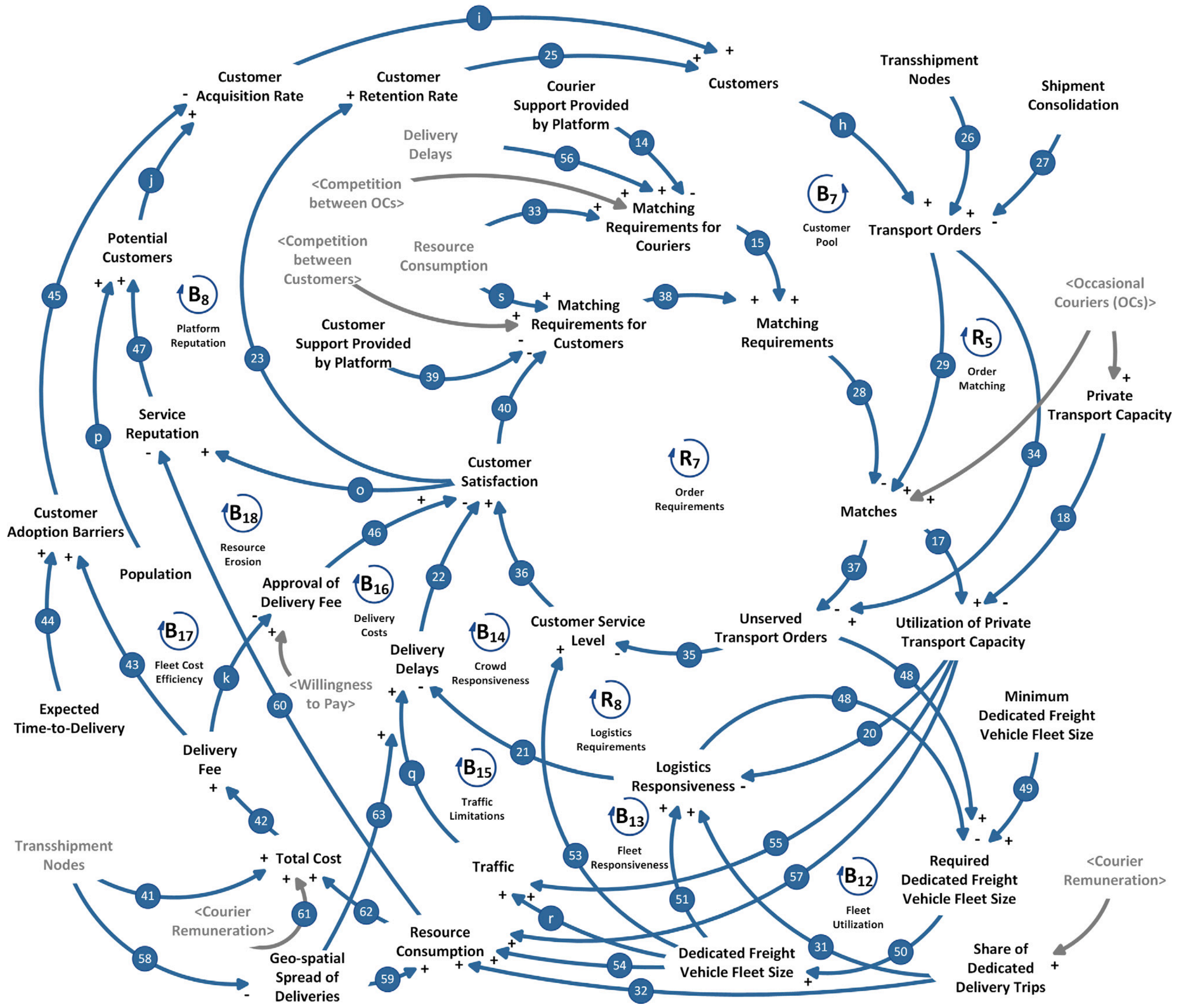

Fig. 8. Fleet cost efficiency and delivery costs in CL delivery systems depend on both private and dedicated fleet size.

5.1.1. Integration of crowd logistics with traditional logistics service providers

Investing in platform capabilities may contribute to maintaining system momentum. In this regard, Li et al. (2019) found that efficient matching algorithms and integrating platform support elements can greatly increase performance. Compared to logistics and network structure investments, platform capabilities and support systems pose a low-cost opportunity to increase stability and performance. We must note, though, that extending logistics and network capabilities in CL does not have to involve extensive funding, as initiatives could also rent capacities from a third-party service provider or use the OCs' capacities (e.g., private garages). As previous research (e.g., Mo et al., 2018; Yıldız, 2021; Voigt and Kuhn, 2022) has highlighted, transshipment and consolidation nodes can increase CL performance, cut matching requirements, and lead to a reduction in both VMT and costs. Our results indicate further potential benefits with respect to reducing OC competition and maintaining system stability, as well as facilitating the scaling of the initiative. Thus, a determining aspect in maintaining momentum is the level of LSP integration.

With respect to the level of LSP integration, our results allow us to divide activities related to CL initiatives into different categories: (i) pure CL initiatives without LSP integration, (ii) CL initiatives with LSP integration, and (iii) LSP delivery networks with CL integration. We must note that the analysis and discussion of the developed CLDs, particularly the R_8 *Logistics Requirements*, B_{13} *Fleet Responsiveness*, and B_{14} *Crowd Responsiveness* loop structures, point towards that pure CL initiatives may suffer from scaling issues and problems with maintaining momentum.

The greater success of initiatives that have started out as CL initiatives may lie in a better understanding of CL's dynamic properties. Considering that LSPs already have resources that can attenuate fluctuations in OC levels, one might wonder why, in practice, successful initiatives have primarily evolved from the CL perspective. After all, the existing customer structure allows for scaling the OC pool more quickly (cf. R_1 *OC Matching* and R_2 *Platform Attraction*). Furthermore, our analysis indicates that with a growing initiative scale, either the level of LSP integration or the share of dedicated trips also has to increase. As a consequence, the increase in the utilization of private transport capacity could decrease the logistics responsiveness offered through CL. Consequently, a larger CL initiative may need a larger number of dedicated trips to support operations. Moreover, dedicated freight vehicles could avert risks associated with CL. Thus, using CL to perform deliveries seems to be more manageable when starting with a dedicated delivery structure rather than building on CL from scratch. One possible explanation for this mismatch is that LSPs may lack an intuitive understanding of system dynamics, leaving them inadequately equipped to manage hybrid systems. As highlighted by the research by Castillo et al. (2022a), these hybrid systems still hold various challenges, such as determining optimal remuneration for OCs to achieve efficient operations.

5.1.2. User pools as system boundaries

As our analysis indicates, customer levels may limit OC levels. Particularly, the structures related to R_1 *OC Matching*, R_5 *Order Matching*, and R_8 *Logistics Requirements* highlight a possible dependence on the customers' side. This poses a significant challenge: Should the initiative focus on attracting OCs or customers? Both OC and order matching are balanced through the B_1 *OC Pool* and B_7 *Customer Pool*, respectively, each side also influences the development of the other. Therefore, the OC pool size may constrain the development of the customer pool and vice versa. While the limitation through the size of the OC pool may be compensated using a dedicated freight vehicle fleet, a lack of transport orders cannot be compensated that easily.

Nonetheless, as the B_2 *OC Competition* loops highlights, competing interests over the potential OC pool must be considered carefully to avoid a possible depletion by triggering a tragedy of the commons loop (cf. Kim, 1993). It is important to note that not only CL initiatives compete over these couriers, but shared mobility initiatives as well (Zhong et al., 2019). Choosing a group of potential OCs that pursue a specific activity, such as shoppers (Dayarian and Savelsbergh, 2020; Cramer and Fikar, 2024), can limit the scope of the required analysis and may help to understand barriers better. Moreover, choosing a group with a routine activity could also facilitate recurring participation and, in this way, increase participation predictability, which in turn may help to understand the necessary extent of LSP integration.

5.1.3. Importance of understanding user retention

Finding the right balance between user retention and winning new users is not a simple task (cf., e.g., the B_9 *New Orders* and B_{10} *Cost of New Orders* loop structures). A significant issue concerns understanding customer and OC retention. User retention dictates how low retention barriers and matching requirements must be to maintain momentum. Thus, the lack of knowledge with respect to retention may contribute to the failure of an initiative. This observation aligns with the conclusions by Castillo et al. (2022b), who highlight that the importance of acquisition and retention rates could be further substantiated using system dynamics. While we did not include behavioral factors in our study and further did not quantify retention rates, the emphasis likely depends on industry and cultural aspects, as indicated by the studies by Le and Ukkusuri (2019) and Ta et al. (2018).

Our results further suggest that to maintain momentum in CL delivery systems, both user acquisition and retention should be facilitated. Assuming that users, once lost, do not return, focusing on new users could lead to initial growth followed by a vicious cycle after depleting the pool of potential users, as indicated by the B_1 *OC Pool* and B_7 *Customer Pool* and the respective loops related to competition. This shows how focusing solely on obtaining new users without considering user retention may be disadvantageous in the long run. However, reducing retention barriers must also be considered in light of its effects on limiting competition over orders and OC availability.

5.1.4. Possibility of user control fallacies

With respect to the regulation of OC numbers, monetary incentives can be used as control mechanisms. For example, the use of surge pricing, a practice commonly adopted and controversially discussed in the neighboring field of shared mobility (Hu et al., 2022a), can be adopted. Even though we were not able to clearly identify what feedback structures lead to the use of surge pricing based on the reviewed literature, our analysis indicates that monetary incentivization, such as surge pricing and tipping, should be treated as a double-edged sword, as it may also lead to counterintuitive behavior (cf., e.g., B_2 *OC Competition*, R_3 *Dedication Fallacy*, and B_{11} *Customer Segregation*). It is not unlikely that additional monetary incentivization could influence the remuneration expectations of OCs, thus leading to anticipation of the incentive by the platform and a resulting higher availability of OCs during the observed surge times with the expectation to receive higher remuneration. Research by Miao et al. (2023) in the area of shared mobility has shown such behavior in ride-sharing drivers. Due to its similarity to CL, it is likely that similar behavior could be expected. Therefore, using monetary incentivization without other control mechanisms may lead to a cascading vicious cycle. One side-effect could be the possible exhaustion of the OC pool.

A related topic that remains unexplored in CL research is whether or not users are an exhaustible resource. Considering the feedback structures identified throughout the previous section, CL presumedly has the potential to undergo a tragedy of the commons development. With a focus on scaling the platform from both a customer's and an OC's side, neglect of retention could exhaust the available pool of potential customers and OCs. As illustrated through the B_8 *Platform Reputation* and R_2 *Platform Attraction* loop structures, users' perception of the platform matters. For example, when platforms focus on profitability over facilitating sustainable operations, the resulting negative impacts on the environment and society through resource consumption, externalities, and social segregation may lead to decreasing service attractiveness and reputation. Considering that the customers' (and possibly also OCs') expectations related to sustainability grow, this could lead to fewer and fewer users that think that CL can be used to provide sustainable logistics services. This way, a strong focus on cost optimization over effectiveness may eventually render CL useless in providing socially and environmentally sustainable services.

5.2. Societal implications

Our analysis indicates that CL affects sustainability both positively and negatively. CL can, for example, help mitigate some of the problems within logistics systems, e.g., by reducing negative externalities caused by freight transportation in urban areas (Kızıl and Yıldız, 2023) or by attenuating issues with truck driver shortages (Marcott, 2022). The subsequent part discusses the potential societal implications, as indicated through our analysis.

5.2.1. Infrastructural and behavioral challenges

The share of dedicated delivery trips may tip the scales on whether CL can contribute to increasing or decreasing sustainability. As the R_3 *Dedication Fallacy* loop suggests, fostering dedicated trips through monetary incentives may encourage OCs to become regular participants rather than OCs. Understanding CL as a job opportunity offers both chances and threats to the OCs' quality of life. On the one hand, it enables the OCs to have a supplemental source of income, potentially allowing them to alleviate financial issues. Yet, when CL becomes a full-time job, the OCs may face significant drawbacks compared to driver jobs in LSPs, such as income fluctuations, no unions, and costs for repairs. These examples clearly show that dedicated trips are at the core of determining the sustainability potential of a CL initiative. In line with de Oliveira Leite Nascimento et al. (2023), we highlight that mode choice does not necessarily imply the level of trip dedication. When users start dedicated journeys to transport parcels (cf. R_3 *Dedication Fallacy* and B_5 *Dedication Gain*), this leads to higher utilization and, thus, externalities and resource consumption. Even if these impacts are smaller when using public transportation, both the B_{18} *Resource Erosion* and B_{15} *Traffic Limitations* loops illustrate that they could lead to negative externalities. Consequently, dedicated trips should be understood as detached from the mode of transportation.

Table 2
Examples for future research opportunities concerning crowd logistics delivery systems.

Topic	Discussed in	Possible research questions
Operations scaling	5.1.2 5.1.3 5.1.4	*How can customers be motivated to use CL?* *How can customer participation be leveraged to facilitate the growth of the courier base and vice versa?* *How can a lack in customer base be compensated?* *Do ridesharing and crowd logistics platforms compete over the same user pools?* *What are the long-term effects of monetary control mechanisms on operations stability and growth?* *What capabilities contribute the most to maintaining momentum in CL initiatives?*
Optimization vs. Effectiveness	5.1.1 5.1.4 5.2.1 5.2.2	*What are the long-term effects of monetary control mechanisms on CL's sustainability potential?* *What dynamic differences issue the greatest challenge for an extension of LSPs through the integration of CL?* *How can a 'healthy' share of dedicated trips for a specific CL initiative be determined?* *To what extent does current practice create social disparity and segregation?* *How do remuneration control mechanisms affect the couriers' quality of life?* *Is the customers' or the couriers' side more strongly affected by adverse social impacts caused by CL?* *What are the infrastructural prerequisites to facilitate the sustainable use of CL for deliveries?* *What are the interdependencies between sustainable use of CL and societal developments?*
Contextuality	5.2.3	*What potential does crowd logistics hold during public emergencies?* *How do societal challenges, such as an aging population and a decreasing number of people with driver's licenses, affect CL?* *How does cultural context impact CL sustainability potential?*

Furthermore, the B_{15} *Traffic Limitations* loop and the links connected to the geo-spatial spread of deliveries indicate that the underlying infrastructure and behavioral patterns within the encompassing environment should be considered to maximize the benefits of CL from a sustainability perspective. An example illustrating the importance of considering the underlying infrastructural and geographical background is the difference between delivering from a store and delivering from a fulfillment center. While the delivery from a retail store may require only a small detour, fulfillment centers are usually not located within urban areas. Thus, they are likely to necessitate additional dedicated trips for the collection.

5.2.2. Drifting goals and the potential for social segregation

A strong focus on profitability within CL delivery systems could start a drifting goals cycle (cf. Kim, 1993), where the original goal, i.e., using OCs to fulfill transport orders in a sustainable manner, becomes second to reducing costs and maintaining high customer service levels. In this case, rather than investing in a supporting fleet of dedicated freight vehicles and integrating both CL and LSP elements (B_{12} *Fleet Utilization*), CL initiatives may heavily rely on dedicated trips by the OCs (R_3 *Dedication Fallacy*). It is likely that remuneration control mechanisms, such as surge pricing or tipping suggestions for customers, are then used to stimulate availability to maintain and grow initiative momentum. This could lead to various negative impacts from both an environmental and social perspective. For example, using remuneration control may lead to an increasingly high share of dedicated trips. Promoting dedicated trips rather than detours increases VMT. Instead of reducing VMT, traffic, emissions, and cost, CL could then lead to an increase. Moreover, it may lead to a shift in costs toward the OCs. The B_2 *OC Competition*, B_3 *Competition Wear*, and B_{11} *Customer Segregation* loops indicate that the use of additional remuneration incentives could further exacerbate fluctuations in OC remuneration and delivery fees, which may lead to social segregation as less attractive areas and timeslots for delivery may be penalized. The CLDs related to customer dynamics indicate a similar potential for issues to those on the OCs' side. Solely relying on OCs can potentially increase delivery uncertainty, traffic, and resource consumption and may lead to high fluctuations in delivery fees. The latter could lead to scenarios where deprived people cannot afford the same services or even where they are not serviced at all.

5.2.3. Areas of operation from a social perspective

CL initiatives that primarily focus on non-monetary incentivization could suffer from scalability issues. As illustrated through the CLDs (cf., e.g., R_1 *OC Matching*, R_5 *Order Matching*), the scalability hinges on matching supply and demand. While the B_{12} *Fleet Utilization* and B_{13} *Fleet Responsiveness* loop structures indicate that a lack of OCs can be compensated through dedicated freight vehicles, the related costs could pose a significant issue (cf. B_{16} *Delivery Costs* and B_{17} *Fleet Cost Efficiency*). Strong community building may be able to alleviate some of these issues.

Relatedly, there are areas where encouraging sustainable CL operations is more prolific than others. For instance, social environments where social capital has a higher significance could possibly leverage the sustainability potential of CL more easily. CL may also be particularly well-suited when available freight transport resources are scarce or to attenuate a sudden and dramatic rise in capacity requirements. For example, CL may increase reach and access where limited freight transportation resources are available. Underserved remote or sparsely populated areas, which are less attractive from the LSP view, could be connected via CL. This can provide a sense of self-sufficiency, particularly for older people with limited mobility. In these situations, profound sympathy may sufficiently substitute monetary incentives, facilitating adequate numbers of OCs to provide meaningful and timely help. We highlight how many people participated in CL activities during the initial phase of the COVID-19 pandemic, e.g., through grocery shopping for the sick and elderly (cf., e.g., Tekin et al., 2021 and Bodroža and Dinić, 2023). This shows how CL may be particularly well suited to alleviate public emergencies.

5.3. Future research opportunities

Through the scoping systems thinking review methodology employed in this paper, we discussed several potential implications that can serve as a basis for further exploration. As highlighted previously, there have been calls for more research on the societal and environmental impacts of CL. We find that these calls have remained mostly unanswered so far. Considering how our research has shown that CL delivery systems can be understood as wicked systems, it is crucial that future research addresses these gaps. Table 2 provides an overview of possible research questions originating from our findings. We find that questions regarding societal and environmental impacts, system boundaries, managerial myopia, and trade-off decisions in CL delivery systems are particularly interesting.

We encourage fellow researchers to consider the potential implications of their research within the context of feedback mechanisms in CL delivery systems. To this end, the CLDs presented in the previous section can facilitate a deeper understanding of how different elements within these systems can be connected. Future research needs to consider and discuss results in light of the dynamic properties of these systems. In this way, missing or unidentified links can be determined, further adding to the structures identified in this paper and connecting them to the larger socio-economic context in which they operate.

However, rather than just examining how CL can be put to better use, one should also consider what can be done to increase CL's sustainability potential. This entails researching what social norms and infrastructural challenges limit and encourage its potential. For example, if cultural idiosyncrasies or infrastructural challenges limit participation willingness, this could severely limit the potential. Beyond these aspects, it is also interesting to consider new areas of application.

Moreover, as the discussion throughout this section highlights, some feedback structures need further investigation. For example, while one could assume that an initiative gains self-sufficiency with growing size, our analysis indicates that the required level of LSP integration to maintain momentum may actually rise. Thus, we presume that integrating CL in existing LSP structures has the potential to be more successful than starting with a pure CL delivery system. As argued in the previous subsections, this requires an understanding that CL and LSP must be treated as dynamically different. Therefore, we highlight the overall importance of research that further examines the dynamic processes involved in LSP integration and hybrid systems.

In addition to questions related to operations scaling, many questions remain regarding the discussion of optimization versus effectiveness, as well as the effects of contextual differences. This includes determining the long-term effects of different control mechanisms, the role of trip dedication, and the impacts on society. Moreover, it remains unclear how demographic changes, such as an aging population or a decreasing number of driver's license holders, may affect CL's sustainability potential.

6. Concluding remarks

As an alternative to LSPs, CL has been advocated as a concept for increasing operational efficiency that could also increase environmental sustainability by reducing resource use and emissions. In addition, previous works have also argued that CL could also contribute to positive societal impacts by providing job opportunities and access in underserved areas.

Yet, our work revealed that research foci have remained mostly singular, ignoring how, as dynamic systems, CL delivery services can be considered a wicked problem, and thus, gains in one part of the system may lead to detrimental changes over time in another. Moreover, we found that there is a general lack of research that considers the societal and environmental impacts. Both in scientific literature and particularly in practice, CL has been considered through an 'LSP lens' which backs the use of CL to reduce costs rather than facilitating sustainable operations.

To move forward, we must better understand how CL delivery systems integrate and interact within their larger socio-economic context and how they can be modeled accordingly. To this end, more research is needed on the societal impacts of CL delivery systems. Furthermore, a better understanding of the impacts of OC and customer behaviors is necessary to facilitate successful and sustainable real-world operations in the future. For example, narrative research could be used to illustrate the effects on OCs, particularly from a social perspective. We also highlight that further empirical research is needed to confirm the results presented in this paper. To this end, an analysis of failed CL initiatives can help to facilitate further insights. In this context, it is also important to investigate how regulations and legal frameworks influence such business dynamics and societal impacts of CL initiatives. Moreover, a deeper understanding of external barriers, catalysts, and control mechanisms for CL delivery systems and their impact on sustainability is needed to guide decision-makers. This also includes examining the wider economic implications of CL in greater detail, such as its impact on shipping rates and profit margins. Developing decision support systems for CL delivery networks based on the CLDs introduced in this work can also foster informed and sustainable decision-making and, thus, should receive further attention. We conclude that future research should focus not only on optimizing operations for a specified point in time but also on examining their long-term effects on business, the environment, and society.

CRediT authorship contribution statement

Florian Cramer: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization. **Christian Fikar:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly for spell checking and in order to improve comma placement and sentence structure. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Literature support for author deduced links

See Table 3.

Appendix B. Loop structures on the couriers' side

See Table 4.

Appendix C. Loop structures on the customers' side

See Table 5.

Appendix D. Loop structures on the platforms' side

See Table 6.

Table 3
Literature support for author deduced links.

ID	Link			Polarity	Supported through
a	OC acquisition rate	→	Occasional couriers	+	Kumar et al. (2018)
b	Potential OCs	→	OC acquisition rate	+	Böcker and Meelen (2017)
c	Population	→	Potential OCs	+	Böcker and Meelen (2017)
d	Platform attractiveness	→	Potential OCs	+	Kim and Son (2009)
e	Matches	→	Matching ratio	+	Cullen and Farronato (2021), Rong et al. (2021)
f	OC Satisfaction	→	Platform attractiveness	+	Kim and Son (2009)
g	Occasional couriers (OCs)	→	Matching ratio	–	Cullen and Farronato (2021), Rong et al. (2021)
h	Customers	→	Transport orders	+	Davlembayeva et al. (2020), Mitropoulos et al. (2021)
i	Customer acquisition rate	→	Customers	+	Kumar et al. (2018)
j	Potential customers	→	Customer acquisition rate	+	Böcker and Meelen (2017)
k	Delivery fee	→	Approval of delivery fee	–	Yang and Xia (2022)
l	Customers	→	Competition between customers	–	Yang et al. (2020)
m	Competition between customers	→	Willingness to pay	+	Yang et al. (2020)
n	Willingness to pay	→	Approval of delivery fee	+	Kung and Zhong (2017)
o	Customer satisfaction	→	Service reputation	+	Ert et al. (2016)
p	Population	→	Potential customers	+	Böcker and Meelen (2017)
q	Traffic	→	Delivery delays	+	Roy et al. (2020)
r	Dedicated freight vehicle fleet size	→	Traffic	+	Kummer et al. (2021)
s	Resource consumption	→	Matching requirements for customers	+	Rong et al. (2021)
t	Competition between customers	→	Matching requirements for customers	+	Yang et al. (2020), Rong et al. (2021)
u	Competition between customers	→	Tips	+	Lei and Pun (2023)
v	Occasional couriers (OCs)	→	Competition between customers	+	Yang et al. (2020)
w	Resource consumption	→	Platform attractiveness	+	Wilhelms et al. (2017), Rong et al. (2021)

Table 4
Identified loop structures related to the couriers' side.

	Loop	Cycle (⟶)
B_1	*OC Pool*	Occasional Couriers (OCs)→ Matching Ratio→ OC Satisfaction→ OC Retention Rate ↺
B_2	*OC Competition*	Competition between OCs→ Courier Remuneration→ OC Satisfaction→ OC Retention Rate→ Occasional Couriers (OCs) ↺
B_3	*Competition Wear*	Competition between OCs→ Matching Requirements for Couriers→ Matching Requirements→ Matches→ Matching Ratio→ OC Satisfaction→ OC Retention Rate→ Occasional Couriers (OCs)↺
B_4	*OC Bidding*	Matches→ Utilization of Private transport Capacity→ Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction→ Customer Retention Rate→ Customers→ Transport Orders→ Competition between OCs→ Courier Remuneration→ OC Satisfaction→ OC Retention Rate→ Occasional Couriers (OCs)↺
B_5	*Dedication Gain*	Share of Dedicated Delivery Trips→ Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction→ Customer Retention Rate→ Customers→ Transport Orders→ Competition Between OCs→ Courier Remuneration↺
B_6	*OC Utilization*	Matches→ Utilization of Private transport Capacity→ Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction→ Customer Retention Rate→ Customers→ Transport Orders↺
R_1	*OC Matching*	Matches→ Matching Ratio→ OC Satisfaction→ OC Retention Rate→ Occasional Couriers (OCs)↺
R_2	*Platform Attraction*	Platform Attractiveness→ Potential OCs→ OC Acquisition Rate→ Occasional Couriers (OCs)→ Matches→ Matching Ratio→ OC Satisfaction↺
R_3	*Dedication Fallacy*	Share of Dedicated Delivery Trips→ Resource Consumption→ Matching Requirements for Couriers→ Matching Requirements→ Matches→ Matching Ratio→ OC Satisfaction→ OC Retention Rate→ Occasional Couriers↺
R_4	*Capacity Gain*	Occasional Couriers (OCs)→ Private Transport Capacity→ Utilization of Private Transport Capacity→ Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction → Customer Retention Rate→ Customers→ Transport Orders→ Matches→ Matching Ratio → OC Satisfaction→ OC Retention Rate↺

Table 5
Identified loop structures related to the customers' side.

	Loop	Cycle (⟶)
B_7	*Customer Pool*	Customers→ Transport Orders→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction→ Customer Retention Rate↻
B_8	*Platform Reputation*	Service Reputation→ Potential Customers→ Customer Acquisition Rate→ Customers→ Transport Orders→ Matches→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction↻
B_9	*New Orders*	Transport Orders→ Competition between OCs→ Courier Remuneration→ Total Cost→ Delivery Fee→ Customer Adoption Barriers→ Customer Acquisition Rate→ Customers↻
B_{10}	*Cost of New Orders*	Transport Orders→ Competition between OCs→ Courier Remuneration→ Total Cost→ Delivery Fee→ Approval of Delivery Fee→ Customer Satisfaction→ Customer Retention Rate→ Customers↻
B_{11}	*Customer Segregation*	Competition between Customers→ Tips→ Courier Remuneration→ Total Cost→ Delivery Fee→ Customer Adoption Barriers→ Customer Acquisition Rate→ Customers↻
R_5	*Order Matching*	Matches→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction → Customer Retention Rate→ Customers↻
R_6	*Fee Validation*	Competition between Customers→ Willingness to Pay→ Approval of Delivery Fee→ Customer Satisfaction→ Customer Retention Rate→ Customers↻
R_7	*Order Requirements*	Matching Requirements→ Matches→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction→ Matching Requirements for Customers↻

Table 6
Identified loop structures related to the platforms' side and operations management.

	Loop	Cycle (⟶)
R_4	*Capacity Gain*	Occasional Couriers (OCs)→ Private Transport Capacity→ Utilization of Private Transport Capacity→ Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction → Customer Retention Rate→ Customers→ Transport Orders→ Matches→ Matching Ratio → OC Satisfaction→ OC Retention Rate↻
B_7	*Customer Pool*	Customers→ Transport Orders→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction→ Customer Retention Rate↻
B_8	*Platform Reputation*	Service Reputation→ Potential Customers→ Customer Acquisition Rate→ Customers→ Transport Orders→ Matches→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction↻
B_{12}	*Fleet Utilization*	Required Dedicated Freight Vehicle Fleet Size→ Dedicated Freight Vehicle Fleet Size→ Logistics Responsiveness↻
B_{13}	*Fleet Responsiveness*	Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction→ Matching Requirements for Customers→ Matching Requirements→ Matches→ Utilization of Private Transport Capacity↻
B_{14}	*Crowd Responsiveness*	Logistics Responsiveness→ Delivery Delays→ Customer Satisfaction→ Matching Requirements for Customers→ Matching Requirements→ Matches→ Unserved Transport Orders→ Required Dedicated Freight Vehicle Fleet Size→ Dedicated Freight Vehicle Fleet Size↻
B_{15}	*Traffic Limitations*	Traffic→ Delivery Delays→ Customer Satisfaction→ Matching Requirements for Customers→ Matching Requirements→ Matches→ Utilization of Private Transport Capacity↻
B_{16}	*Delivery Costs*	Delivery Fee→ Approval of Delivery Fee→ Customer Satisfaction→ Customer Retention Rate→ Customers→ Transport Orders→ Unserved Transport Orders→ Required Dedicated Freight Vehicle Fleet Size→ Dedicated Freight Vehicle Fleet→ Resource Consumption→ Total Cost↻
B_{17}	*Fleet Cost Efficiency*	Total Cost→ Delivery Fee→ Customer Adoption Barriers→ Customer Acquisition Rate→ Customers→ Transport Orders→ Unserved Transport Orders→ Required Dedicated Freight Vehicle Fleet Size→ Dedicated Freight Vehicle Fleet→ Resource Consumption↻
B_{18}	*Resource Erosion*	Resource Consumption→ Service Reputation→ Potential Customers→ Customer Acquisition Rate→ Customers→ Transport Orders→ Matched→ Utilization of Private Transport Capacity→ Logistics Responsiveness→ Required Dedicated Freight vehicle Fleet Size→ Dedicated Freight Vehicle Fleet Size↻
R_5	*Order Matching*	Matches→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction → Customer Retention Rate→ Customers↻
R_7	*Order Requirements*	Matching Requirements→ Matches→ Unserved Transport Orders→ Customer Service Level→ Customer Satisfaction→ Matching Requirements for Customers↻
R_8	*Logistics Requirements*	Required Dedicated Freight Vehicle Fleet Size→ Dedicated Freight Vehicle Fleet Size→ Customer Service Level→ Customer Satisfaction→ Matching Requirements for Customers → Matching Requirements→ Matches→ Utilization of Private Transport Capacity→ Logistics Responsiveness↻

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3 Article 3

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Rethinking accessibility: Catalyzing early-stage diffusion of grocery innovations using mobile pop-up stores

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ABSTRACT

The recognition of local actors as pivotal agents for sustainability in grocery supply chains has grown significantly. However, despite the support by some enterprises, from venture capital and media, numerous micro-, small-, and medium-sized enterprises (MSMEs) in the grocery industry encounter challenges related to product diffusion and market reach. Consequently, numerous innovative products originating from startups without sufficient support encounter difficulties in reaching consumers, potentially facing marginalization. Recognizing the crucial role of adopting such products can stimulate consumer interest and position retailers as leaders in offering sustainability-driven choices. While listing a new product can lead to a competitive advantage, it can also cause loss when the product is rejected. This research investigates the initial phase of product diffusion by comparing traditional stationary brick-and-mortar stores to the agility of mobile pop-up stores. Therefore, our work contributes to research on spatiotemporal and multi-stage product diffusion and the emerging field of mobile retail. An agent-based simulation model is employed to simulate the product diffusion process, and a regression model is used to identify promising store locations. Our exploration shows how combining ABS and ML methodologies can provide valuable decision support for both retailers and MSMEs. In addition, our study elucidates how enhancing access using mobile stores influences the early stages of product diffusion. While, in general, mobile stores show adequate performance in terms of market penetration, using selected stationary stores leads to higher sales due to repeat purchases. Moreover, combining both selected stationary stores and mobile stores can improve performance compared to either choosing selected or mobile stores. The results further show that increasing the store attractiveness heterogeneity, i.e., how strongly customers' perception of store attractiveness varies, positively mediates the potential of mobile stores. Our study indicates that mobile stores could be well-suited to facilitate initial product diffusion, particularly for clustered customer dispersion settings.

1. Introduction

From a grocery retailer's perspective, deciding whether to list a new product can be challenging, particularly for innovative and new types of products and brands. In the physical space, shelf space is limited, and listing a new product may require delisting another one. Moreover, additional challenges, such as product perishability, can obstruct operations scaling and the willingness to list a new product. Coincidentally, recognizing the crucial role of adopting such products can stimulate consumer interest and position retailers as leaders in offering sustainability-driven choices (Marín-García et al., 2020). The failure to swiftly incorporate and promote these innovations into their offerings can result in missed opportunities for retailers to differentiate themselves in the market. Simultaneously, a retailer's offering of sustainable choices can facilitate respective consumer behavior (Jung et al., 2022; Su et al., 2022).

However, without sufficient access to the market, the development of new products, e.g., novel food products like plant-based meat alternatives, product diffusion can be stifled, limiting access to sustainable choices for consumers (Baugreet et al., 2017; Anderson et al., 2019). In product diffusion, distribution precedes market share and constitutes an important factor in building new brands (Bronnenberg et al., 2000; Ataman et al., 2008). For MSMEs, this means that they must somehow facilitate product adoption, which simultaneously depends on a product's availability. Therefore, MSMEs can initially face a chicken-egg problem: To facilitate product adoption, customers need to be able to access the product (Jones and Ritz, 1991; Montaguti et al., 2002; Anderson et al., 2007); however, to provide access to the product, (a certain level of) product adoption can be required (Bronnenberg et al., 2000; Ogawa and Piller, 2006; Ge et al., 2021). Particularly new market entrants without prior connections to retailers face increased barriers to product introduction (van Everdingen et al., 2011). Deliberately imposing (initial) constraints in product supply can accelerate product diffusion and increase profits (Nadar et al., 2021; Pathak and Balakrishnan, 2024); however, in general, supply restrictions during the product takeoff phase lead to service quality issues and a reduced speed of diffusion (Kumar and Swaminathan, 2003; Balakrishnan and Pathak, 2014). Examples from the introduction and diffusion of new and sustainable technologies, such as electric vehicles, show that product diffusion in such codependency scenarios can be hard to manage (Brozynski and Leibowicz, 2022; Luo et al., 2023; Parameswaran et al., 2023). Therefore, understanding how product diffusion can be accelerated or impeded can play an important role in determining whether

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a new product or service will be successful. While in the physical space, retailers' shelf space is limited and valuable (Hübner et al., 2021), in the online space, new products or brands can lack visibility due to choice overload (Long et al., 2021; Sethuraman et al., 2022; Turri and Watson, 2023). Increasing assortment width in online retailing can also impact timely deliveries (Gopalakrishnan et al., 2023). Moreover, projections by Bain & Company for grocery online retailing indicate that EBIT margins will continue to decline (Kamel et al., 2023).

A concept that can alleviate some of the risks associated with operating a brick-and-mortar store for MSMEs and reduce the pressure on retailers is the pop-up store concept, in which stores are set up temporarily to boost product and brand awareness and to provide short-term market access. One distinctive feature of pop-up stores helps to facilitate sales (Henkel et al., 2022): a pop-up store's ephemerality, i.e., the increased customer desire due to the time-limited nature of the offering. In this regard, the short-lived existence of pop-up stores has a significant effect on the perceived uniqueness of these stores, which in return has a significant effect on a customer's willingness to pay but no effect on brand loyalty (Zogaj et al., 2019). While traditional pop-up stores are stationary, i.e., their location is fixed and hence limited in the area they can cover, using mobile retail stores (stores that can change location) could enhance pop-up store operations. Consequently, in line with the findings of Zogaj et al. (2019), we argue that mobile pop-up stores can assist retailers in fostering product diffusion, thus boosting sales and allowing for changing assortment without losing brand loyalty, as the perceived uniqueness stems from the store itself rather than from the offered assortment.

Past research on mobile retail has focused on using mobile stores, labeled 'mobile produce markets' (Hsiao et al., 2019), to alleviate issues in areas with limited access to fresh and healthy food choices, such as so-called food swamps or food deserts. Apart from the focus on using mobile retail to provide access to healthy and nutritious food choices, the concept remains widely unexplored in an academic context and, in particular, from an Operations Management perspective. In this work, we explore how store mobility can impact product diffusion. We combine agent-based simulation modeling (ABS) with machine learning (ML) to answer the following questions:

> *How do store mobility, location selection, and product rejection affect the initial stages of the product diffusion process?*

Consequently, we evaluate whether the diffusion process is dominated by access to traditional grocery stores or whether alternative distribution channels, such as mobile pop-up stores and micro-stores, can serve as viable options to stimulate growth in the initial phase of product diffusion. To this end, we consider several different scenarios: (i) We consider operating (mobile) pop-up stores to facilitate product adoption by affording customers access using the city of Hamburg, Germany and new products from the food industries as a sample case, (ii) we further consider a partial adoption in some of the available (stationary) retail stores in the given region based on both random selection and predicted potential, (iii) we also simulate the impact of product rejection probability on product diffusion on either option. Finally, (iv) we study stylized geographical customer dispersion settings based on benchmark instances to facilitate further insights. In this way, this work examines how the introduction of alternative distribution channels impacts the diffusion process of local products and whether mobile stores can serve as an intermediate solution to reducing risk and enabling competitive advantage for retailers while empowering MSMEs.

Our research contributes to the research on multi-stage product diffusion and the emerging field of mobile retail. Several works have tackled product diffusion from a multi-stage perspective; however, most of these works model a macro-level view, which omits individual behavior (Ferreira and Lee, 2014). This is particularly problematic considering the prevailing homogeneity assumptions of spatial customer dispersion in such models (Garber et al., 2004). Among the works that include a multi-stage perspective on product diffusion, several (Jones and Ritz, 1991; Bronnenberg et al., 2000; Anderson et al., 2007; Peres and van den Bulte, 2014) consider the impact of retail distribution on product diffusion. While these studies highlight the importance of retail channels in the product diffusion process, to the best of our knowledge, no work has yet considered the impact of spatiotemporal retail coverage on product diffusion. Considering retailers' planning problem with the limited shelf space in the physical space (Hübner et al., 2021) and that the spatial dimension can play a key role in better understanding successful product diffusion processes (Garber et al., 2004; Fibich and Golan, 2023), our study explores the impact of changing spatiotemporal retail coverage on the product diffusion process. We further consider a novel application for mobile stores, thereby also advancing research in the emerging field of mobile retail. Our experiments investigate whether mobile pop-up stores can provide adequate support for the initial product diffusion process to alleviate issues with listing and delisting decisions for retailers.

The remainder of the paper is structured as follows: First, related work is presented in Section 2. After that, we elaborate on the methodology in Section 3, followed by a description of the simulation experiments in Section 4. The results are presented in Section 5 and discussed in the subsequent Section 6. The paper closes with concluding remarks, highlighting future research opportunities in Section 7.

2. Related work

The following section gives an overview of related work on mobile retailing and the combination of ABS and ML.

2.1. Research on mobile retailing

Mobile retailing is referred to with different names and keywords in academic literature. Examples include 'stores on wheels' (Gauri et al., 2021), 'stall economy' (Cao and Qi, 2023), and 'mobile produce markets' (MPM) (Hsiao et al., 2019). A major share of the literature focuses on MPMs to alleviate issues with food deserts and swamps, i.e., to provide access to healthy and nutritious food (Hsiao et al., 2019). Even with this narrow focus, studies have primarily focused on operations management and health impacts, e.g., by considering how operations can be optimized through assortment configuration and routing (cf., e.g., Wishon and Villalobos (2016a)). One example is the mathematical model introduced by Widener et al. (2012) for a mobile produce distribution system. They formulate an inaccessibility measure and suggest a spatial optimization model based on the capacitated p-median problem to identify stopping locations. Later, Wishon (2016) conducted a comprehensive examination of operational challenges for MPMs and explored assortment configuration (Wishon and Villalobos, 2016a), as well as routing (Wishon and Villalobos, 2016b) problems. Robinson et al. (2016) provide one of the first empirical studies on how MPMs operate. Weissman et al. (2020) use a survey to facilitate insights into the operational activities of existing initiatives. Kasprzak et al. (2022) use semi-structured interviews to gain insights into what challenges impede implementations of the MPM concept. Except for the work by Cao and Qi (2023) on 'retail on wheels', the current body of research on mobile retail facilities has focused primarily on MPMs used as interventions against food deserts in North America. To the best of our knowledge, none have considered the use of mobile retailing in the context of product diffusion.

2.2. Agent-based simulation and machine learning procedures for smarter planning

As Davis et al. (2007, p. 480) highlight, "[...] simulation can be a powerful method for sharply specifying and extending extant theory in useful ways." We use ABS to model the product diffusion process. In ABS, individual decision units that are acting based on pre-defined decision rules (agents) interact with each other, creating a dynamic environment (Macal, 2016). ABS holds many potentials for developing theory related to the product diffusion process (Rand and Stummer, 2021). For example, Gu and Xu (2022) use ABS to explore how targeting key connecting nodes in social networks, so-called bridges, affects product diffusion. Their research shows that targeting bridges can increase market share. Yan and Hu (2023) use ABS to evaluate the effect of within-product and cross-product word of mouth (WOM) on product diffusion. The study highlights that both within- and cross-product WOM are important for product diffusion. Hu et al. (2018) apply ABS to explore which target groups to pursue to optimize product diffusion. They find that the optimal choice of which consumers to target and how to target them depends on budgetary constraints. In our work, ABS is used to simulate how the level of access to the product affects the product diffusion process

Our work combines simulation with ML to explore and evaluate a sample case (City of Hamburg, Germany, cf. Section 4) on store mobility as well as rejection probability and its impact on the product diffusion process. Several studies highlight the benefits of combining simulation and ML procedures in settings with high levels of uncertainty: For instance, Minbashi et al. (2023) combine a random forest (RF) with a macro simulation to predict train-yard arrival, highlighting the potential to use combined models for decision support. Likewise, the research by Cavalcante et al. (2019) shows how the combination of simulation and ML can provide decision support for the selection of resilient suppliers. Reich et al. (2021) use simulated results that are grounded in empirical data to approximate real-world data to create predictions with a recurrent neural network (NN). Their results show that data synthesis through simulation can alleviate issues with low data quality to make better predictions. Liu et al. (2023) use discrete event simulation (DES) to evaluate the effects of false predictions for defect detection. The research shows that simulation-based evaluation can help identify missed aspects and future research opportunities.

de Sousa Junior et al. (2020) evaluate the integration of simulation with different ML techniques and show that combining simulations with ML can decrease the optimality gap and significantly reduce computational time. Feng et al. (2018) integrate an artificial NN to reduce computational effort for a simulation optimization related to building construction based on DES and particle swarm optimization. Their results show significant time savings at the cost of slightly worse results. The work of Shashaani and Vahdat (2023) shows how the combination of simulation optimization and ML can lead to an improved feature selection. Sobottka et al. (2019) use NN as a surrogate model to reduce computational effort for a complex hybrid simulation model. The food industry case study shows how a surrogate ML model can serve to evaluate intermediate planning solutions. Similarly, the review by Wang et al. (2022) highlights the potential of combining simulation and ML techniques by using ML to create surrogate models or using simulations to train models. The presented examples show the utility of combining simulation and ML techniques to provide decision support, especially in a (highly) dynamic and computationally expensive context.

3. Methodology

Figure 1 gives an overview of the methodological framework used in this work. At the core, an ABS model simulates the product diffusion process based on customer shopping behavior and store availability. Additionally, an ML-based relocation model is integrated to facilitate relocation choices considering empirically collected customer behavior. The subsequent section first details the simulation model and then the prediction model choice. Table 1 gives an overview of the model notation.

3.1. Input data and initialization

The simulation model takes several data sources as input to initialize each simulation run. The pseudocode in Table 2 describes the steps of the initialization process. Each store

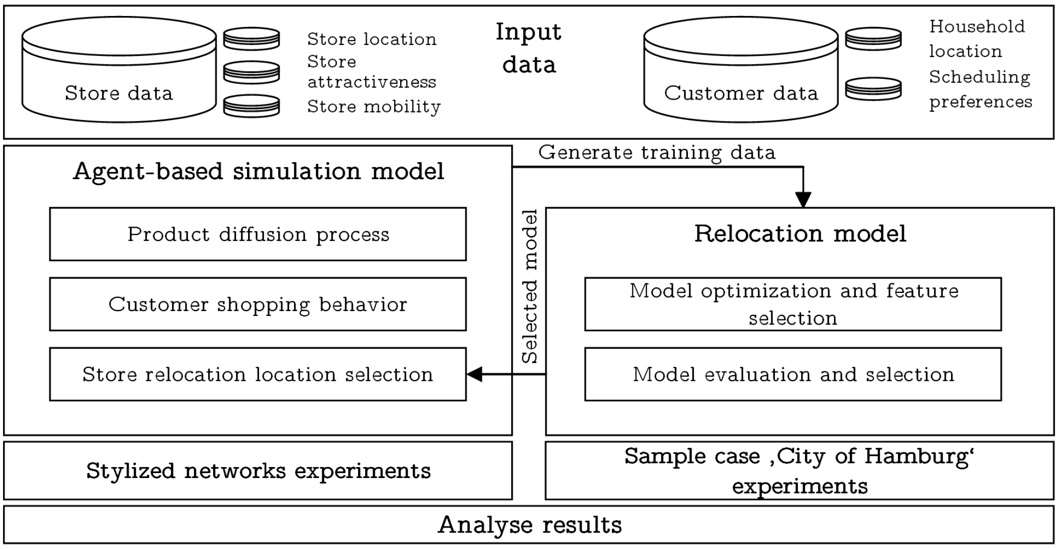


Figure 1: Methodological framework employed in this study

is initialized with a starting location and either the ability to relocate or remain stationary (cf. Subsection 3.2.3). Relocation events are scheduled, repeating within the specified relocation frequency. For each household, the probability of visiting a certain store is set at the beginning. After that, the customers are initialized (cf. Subsection 3.2.2). In addition, further scheduling events for each shopping cycle (week) are scheduled. Furthermore, for each period, advertisement and word of mouth (WOM) checks (cf. Subsection 3.2.1), as well as data collection, are set. The initialization process yields an initial schedule of events which is passed to the simulation for processing.

3.2. Agent-based simulation model

The ABS model consists of three major parts: (i) the modeling of the product diffusion process, (ii) the modeling of customer shopping behavior, and (iii) the implementation of a store relocation procedure. Figure 3 depicts pseudocode for a single simulation run. After the initialization, events are processed and created sequentially until the end of the simulation is reached.

3.2.1. Product diffusion process

The product diffusion process involves several actors and aspects, with customers and retailers assuming crucial roles. In general, customers can become aware of a product through different outlets. Once the customer is aware of the product and wants to try it, the adoption process hinges on access to it. If a customer is inclined to test a new product, he or she will try to buy it. However, if there is no option to purchase the product, the customer cannot adopt the product. Thus, retailers can be considered as enablers in the diffusion process. Without the retailers, product diffusion can become severely limited (Sharma et al., 2019).

Figure 2 depicts the adoption journey for each customer agent within the simulation. To model the first stage, we extended the idea behind the Bass (1969) diffusion model by incorporating two mechanisms to create product awareness. Firstly, customers can become aware of the product through advertisements. Secondly, customers can be notified through contacts within their social network via WOM. Both processes are modeled as Bernoulli processes. The probability of adopting due to advertisement depends on a single draw, whereas WOM depends on the number of adopters N_{tc} within the social network of the customer c. In this regard, the advertisement probability can be understood as the probability with which a customer household c will become actively interested in the product within period t without considering WOM from their immediate social network (1). In contrast, the activation via WOM depends on the number of households that promote the product within the customer's immediate social network ($c_{network}$) during period t. Only those immediate network members n that have become adopters ($n_t^{adopter} = 1$) are considered for the spread of WOM. For a successful activation via WOM, a single success is required; thus, we modeled a binomial coefficient where the number of draws equals N_{tc}, and the number of occurrences is one (2).

$$Pr(AD_{success})_{tc} = p_{advert} \tag{1}$$

$$Pr(WOM_{success})_{tc} = \begin{cases} 0 \text{ if } N_{tc} = 0 \\ N_{tc}\ p_{wom}\ (1 - p_{wom})^{(N_{tc}-1)} \end{cases}$$

s.t.

$$N_{tc} = |\{n \mid n \in c_{network}, n_t^{adopter} = 1\}| \tag{2}$$

In any case, the adoption process depends on the customer's shopping behavior and product availability. To

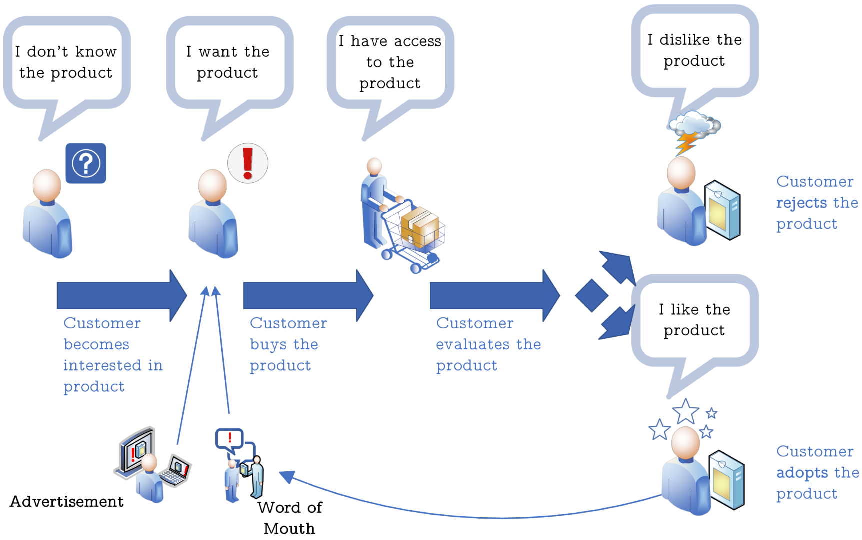


Figure 2: The agent product diffusion journey

model the product diffusion process, we modeled a sequential process in which agents first become aware of the product before deciding to adopt it. The agent checks whether he or she was exposed to information on the product in a defined time interval. Once the agent is aware, the agent will try to buy the product during their subsequent shop visits.

Following the ideas presented in the extended Bass diffusion model by Horvat et al. (2020), we included the possibility for customers to either adopt or reject the product. After the initial purchase, the agents decide, based on a set probability for product rejection, whether the product is adopted or rejected. Customer agents that have already adopted the product will buy a specified amount of the product each subsequent cycle. Customers who have transitioned to the state of adoption further spread information on the product within their social network repeatedly, thus facilitating WOM adoption. To model product diffusion through WOM, each agent is equipped with an immediate social network. Figure 3 shows an exemplary configuration of a customer's (focal person) social network. Each customer acts as a node within a network, thereby forming a social network in which customers' decisions are influenced by the decisions of their neighbors on the network (immediate network). The immediate social network of a customer c ($c_{network}$) thus constitutes an induced subgraph of the entire social network graph G. Within the social network, adopters can act as facilitators of WOM, whereas rejecters can cut off parts of the network. In the early stages of product adoption, customers can be more spatially dispersed, whereas, in the later stages of diffusion, local diffusion becomes dominant (Lengyel et al., 2020). Therefore, we chose to model the connections between customers within the social network to be randomly distributed. Hence, the social networks formed in the model do not need to consist of a connected graph.

3.2.2. *Customer shopping behavior*

The shopping behavior of customers is assumed to be cyclical, e.g., on a weekly basis. Table 4 illustrates the pseudocode for a single customer's shopping process. Upon the visit to the store, an agent who is aware of the product will check whether the product is available at the chosen location and, if available, purchase one unit. All customers have preferences for weekdays and times, as well as a shopping frequency within a given cycle, e.g., three times per week. The chosen timeslots (within a defined interval size, e.g., timeslots of two hours) are set randomly based on individual preference for each new cycle. For example, Customer A can go shopping on either Monday, Tuesday, or Friday between 8:00 a.m. and 10:00 a.m. and between 8:00 p.m. and 10:00 p.m. Customer A has a shopping frequency of twice per week. In the first week, Customer A may choose to go shopping on Mondays at 8:00 a.m. and Tuesdays at 8:00 a.m., whereas in the second week, he or she chooses to go shopping on Tuesdays at 8:00 p.m. and Fridays at 8:00 a.m.

To determine which outlet is visited, we used the Huff (1963) gravity model with the total weekly opening hours as a measure of store attractiveness. The model allows us to calculate the probability of visiting a store location from each possible residential address p_{hl} (3). The store choice is checked for each shopping trip individually through a roulette wheel draw based on the calculated probabilities for all store locations.

$$p_{hl} = \frac{Attractiveness_l Distance_{hl}^{-1}}{\sum_{j=1}^{L} Attractiveness_j Distance_{hj}^{-1}} \tag{3}$$

3.2.3. *Store relocation location selection*

The difference between stationary and mobile stores is highlighted in Figure 4. While stationary retail stores have a fixed location, mobile ones switch locations after a fixed

Table 1
Model notations

Notation	Description	
Sets and indices		
$\mathcal{B}$	$b \in \{1, ..., B\}$:	set of customer type profiles
$\mathcal{C}$	$c \in \{1, ..., C\}$:	set of customers
$\mathcal{E}$	$i \in \{1, ..., E\}$:	set of events
$\mathcal{H}$	$h \in \{1, ..., H\}$:	set of household locations
$\mathcal{L}$	$l \in \{1, ..., L\}$:	set of store locations
$\mathcal{M}$	$m \in \{1, ..., M\}$:	set of mobile stores
$\mathcal{S}$	$s \in \{1, ..., S\}$:	set of retail stores
$\mathcal{T}$	$t \in \{1, ..., T\}$:	set of periods
Model parameters and variables		
α	weight factor for repeat sales	
β	prescribed social network size	
$c_{location}$	household location ($h \in \mathcal{H}$) allocated to customer c	
$c_{network}$	induced subgraph of G including all immediate social connections of customer c	
c_{type}	customer type ($b \in \mathcal{B}$) of customer c	
f_{cycle}	cycle frequency	
$f_{relocation}$	relocation frequency	
G	social network, where the customers are nodes and the connections between them are edges	
L'	descending list of location potentials for the consecutive period	
$n_t^{adopter}$	property whether social network member n is an adopter (1) or not (0) during period t	
N_{tc}	number of adopters in customer's (c) immediate network during period t	
μ_c^{volume}	average repurchase volume for repeat sales for customer c	
Φ_{lt}	total sales potential of location l in period t	
$\phi_{lt}^{adoption}$	adoption potential of location l in period t	
ϕ_{lt}^{repeat}	repeat sales potential of location l in period t	
p_{advert}	probability of advertisement success	
p_{cl}	probability that customer c visits location l	
p_{hl}	probability of household h to visit location l	
p_r	probability of product rejection	
p_{wom}	probability of WOM success	
$sales_{ct}$	cumulative sales to customer c in period t	
$sales_{lt}^{adoption}$	cumulative adoption sales at location l in period t	
$sales_{lt}^{repeat}$	cumulative repeat sales at location l in period t	

period. This allows the mobile retail unit to cover different areas at different times and days throughout the week. We assume that a (stationary) store location can be equipped to host a mobile store, thus allowing access (temporarily) to the product even when the stationary retail store does not offer it.

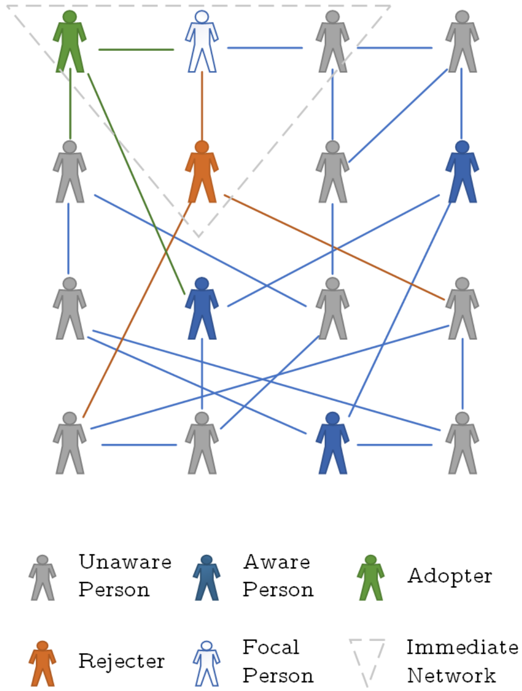


Figure 3: Each customer agent has an immediate social network that guides the WOM diffusion process

Consequently, we model access to the product as a defining feature of the product diffusion process.

To decide to which location to relocate, the potential, i.e., the ability to contribute to product diffusion and repeat sales, for each possible location during the period until the next relocation checkup is predicted. Locations are then assigned based on a greedy approach, assigning the location with the highest potential first. To evaluate the potential Φ_{lt} of location l during period t, we considered the possibility of focusing on either adoption or repeat sales (with gradient α), where $\alpha = 0$ corresponds to a sole focus on adoption and $\alpha = 1$ corresponds to a sole focus on repeat sales (4). The adoption potential $\phi_{lt}^{adoption}$ is then evaluated by considering the number of potential adopters left for the location and their likelihood to visit the location (5) and the repurchasing potential ϕ_{lt}^{repeat} (6) based on the adopters at the location weighted by α.

$$\Phi_{lt} = (1-\alpha)\, \phi_{lt}^{adoption} + \alpha\, \phi_{lt}^{repeat} \tag{4}$$

$$\phi_{lt}^{adoption} = \sum_{c \in \{c \,|\, c \in \mathcal{C}, sales_{ct}=0\}} p_{cl} \tag{5}$$

$$\phi_{lt}^{repeat} = \sum_{c \in \{c \,|\, c \in \mathcal{C}, sales_{ct}>0\}} p_{cl}\, \mu_c^{volume} \tag{6}$$

For the sample case, we assume an empirical setting where customer visits and location are stochastic and unknown to the retailer. Thus, the retailer needs to estimate

Table 2
Pseudocode for simulation initialization

Pseudocode for the simulation initialization process

Input: Set of household locations $\mathcal{H}$, Set of customers $\mathcal{C}$, Set of store locations $\mathcal{L}$, Set of stores $\mathcal{S}$, Set of periods $\mathcal{T}$, Set of customer type profiles $\mathcal{B}$, Cycle frequency f_{cycle}, Relocation frequency $f_{relocation}$, Prescribed social network size β, $seed$

Output: Set of events $\mathcal{E}$

function initialization ($\mathcal{H}$, $\mathcal{C}$, $\mathcal{B}$, $\mathcal{L}$, $\mathcal{S}$, $\mathcal{T}$, $seed$, $f_{relocation}$, β):
    set random number generator seed to $seed$
    $G \leftarrow$ create social network graph, where each customer c represents a vertex
        with a prescribed degree of β
    for each store s in $\mathcal{S}$ **do:**
        initialize location of store s based on $\mathcal{L}$
    for each household h, store location l in $\mathcal{H}$, $\mathcal{L}$ **do:**
        calculate store location visit probability p_{hl}
    for each customer c in $\mathcal{C}$ **do:**
        $c_{location} \leftarrow$ choose random from $\mathcal{H}$
        $c_{type} \leftarrow$ choose random from $\mathcal{B}$
        $c_{network} \leftarrow$ induced subgraph from G including all immediate social connections of customer c
        set p_{cl} based on $c_{location}$
        set μ_c^{volume} based on c_{type}
    for each period t in $\mathcal{T}$ **do:**
        schedule advertisement and WOM checks
        if $t \ \% \ f_{relocation} = 0$ **do:**
            schedule relocation event
        if $t \ \% \ f_{cycle} = 0$ **do:**
            schedule shopping trip scheduling event for respective cycle
        schedule data collection
    return Set of events $\mathcal{E}$
end function

Table 3
Pseudocode for the simulation model

Pseudocode for a single simulation run

Input: Set of household locations $\mathcal{H}$, Set of customers $\mathcal{C}$, Set of store locations $\mathcal{L}$, Set of stores $\mathcal{S}$, Set of periods $\mathcal{T}$, Set of customer type profiles $\mathcal{B}$, Set of mobile stores $\mathcal{M}$, Relocation freqency $f_{relocation}$, Rejection probability p_r, Prescribed social network size β, WOM probability p_{wom}, Advertisement probability p_{advert}, $seed$

Output: $sales_{ct}$, $sales_{lt}^{adoption}$, and $sales_{lt}^{repeat}$ for each period $t \in \mathcal{T}$

simulation experiment ($\mathcal{H}$, $\mathcal{C}$, $\mathcal{B}$, $\mathcal{L}$, $\mathcal{S}$, $\mathcal{M}$, $\mathcal{T}$, $seed$, $f_{relocation}$, p_{wom}, p_{advert}, p_r, β):
    initialization ($\mathcal{H}$, $\mathcal{C}$, $\mathcal{B}$, $\mathcal{L}$, $\mathcal{S}$, $\mathcal{T}$, $seed$, $f_{relocation}$, β)
    while period $t \leq T$ **do:**
        for each event i in $\mathcal{E}$ **do:**
            if i is advertisement event **do:**
                for each customer c in $\mathcal{C}$ **do:**
                    if c is not aware **do:**
                        check awareness via ads and WOM based on p_{advert} and p_{wom}
            if i is shopping scheduling event **do:**
                for each customer c in $\mathcal{C}$ **do:**
                    if c is aware **do:**
                        schedule random trips based on preferred timeslots of c_{type} for next cycle
            if i is shopping event **do:**
                execute shopping for customer c assigned to event i
            if i is relocation event **do:**
                $L' \leftarrow$ sort locations according to predicted potential for each l in L for period $t+1$
                for each mobile store m, each location l in $\mathcal{M}$, L' **do:**
                    relocate m to l
            if i is data collection event **do:**
                collect data
    return collected data
end simulation

Table 4
Pseudocode for the processing of customer shopping events

Pseudocode for customer shopping

Input: Customer c, Period t, Rejection probability p_r
Output: $None$

function shopping (c, t):
    $l \leftarrow$ store roulette draw based on $c_{location}$
    if product is sold at location l **do:**
        if c is aware and c is not adopter and c is not rejecter **do:**
            $sales_{lt}^{adoption} \leftarrow sales_{lt}^{adoption} + 1$
            if $Pr(X > p_r)$ **do:**
                c adopts product
            else:
                c rejects product
        else if c is adopter and c has not bought product this cycle before **do:**
            $sales_{lt}^{repeat} \leftarrow sales_{lt}^{repeat} + \mu_c^{volume}$
end function

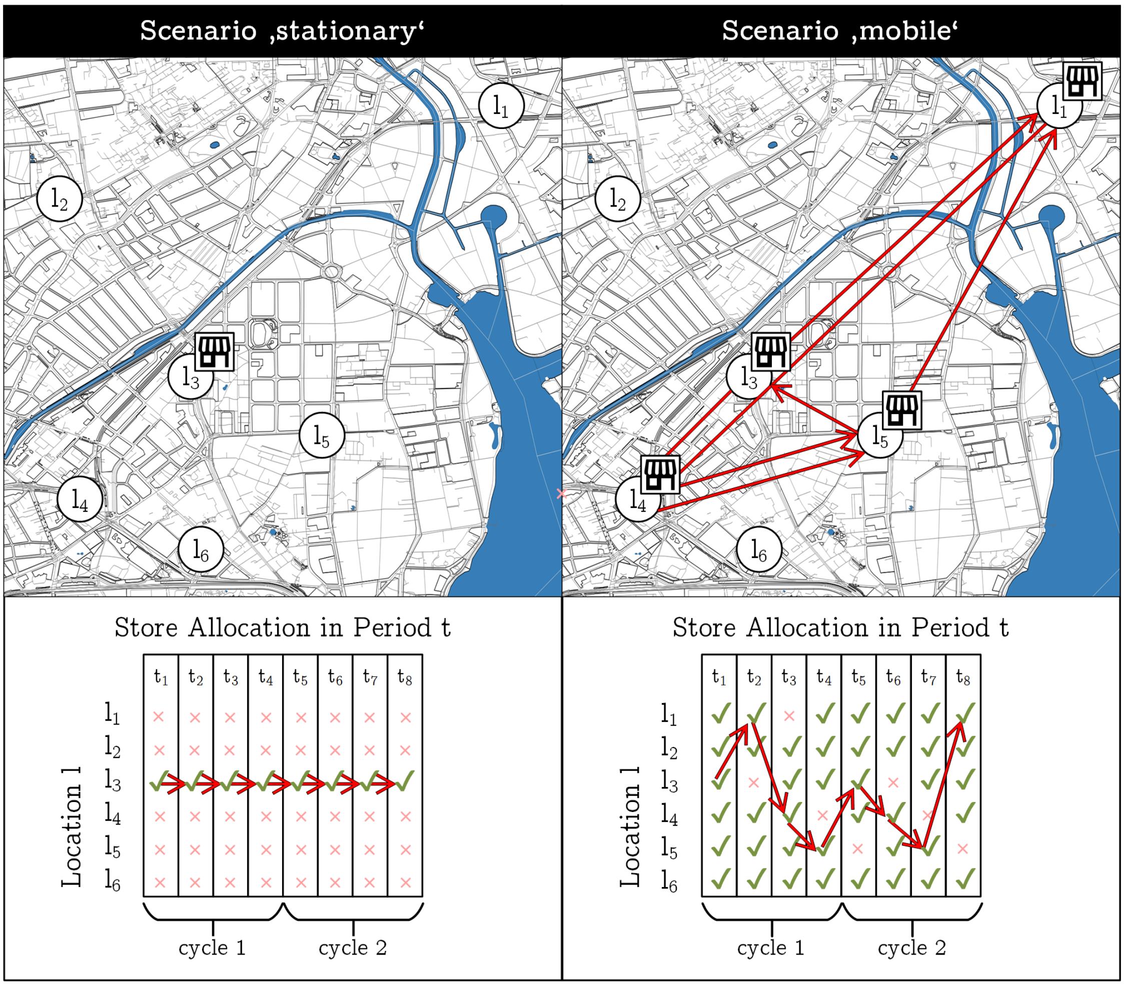


Figure 4: Comparison between stationary and mobile store location allocation

each location's potential through predictions. To this end, we use an ML-based regression model. For the stylized network experiments, the potential is calculated based on the current period data. This is possible as we assume that in the stylized setting, household locations are known to the retailer.

3.3. Relocation model

Several supervised ML regression models were considered to select an appropriate model for integration within the simulation. For the comparison, the models were trained and tested on a dataset that was created with the simulation model based on the average values for 100 replications for the baseline scenario with all stores selling the product.

3.3.1. *Model optimization and evaluation*

The simulated data was pre-processed with one-hot-encoding for the non-numerical data and a max-min scaler for numerical values to provide a purely numerical and scaled input for the regression models. The hyperparameters for each model were optimized to allow a more comprehensive comparison. To this end, we used Bayesian optimization to determine optimal values for the hyperparameters. To prevent overfitting, we employed cross-validation with 10-fold cross-validation, data augmentation (see Table 5), and considered the effects of feature selection through recursive feature elimination.

The selected features (predictor variables) include several aspects. Related to the ratio of sales to market penetration, we included the adoption-to-sales gradient α (cf. Subsection 3.2.3). With regard to product adoption and total sales, both the number of potential adopters left at the location (calculated based on the Huff model probabilities and adoption sales at the location) and the repeat sales potential (estimated through the number of adopters at the location) were considered. In addition, the potential of the previous period was also included. Related to store-specific aspects, we included store classification (e.g., urban integrated location) based on a classification by the administration of the considered region as well as district and the store identifier (as a categorical feature). For the temporal component, we considered days and weeks passed since the start of the simulation. The predictor variables for the final model are shown in Table 5.

For a comparison of prediction errors, we considered the mean absolute error (MAE), the mean squared error (MSE), the mean squared percentage error (MAPE), and R2, which are commonly used to compare model performance, and used R2 for the selection (Chicco et al., 2021).

3.3.2. *Model selection and training*

For the model selection, we tested different ML models commonly used in academic research (Kraus et al., 2020; Akbari and Do, 2021; Bertolini et al., 2021; Lee, 2021): The initial model selection included a linear regression model (LR), a support vector regression (SVR), a decision tree regression model (DT), a random forest (RF) regression model, a k-nearest neighbors regression model (KNN), and a feedforward neural network (MLP, multi layer perceptron). As Table 6 shows, the MLP outperforms the other models. While the results for SVR and MLP are similar, the MLP shows slightly better performance. Consequently, we chose to use an MLP model within the simulation model to predict location potential. To train the model, we used data generated through 100 replications for the baseline scenario of the sample case with product availability at all store locations.

Table 5
Selected predictor variables (features) for chosen regression model

Feature	Description	Source
alpha	weight of repeat sales	*simulation*
day	days since the start of the simulation	
week	weeks since the start of the simulation	
sales potential	mean sales potential at store location	
adoption potential	mean adoption potential at store location	
potential$_{t-1}$	previous relocation period's store potential	
area	area where a store is located in	*City of Hamburg, State Office for Geoinformation and Surveying (2021)*
district	district where a store is located in	
site type	classification of the store site, e.g., 'integrated urban location'	
store identifier	unique store identifier string	

Table 6
Average performance of the considered regression models with 10-fold cross validation

Model	MAE	MAPE	MSE	R2
DT	5.1671	0.0959	40.4713	0.6996
KNN	0.5162	0.0148	1.6547	0.9709
LR	5.0599	0.0904	39.9225	0.7096
MLP	0.0410	0.0011	0.0075	0.9999
RF	5.1967	0.1077	43.0693	0.7525
SVR	0.0969	0.0023	0.0228	0.9997

4. Computational experiments

The subsequent section details the experiment parametrization and design of experiments for the sample case as well as the stylized network experiments.

4.1. Sample case City of Hamburg

As a sample case, we consider the use case of launching a new vegan food product within the sales territory of one of Germany's major retail chains. The City of Hamburg is frequently used as a test market for food products within Germany as it features a large (approximately 1.89mio. in 2022) and diverse (people from 170 different nations in 2022) population (Federal Statistical Office of Germany, 2024b,a). Moreover, Hamburg is heavily investing in accelerating food innovations, featuring one of the largest food start-up milieus, hosting over 161 residential food start-ups in early 2024 (Startup City Hamburg, 2024). According to German registration offices, Hamburg's population was allocated to 1.061.232 households in 2022 (Statistik Nord, 2023). For the

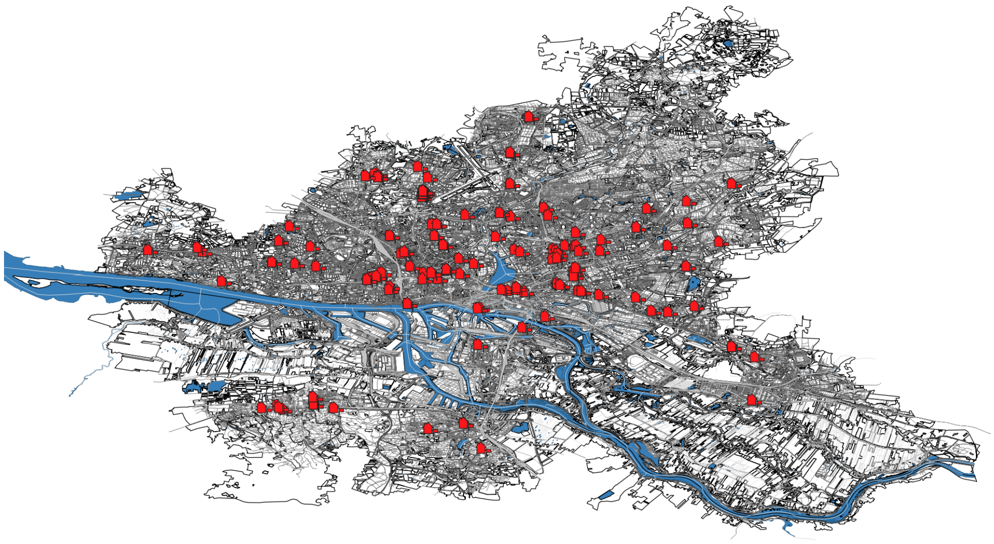


Figure 5: Geospatial dispersion of the retail stores within the city of Hamburg

sample case, the model allows different households to live at the same address. For the additional stylized network experiments, we assumed unique household locations. As shown in Figure 5, the retail chain has 60 store locations with a parking lot within 30m of the store in the city limits of Hamburg. The stores are either owned by the chain or by individual grocers that sell under the retailer's brand. While grocers are allowed to make individual decisions, some parts of the assortment are regulated by the retail chain. Thus, in the case of new products, there are two possibilities: The product can either be allocated centrally in selected markets by the retail chain or decentralized by each grocer individually. We will refer to these options as '*selected*' in case of allocation by the chain and '*random*' for an individual selection by the grocers. For the *selected* store setting, stores are allocated according to the predicted potential over the simulated time frame for each location, starting with the highest potential. In the *random* store setting, locations are chosen at random.

4.2. Baseline scenario

For our experiments, we assume a target population that reflects both the market share of the retailer as well as the share of vegan consumers. According to market research (Tradedimensions, 2023), the chosen retailer has a market share of approximately 21.2%. Regarding the share of vegan consumers in Germany, Statista Consumer Insights (2023) found that around 3% of Germans are vegans. We aggregate product diffusion on the household level, assuming that agents represent the entire household. Considering the number of households, the retailer's market share, and the share of vegan consumers, we derived a target population of 6.749 households. For the geospatial distribution, we used a dataset of real-world residential addresses in Hamburg provided by the Hamburg State Office for Geoinformation and Surveying (2022), which contains 193.314 unique addresses. For each simulation run, every household is allocated randomly to one of these addresses.

Empirical data suggests that the purchasing decision for new and innovative products in new markets is 46% based on WOM and 40% based on advertising (Bughin et al., 2010). Maintaining this ratio, we calibrated the effect of WOM and advertising in such a way that after a period of 13 weeks (91 days), approximately 86% of the eligible population had adopted the product when all retail stores sold the product. To model shopping behavior, i.e., shopping frequency, preferred shopping days, and hours (within 2-hour time windows), we obtained empirical data from Fikar et al. (2021), which contains survey data from 432 respondents. Each household randomly selects one of the 432 profiles at the beginning of a simulation run. Each week, shopping activities are then scheduled randomly according to frequency and preference. In addition, we assumed that once a household has adopted the product, the household will buy one unit every subsequent week. Following research by Hill and Dunbar (2003), we chose an average social network size of 150 contacts for each household.

4.3. Design of experiments

Table 7 lists the chosen parameter values for the case study experiments. For all experiments, we ran 100 replications for each scenario. Related to the store network configuration, we chose to vary the selection of *selected* stationary retail stores, *randomly* chosen stationary stores, and *mobile* stores. Based on the results for the *selected* stores (1 to 60 stores offer the product), we decided to explore *mobile* and *random* stores up to a value of 20. A higher number showed strongly diminishing returns for market penetration, i.e., the number of adopters. We varied the adoption-to-sales gradient $\alpha \in [0, 1]$ within 0.2 intervals in the baseline scenario for an initial exploration. Comparing the results after 91 days (13 weeks) using a minimum-regret decision rule, we

Table 7
Parametrization of the sample case experiments

Parameter		Range/Value
Advertisement probability	p_{advert}	0.00952
Average sales volume for repeat sales		1
Customer population size	C	6,749
Cycles frequency	f_{cycle}	13
Number of *mobile* stores		[0, 20]
Number of *selected* stores		[0, 20]
Number of *random* stores		[0, 20]
Random seed	$seed$	[0, 100)
Rejection probability	p_r	[0, 0.75] in 0.25
Relocation frequency	$f_{relocation}$	1
Simulation periods	T	91
Prescribed social network size per customer	β	150
WOM probability	p_{wom}	0.0002467

Table 8
Deviating parametrization of the stylized networks

Parameter		Range/Value
Advertisement probability	p_{advert}	0.0111
Customer population size	C	1,000
Number of *mobile* stores		[0, 5]
Number of *selected* stores		[0, 10]
Number of *random* stores		[0, 10]
Prescribed social network size per customer	β	22
WOM probability	p_{wom}	0.01288

Table 9
Store cluster distances for stylized networks for store clusters with 100 customers each and for the mapped sample case

	intra-cluster distance		inter-cluster distance	
	mean	**stdv**	**mean**	**stdv**
C1	282	100.71	401.77	196.01
C2	240.35	88.74	389.11	201.41
R1	272	96.63	399.57	198.20
RC1	282.85	102.27	398.57	194.55
*Sample case**	159.34	34.68	140.13	42.87

*mapped to a 500×500 Cartesian coordinate system, intra-cluster distance calculated based on fuzzy membership using Huff probabilities

determined that $\alpha = 0.8$ led to the best results in terms of market penetration and total sales in our experiments. For the relocation frequency, we chose a relocation interval of one day. In addition to studying the effects of changing the number of stationary and mobile stores, we also varied the rejection probability $p_r \in [0, 1]$ to simulate different product attractiveness, such as niche and hype products. To this end, we explored values between 0.0 and 0.75 in a 0.25 increment, which we refer to as '*no rejection*' ($p_r = 0.0$), '*low rejection*' ($p_r = 0.25$), '*medium rejection*' ($p_r = 0.5$), and '*high rejection*' ($p_r = 0.75$) probability.

4.4. Stylized network experiments

In addition to the sample case, which is grounded in empirical data, we also analyze several stylized customer network settings based on the benchmark instances for 1,000 customers by Gehring and Homberger (2001) to explore the impact of varying customer dispersion. We consider four archetypical customer dispersion scenarios based on their benchmark instances C1 (small clusters) and C2 (large clusters) for clustered regions, R1 for random customer dispersion, and RC1 for random clustered customer locations. In addition, we substantiated the findings based on these dispersion patterns through additional experiments based on customer dispersion patterns from the DIMACS (2021) vehicle routing challenge and instances from Uchoa et al. (2017). The results and a visual representation of the related dispersion patterns can be found in Appendix A. We assume 10 active stores within each setting, with each store located so that it covers an equal share of the population (10%) at minimal distances. For the prescribed social network size β, we changed the value relative to the reduction in population size (compared to the case study), e.g., for the Gehring and Homberger (2001) instances, β was set to 22 per customer. Table 8 highlights the changes in parametrization for the stylized network experiments.

Figure 6 portrays the customer dispersion and store locations within the benchmark region, which is limited to a Cartesian coordinate system with axes ranging between 0 and 500. Furthermore, the figure illustrates the geospatial dispersion for the sample case mapped to the same coordinate system. Table 9 shows the inter- and intra-cluster distances for each setting. We further analyze the impact of varying store attractiveness with coefficients of variation (CV) of 0.00, 0.25, 0.50, and 0.75.

5. Results

To compare the performance between the three store selection settings, we consider the two metrics used to calculate location potential: market penetration, i.e., the population that has adopted the product, and repeat sales, i.e., the number of repurchases. For better comparison, we calculate the relative shares (in relation to the total population) of the two metrics in this section.

5.1. Results from the sample case experiments

In the following subsection, the results for the chosen sample case, the City of Hamburg, are presented.

5.1.1. Impact of changing store numbers

Figure 7 illustrates the impact of changing the number of stores for either *mobile*, *selected*, or *random* stores in a *no rejection* scenario. The results show that in terms of market penetration, the *selected* stores outperform both *mobile* and *randomly* chosen stationary ones. However, as Figure 7a shows, the difference between *selected* and *mobile* stores is relatively small. Figure 7b shows a similar development

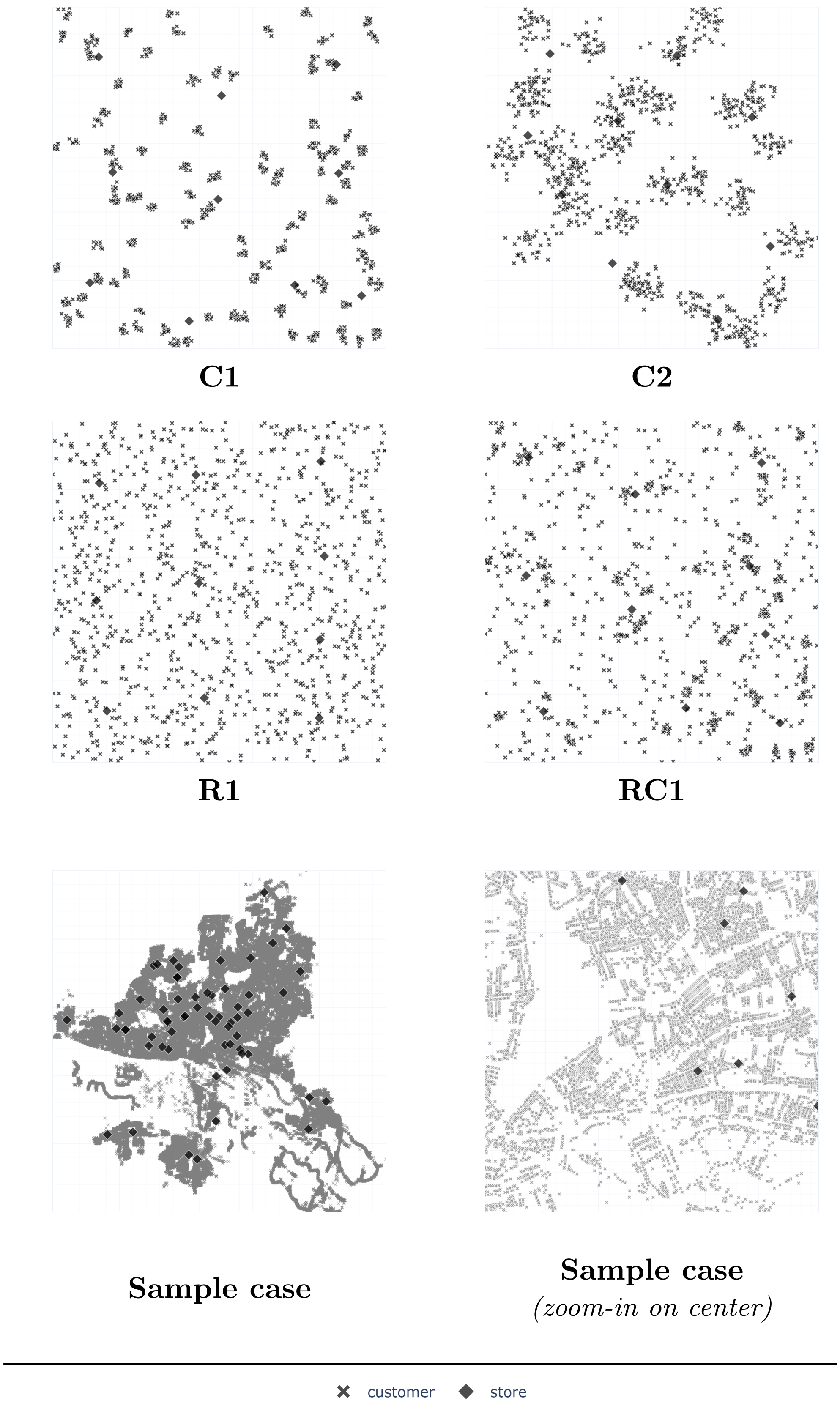


Figure 6: Visualization of stylized networks based on Gehring and Homberger (2001) C1, C2, R1, and RC1 benchmark instances with 1,000 customer locations and 10 added store locations, as well as sample case household and store locations mapped to a 500x500 Cartesian coordinate system

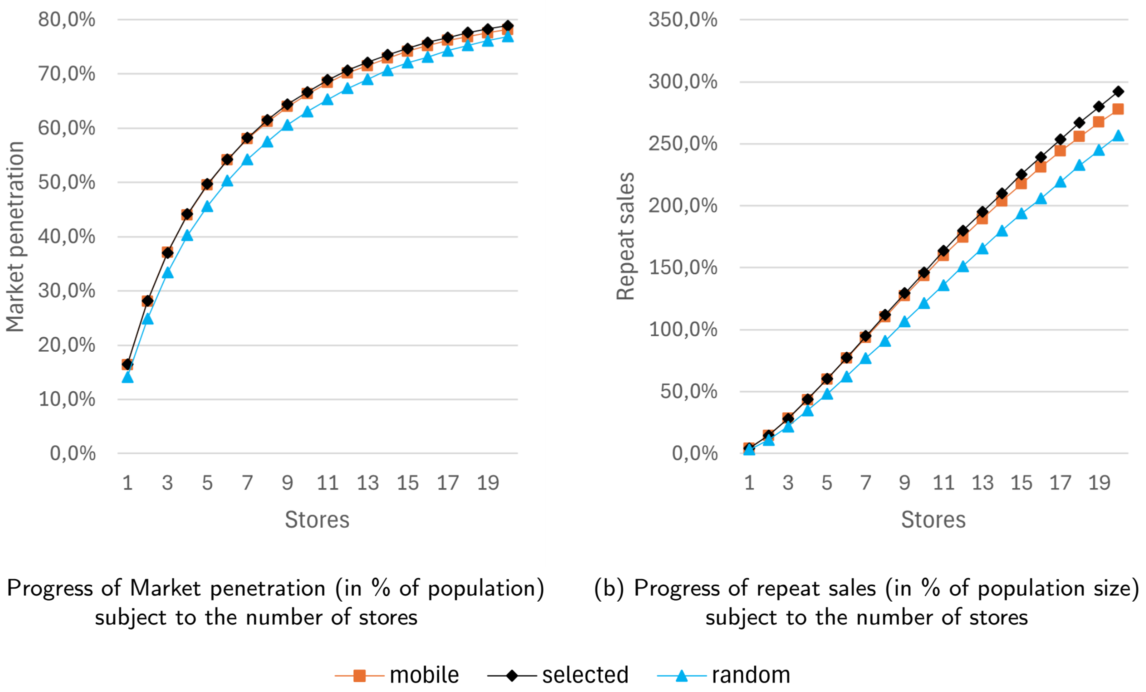


Figure 7: Development of market penetration and repeat sales for a no rejection scenario after 91 days

for repeat sales, albeit with a more pronounced difference with growing store numbers. One reason for this finding is that repeat sales can be achieved more consistently when the store locations are fixed. For both metrics, the *random* store selection performs noticeably worse than the other two.

5.1.2. Comparison of heterogenous and homogeneous store selection scenarios

We compared selecting and operating three stores to check the effects of a homogeneous and heterogeneous store selection procedure. In a homogeneous one, all stores were selected with the same selection procedure, while a heterogeneous one allows the mixing of different procedures. As Table 10 shows, the results indicate that combining *selected* and *mobile* stores, can provide adequate performance for market penetration and repeat sales. For scenarios involving *random* selection, the heterogeneous selection leads to noticeable improvements over a pure *random* selection for both market penetration and repeat sales.

Taking a closer look at combining *selected* with *mobile* stores (for up to a total of 20 stores), as shown in Table 11, implies a potential positive impact of selection heterogeneity on market penetration. The homogeneous store settings of only selecting *mobile* or *selected* stores are relatively balanced, with a slight advantage for *selected* stores with increasing store numbers. Switching from a homogeneous to a heterogeneous setting, even for a single store, can lead to an increase in market penetration. Furthermore, the extension revealed that regarding repeat sales, a heterogeneous choice can also lead to better results, with higher shares of *selected* stores providing the best results.

Table 10
Comparison of the progress of market penetration and repeat sales for three stores after 91 days with different store type scenarios

	Stores		Market	Repeat
mobile	*random*	*selected*	penetration	sales
0	0	3	0.3705	0.2822
3	0	0	0.3703	0.2824
2	0	1	0.3701	0.2819
1	0	2	0.3700	0.2826
1	1	1	0.3578	0.2602
0	1	2	0.3576	0.2603
2	1	0	0.3569	0.2602
1	2	0	0.3458	0.2389
0	2	1	0.3447	0.2387
0	3	0	0.3336	0.2197

5.1.3. Temporal offset in market penetration

As the previous results highlighted, using *mobile* stores can accelerate product diffusion significantly, particularly compared to a *random* store selection. We used polynomial regressions to estimate the temporal offset, i.e., how many more days it takes to reach a certain level of market penetration when using a *random* selection procedure compared to *mobile* stores. As Figure 8 shows, first, the temporal offset decreases with the growth of store numbers. When the increase in market penetration per added store diminishes, the temporal offset starts rising again. This rise can be explained by the increasing difficulty in capturing new customers with growing market penetration (decreasing slope of the S-shaped product diffusion curve toward the

Table 11
Comparison of different heterogeneous store combinations of *mobile* and *selected* stores

mobile stores \ *selected* stores	0	1	2	3	4	5	6	7	8	9
0	0.00%	16.43%	28.03%	37.05%	44.16%	49.70%	54.31%	58.35%	61.59%	64.39%
1	16.37%	28.18%	37.00%	44.03%	49.67%	54.42%	58.21%	61.57%	64.36%	66.79%
2	28.12%	37.01%	43.93%	49.77%	54.30%	58.07%	61.57%	64.39%	66.67%	68.89%
3	37.03%	44.07%	49.77%	54.43%	58.14%	61.47%	64.35%	66.72%	68.81%	70.64%
4	43.93%	49.64%	54.38%	58.21%	61.50%	64.42%	66.65%	68.75%	70.77%	72.12%
5	49.62%	54.40%	58.17%	61.61%	64.33%	66.64%	68.71%	70.42%	71.98%	73.43%
6	54.30%	58.16%	61.47%	64.35%	66.62%	68.73%	70.48%	72.05%	73.44%	74.68%
7	58.08%	61.42%	64.33%	66.53%	68.71%	70.55%	72.02%	73.47%	74.68%	75.76%
8	61.26%	64.13%	66.51%	68.56%	70.41%	71.95%	73.41%	74.64%	75.66%	76.53%
9	64.16%	66.51%	68.58%	70.43%	72.08%	73.32%	74.60%	75.56%	76.46%	77.31%

(a) comparison of market penetration (in % of population size)

mobile stores \ *selected* stores	0	1	2	3	4	5	6	7	8	9
0	0.00%	4.36%	14.55%	28.23%	43.80%	60.37%	77.21%	94.88%	112.35%	129.85%
1	4.40%	14.74%	28.26%	43.62%	60.40%	77.27%	94.78%	112.30%	129.30%	146.42%
2	14.64%	28.19%	43.52%	60.34%	77.41%	94.34%	112.33%	129.45%	146.54%	163.37%
3	28.24%	43.57%	60.26%	77.53%	94.39%	111.87%	129.42%	146.23%	163.05%	179.11%
4	43.40%	60.00%	77.23%	94.63%	112.04%	129.48%	145.80%	162.78%	179.99%	195.10%
5	60.16%	77.47%	94.56%	112.58%	129.28%	145.72%	162.52%	178.69%	193.74%	209.64%
6	76.95%	94.38%	111.95%	129.14%	145.67%	162.21%	178.13%	193.81%	209.50%	224.43%
7	94.21%	111.40%	129.50%	145.40%	161.81%	178.23%	193.59%	209.28%	224.47%	238.27%
8	111.05%	128.37%	145.09%	161.61%	177.43%	193.65%	208.44%	223.38%	237.58%	250.78%
9	127.92%	144.67%	161.28%	177.30%	193.25%	207.74%	223.17%	237.03%	249.90%	264.03%

(b) comparison of repeat sales (in % of population size)

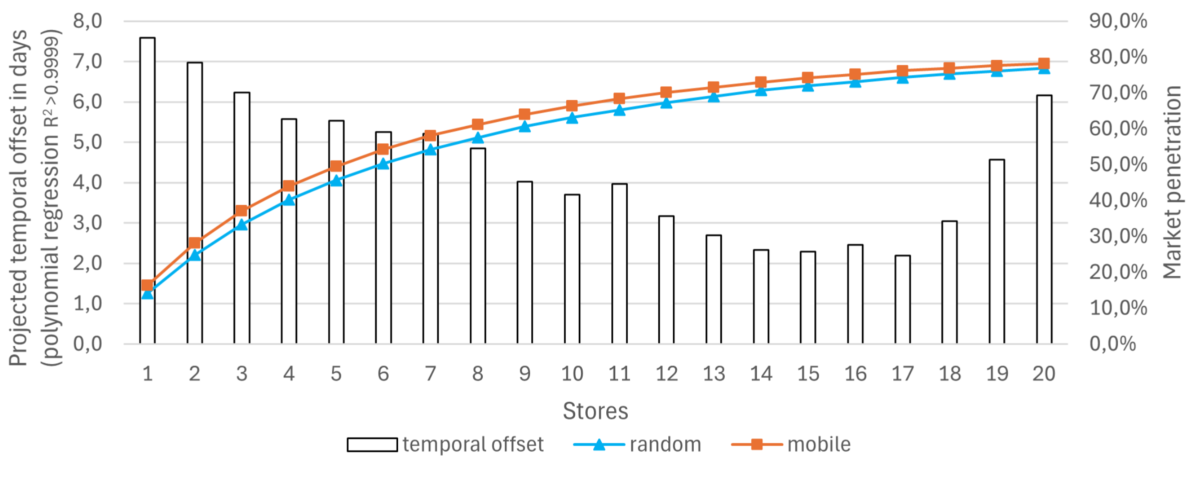


Figure 8: Projected temporal offset in days between *random* and *mobile* stores and respective market penetration subject to the number of stores

end) as facilitating new adopters becomes more difficult when the share of potential adopters left is low. Furthermore, the geospatial dispersion of customers is of importance as *mobile* stores enable one to reach distant customers better.

5.1.4. Impact of rejection probability

So far, the calculated scenarios assume that customers do not reject products. Product rejection, however, not only leads to lower market penetration and repeat sales but also affects the temporal offset between selection procedures. Figure 9 highlights how rejection probability shows a different impact on the temporal offset between *mobile* and *random* store selection with increasing store numbers. For 20 stores, a *low rejection* probability leads to a reduction to two and a half day offset at the end of the simulation period. For

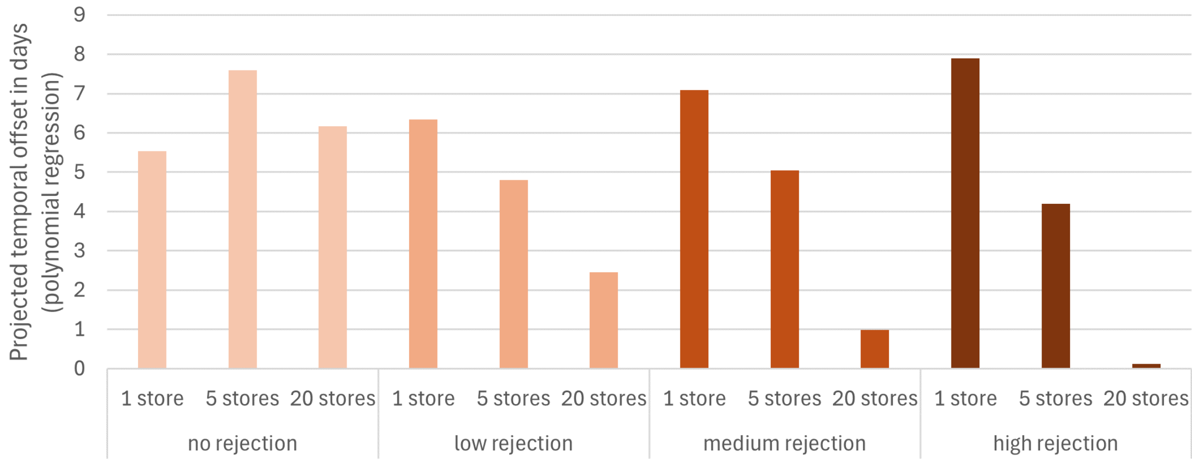


Figure 9: Impact of rejection probability on projected temporal offset between *random* and *mobile* stores

Table 12
Impact of rejection probability and increasing store number on the product diffusion (market penetration) subject to store type

		mobile	*selected*	*random*
1 store	*no rejection*	16.37%	16.43%	14.25%
	low rejection	11.83%	11.97%	10.45%
	medium rejection	7.83%	7.72%	6.86%
	high rejection	3.84%	3.79%	3.35%
5 stores	*no rejection*	49.62%	49.70%	45.78%
	low rejection	35.04%	34.86%	32.49%
	medium rejection	22.01%	21.79%	20.43%
	high rejection	10.26%	11.80%	9.61%
20 stores	*no rejection*	78.18%	78.92%	76.89%
	low rejection	54.55%	54.95%	53.64%
	medium rejection	33.18%	33.32%	32.63%
	high rejection	14.70%	14.83%	14.55%

higher rejection scenarios, the temporal offset was reduced to almost zero.

Table 12 highlights the impact of different rejection probabilities on market penetration. Each scenario shows that increasing the rejection probability leads to marginally different behaviors for the three store settings. *Selected* stores show the highest market penetration for higher store numbers and lower rejection scenarios. With a decreasing number of stores and an increase in rejection probability, the *mobile* stores start showing a better performance. In any case, a *random* selection performs worst.

5.2. Results from the stylized network experiments

Figure 6 illustrates that the sample case customer dispersion structure could be classified as close to C2 (large clusters) or RC1 (random dispersion mixed with clusters). The stylized network experiment results confirm the sample case's findings in most settings. However, the results also show that the sample case cannot be generalized to all customer dispersion settings. Additional experiments run on benchmark instances from DIMACS (2021) and Uchoa et al. (2017) (cf. Appendix A) further corroborate the results from the stylized experiments. In particular, areas with a small cluster (C1) dispersion structure show a higher potential for mobile stores than the sample case.

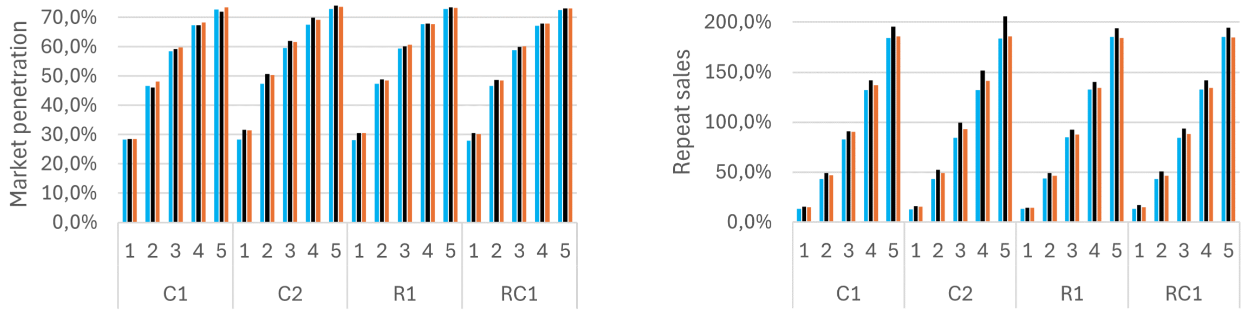
Moreover, we further investigated the impact of store attractiveness. As Figure 10 illustrates, with increasing store attractiveness heterogeneity, i.e., when customers have strong preferences on which store to visit, mobile store performance regarding market penetration increases, making it the best choice in such settings. This is interesting, as the sample case illustrates a setting with rather homogeneous store attractiveness (CV=0.05).

5.2.1. *Influence of customer dispersion pattern*

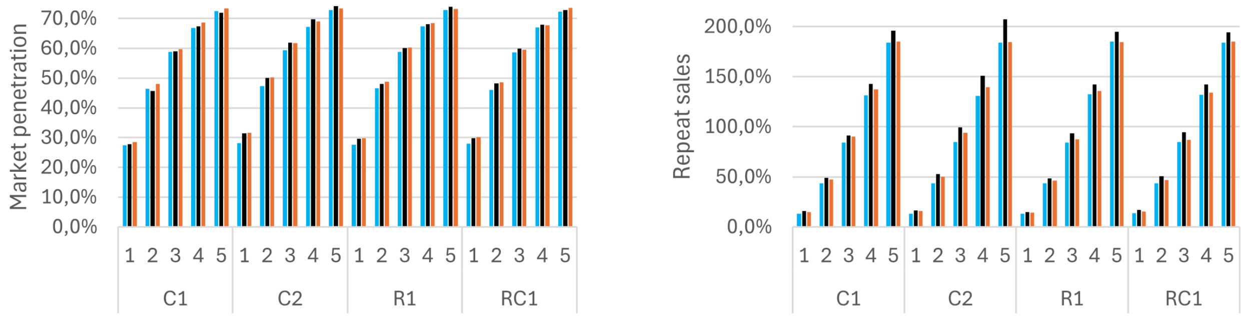
The different customer dispersion patterns mediate the influence of store selection on market penetration. For repeat sales, no substantial difference can be noted. Figure 10a shows that without exception, *selected* stores lead to the highest repeat sales. Concerning market penetration for small clusters (C1), *mobile* stores provide the best performance. For larger clusters (C2), *selected* stores lead to the highest market penetration, followed by *mobile* stores. For a random dispersion (R1), depending on the number of stores, either *selected* or *mobile* deliver the best performance. Random clustering (RC1) shows a behavior similar to that of a random dispersion.

5.2.2. *Impact of store attractiveness heterogeneity*

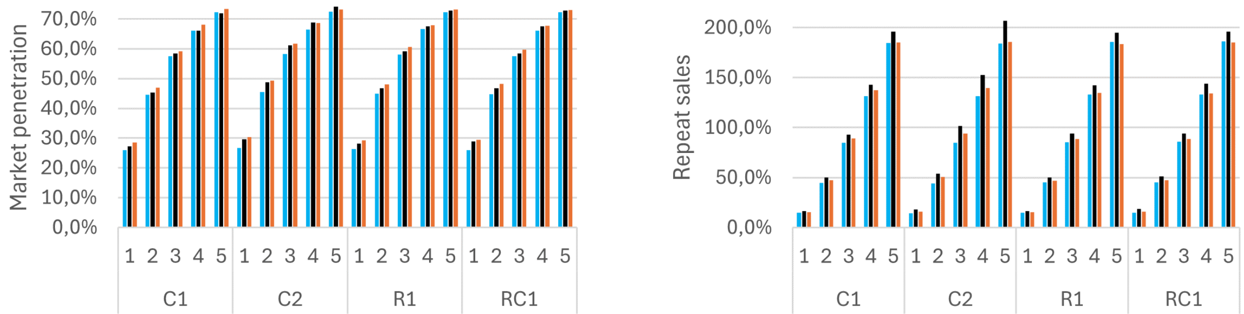
In addition to the impact of the dispersion patterns, store attractiveness influences performance. As Figure 10b-d highlights, increasing store attractiveness heterogeneity works in favor of *mobile* stores. With a CV of 0.75, *mobile* stores provided the best performance in terms of market penetration for all tested store numbers and dispersion



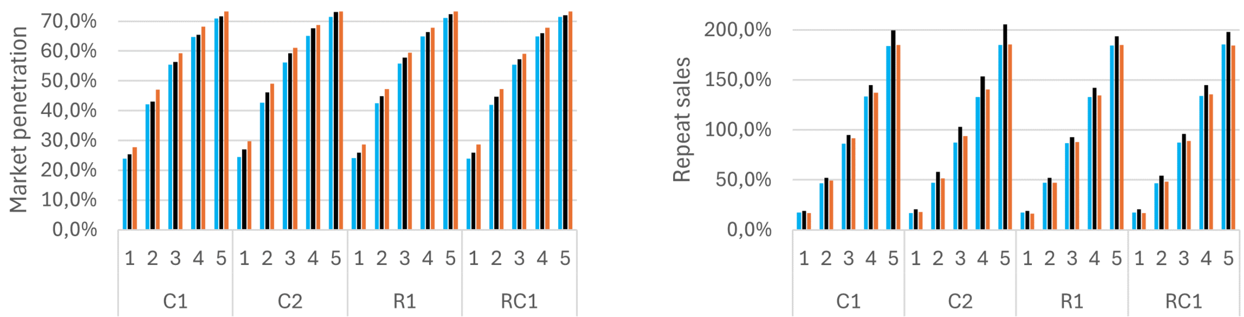
(a) store attractiveness cv = 0.0



(b) store attractiveness cv = 0.25



(c) store attractiveness cv = 0.5



(d) store attractiveness cv = 0.75

random selected mobile

Figure 10: Different customer dispersion patterns mediate how store selection impacts the adoption process

patterns. Furthermore, with increasing store attractiveness heterogeneity, the difference in market penetration between *random* stores and the other two settings further increases, leaving them to be the worst choice in any case. In contrast, regarding repeat sales, the performance of *random* stores increases for small clusters, large clusters, and most cases of random dispersion and random clustering with increasing store attractiveness heterogeneity. For the other two store types, small and large clusters yield better performance at low store numbers with increasing attractiveness heterogeneity and slightly worse with higher store numbers. For random clustering, an increase showed overall higher repeat sales for all store types. Independent of store attractiveness heterogeneity, the *selected* store selection remains the best choice for all scenarios in terms of repeat sales.

6. Discussion

In the subsequent section, we discuss the implications and limitations of our work. In addition, we highlight future research opportunities.

6.1. Managerial and theoretical implications

Our results elucidate how combining simulation, particularly ABS, with ML can help to better understand the product diffusion process, thus providing decision support for the listing process of new and innovative products. The stylized network experiments show that depending on the customer dispersion and store attractiveness heterogeneity setting, either *selected* or *mobile* stores deliver the best performance for facilitating market penetration. We find that particularly customer dispersion patterns with small clusters benefit *mobile* stores. Moreover, independent of the customer dispersion pattern, the more heterogeneous customers' evaluation of store attractiveness is, the stronger the case for *mobile* stores becomes. However, *mobile* stores cannot achieve the same level of repeat sales as *selected* stores. Then again, considering the problem of limited shelf space, selecting particular stores can become difficult. Thus, while *mobile* stores cannot compete regarding repeat sales, they can clearly accelerate product diffusion at an early stage. In this way, *mobile* stores can be used as incubators, reducing risk on both the retailers' and the MSMEs' side. For retailers, the mobile stores provide additional shelf space for experimentation. This shelf space can serve MSMEs as a first stage to provide access to the product and thus enable initial product diffusion. While the results from the sample case highlight the potential of mobile stores to facilitate market penetration in an urban/metropolitan region, the stylized network experiments highlight that the potential could be even higher in regions with small customer clusters and moderate distances between these clusters, e.g., in rural areas.

In addition, the feedback gained through accelerating the product diffusion process can be used in the early stages of product development to identify whether a product needs further refinement or different features. This can allow MSMEs to identify how specific their advertisement and customer targeting must be. Products with a potentially high rejection probability have a much smaller target audience and, therefore, need a more specific customer targeting process (Toften and Hammervoll, 2010). As research by Chang and Taylor (2016) highlights, recognizing the need to involve customers in the product development process early on can be beneficial when developing new products. It must be noted, though, that their analysis shows that the involvement of customers in new product development is less effective in the development stages. Therefore, the feedback gained during the initial sales phase has a lower effect than involvement in earlier stages. Nonetheless, the decision support offered can allow retailers to provide MSMEs with support services. In this way, collaborations between retailers and MSMEs can lead to better product development and marketing (Matsuhisa and Matsubayashi, 2024), facilitating an overall enhanced product diffusion process.

Given that a growing number of retailers collect data on customer shopping behavior and preferences, we highlight the potential of combining ABS and ML to predict the product diffusion process. Integrating customer-specific data can enable more accurate predictions and enhance store/location selection, enabling even more sophisticated decision support. Even without these data, the performance of the *mobile* stores in the sample case is almost on par with the *selected* store setting, clearly highlighting the potential for decision support. Especially for perishable products, such as food, a better understanding of the potential of a product can lead to more sustainable operations. Moreover, the impact of rejection probability on the temporal offset in market penetration could be used to identify the product's potential: When both a *randomly* selected and a *mobile* store list the product, the temporal offset could be used to estimate the rejection probability. Recent work by Allaway et al. (2024) highlights how recognizing customer rejection behavior early on can be crucial for product listing and delisting decisions.

The analysis of the results further highlights that *mobile* stores can greatly facilitate the product diffusion process when retailers are uncertain about a product's potential. When only a few stores offer the product, supplementing these stores with a single *mobile* store can lead to a significant boost, saving time in terms of market penetration progress. Considering a retail chain with both self-owned stores and independent grocers, the results indicate that *mobile* stores could be particularly well-suited to boost progress. When each store manager decides by themselves whether he or she will list the product, i.e., store selection is *random*, *mobile* stores can accelerate product diffusion significantly. While this allows for faster identification of products that are less attractive, it also allows retailers to reduce the chance of missing products, which could lead to a competitive advantage (Fornari et al., 2009; Marín-García et al., 2020).

In line with previous research, such as Iyengar et al. (2015), Kato and Hoshino (2021), Dass et al. (2023) and

Lotfi et al. (2024), our results further stress the importance of differentiating between adoption and repeat sales, i.e., the development of total sales and market penetration. The results indicate that mobile stores would be better suited for the initial phase of the product diffusion process, and after that, the product should be moved to selected stationary markets for higher repeat sales. The research further emphasizes the role of retailers in the product diffusion process and the resulting responsibility for retailers to shape the transition towards more sustainable supply chains. In particular, we highlight that retailers can provide a better understanding of the product diffusion process for different product categories and features through the customer and sales data they collect.

6.2. Study limitations and future research opportunities

While this study provides valuable insights into the impact of mobile stores on the product diffusion process, it is also subject to several limitations. For example, we must note that our study is limited due to the focus on a single retail chain. We do not take into account how the interaction between different retail entities can shape the product diffusion process when utilizing mobile stores as accelerators for market penetration. Thus, we do not consider the impact of competition. However, considering the results on store attractiveness heterogeneity, we think that it is likely that competition could further increase the potential of using mobile stores. Further research is needed to elucidate whether and how the impact of mobile stores would change when multiple retail chains use or even share mobile stores to provide access to the same or different products. Although the dispersion patterns studied in our work cover a wide range of contemporary realities, we cannot guarantee that they cover all eventualities. Therefore, we encourage the study of more specialized and diverse dispersion patterns. Furthermore, it would be interesting to see if co-location effects could further increase the benefits of using mobile stores to accelerate the product diffusion process and to what extent competitors would profit from another retail chain's mobile store activities.

In addition to the limitation of focusing on a single retail chain, we must also point out the limitations regarding the retail setting. While cyclical shopping behavior is realistic for grocery retailing, other sectors can show acyclical customer shopping behavior. Furthermore, we assumed that during one shopping cycle, a mobile store cannot visit the same location on consecutive days, i.e., stores must change location every day. Considering the possibility that mobile stores can change location within any chosen frequency (e.g., every two hours, two days, two weeks) and that customer mobility data could be used as another input to predict location potential, our results may underestimate the potential of mobile stores. We thus highlight the need to investigate how a higher data granularity, e.g., by using data from customer loyalty programs, impacts the potential of mobile stores. Furthermore, in addition to using ML-based models to facilitate relocation choices, it would also be interesting to see how they can be used to predict the time when products should be transferred from mobile to stationary shelves.

On a different note, we must add that we modeled the mobile stores without any capacity and supply restrictions. We also assumed that the mobile store size fits all locations, which may not be the case in practice due to limited parking spaces. Future research needs to address how store and network configuration can be optimized, considering optimal store capacity and size, as well as appropriate replenishment policies. Furthermore, for the experiments, we assumed that social network size is uniform, and that the opinion of each customer has the same weight. Thus, future research can also address how different marketing strategies, e.g., targeting network bridges (influencer marketing), would impact mobile store relocation choices.

7. Concluding remarks

In this study, we consider how the impact of store mobility, store selection, and product rejection probability can influence the product diffusion process. Therefore, a decision support system that combines ABS and ML was developed. It was tested based on empirical data collected from the City of Hamburg, Germany, as well as on four stylized customer dispersion patterns. Our work highlights that mobile stores have the potential to play a crucial role in the initial stages of product diffusion. The study contributes to a better understanding of the product diffusion process subject to product access and rejection probability and how, in the physical space, mobile stores can substitute for the lack of stationary stores that sell the product.

We show that both location selection and rejection probability can significantly impact the product diffusion curve. We further illustrate that combining ABS with ML can serve as valuable decision support when considering the introduction of mobile stores, as it allows exploring which network configuration is suited for the retailer's needs and different projections regarding product potential. Our results show that, in general, mobile stores can prove a useful business model to accelerate product diffusion as well as alleviate and identify associated risks for retailers. However, we also find that mobile stores cannot substitute stationary stores in terms of repeat sales potential.

Declaration of interests

None.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly for spell checking and in order to improve comma placement and sentence structure. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

A. Additional Experiments

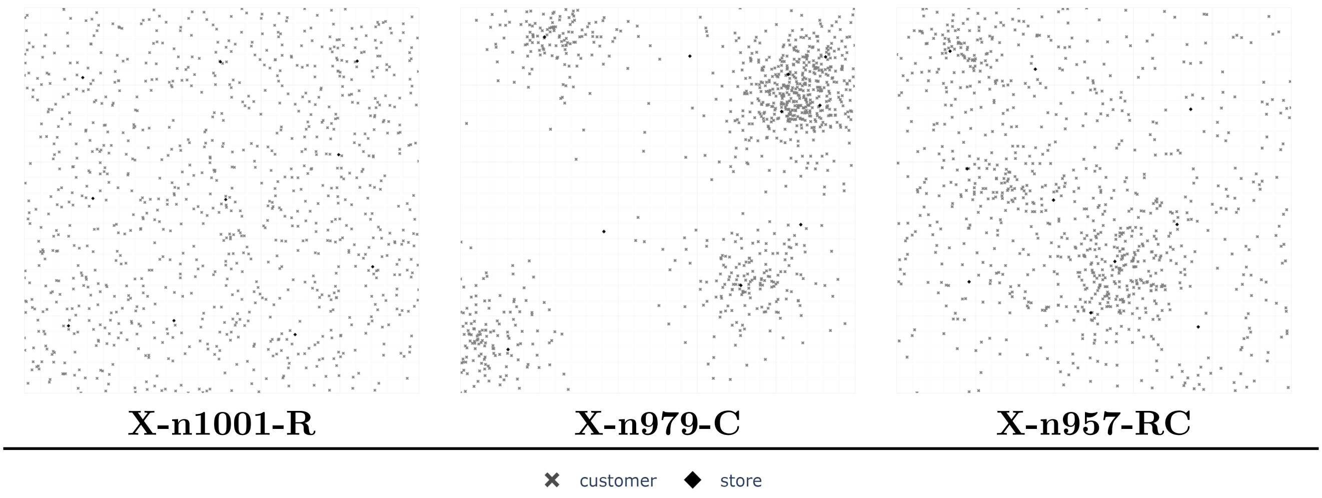


Figure 11: Customer dispersion patterns from Uchoa et al. (2017) R, C, and RC instances mapped to a 500x500 Cartesian coordinate system

Table 13
Results for R, C, and RC instances from Uchoa et al. (2017)

		Market penetration			**Repeat sales**		
	stores	*random*	*selected*	*mobile*	*random*	*selected*	*mobile*
X-n979-C	1	0.28182	0.278671	0.283558	0.132761	0.182004	0.17363
	2	0.463057	0.449703	0.474182	0.435849	0.533078	0.47092
	3	0.583037	0.58773	0.595849	0.839775	0.931104	0.859387
	4	0.664509	0.66316	0.673957	1.317485	1.398098	1.335337
	5	0.718855	0.7241	0.71999	1.826503	1.915787	1.815838
X-n1001-R	1	0.28319	0.30063	0.3	0.13209	0.14396	0.14333
	2	0.46919	0.48451	0.48171	0.43364	0.48627	0.46033
	3	0.59294	0.59969	0.60621	0.8462	0.92255	0.87317
	4	0.67484	0.67825	0.68194	1.3245	1.4101	1.35218
	5	0.73061	0.73185	0.73428	1.85611	1.93033	1.84899
X-n957-RC	1	0.283912	0.305251	0.303933	0.128902	0.142395	0.142374
	2	0.468515	0.487646	0.485094	0.431213	0.481088	0.472207
	3	0.588923	0.602877	0.601684	0.837678	0.915858	0.908316
	4	0.663755	0.679079	0.676464	1.303138	1.446642	1.371695
	5	0.723421	0.722657	0.722071	1.847981	1.970722	1.82137

Table 14
Results for the DIMACS (2021) (Loggi & ORTEC) instances

		Market penetration			Repeat sales		
	stores	*random*	*selected*	*mobile*	*random*	*selected*	*mobile*
Loggi-n401-k23	1	0.2539	0.2731	0.2826	0.1333	0.1558	0.1459
	2	0.391	0.4199	0.4192	0.3938	0.4695	0.4578
	3	0.4768	0.4949	0.5001	0.7364	0.8522	0.8259
	4	0.5313	0.5364	0.5434	1.1306	1.2741	1.1991
	5	0.5654	0.5767	0.5677	1.5385	1.7203	1.5208
Loggi-n501-k24	1	0.2728	0.2862	0.2889	0.1225	0.1392	0.1425
	2	0.4204	0.4404	0.4368	0.3994	0.459	0.4441
	3	0.5134	0.5278	0.5202	0.7547	0.85	0.8026
	4	0.5697	0.5781	0.5709	1.1666	1.276	1.1971
	5	0.6043	0.6111	0.6058	1.5854	1.7196	1.593
Loggi-n601-k19	1	0.2581	0.298	0.2947	0.1327	0.1834	0.153
	2	0.4178	0.4475	0.4492	0.4087	0.4888	0.4558
	3	0.5213	0.5399	0.5387	0.7763	0.8744	0.8377
	4	0.58	0.5988	0.5935	1.1897	1.3174	1.2424
	5	0.6247	0.6407	0.631	1.6435	1.7929	1.6375
Loggi-n901-k42	1	0.2842	0.3025	0.2995	0.1219	0.1405	0.1356
	2	0.4627	0.4786	0.4767	0.4227	0.4608	0.4564
	3	0.5733	0.5908	0.585	0.812	0.882	0.8582
	4	0.6499	0.6616	0.6539	1.2731	1.3752	1.3082
	5	0.6998	0.7107	0.7001	1.7776	1.8947	1.7736
Loggi-n1001-k31	1	0.2922	0.3185	0.3137	0.128	0.1579	0.1519
	2	0.4789	0.5028	0.5024	0.436	0.5136	0.4946
	3	0.5994	0.6214	0.6205	0.848	0.9751	0.9346
	4	0.6808	0.6971	0.6907	1.3346	1.5012	1.4006
	5	0.7332	0.7452	0.7324	1.8603	2.0557	1.844
ORTEC-n240-k12	1	0.256	0.2703	0.2643	0.1157	0.1369	0.1262
	2	0.3875	0.396	0.3932	0.378	0.4113	0.4011
	3	0.4541	0.4668	0.461	0.6966	0.7625	0.7388
	4	0.5005	0.5043	0.5081	1.0754	1.1436	1.105
	5	0.5295	0.5308	0.5289	1.4473	1.521	1.4543
ORTEC-n320-k21	1	0.2595	0.2826	0.275	0.1179	0.1496	0.1398
	2	0.395	0.4155	0.412	0.3842	0.4448	0.4241
	3	0.4751	0.487	0.4876	0.7179	0.8051	0.7868
	4	0.5198	0.5357	0.5287	1.0846	1.2228	1.157
	5	0.5523	0.5567	0.5513	1.4869	1.628	1.4928
ORTEC-n400-k18	1	0.2591	0.2935	0.2958	0.1247	0.1709	0.1696
	2	0.4004	0.4324	0.4289	0.3817	0.5262	0.4925
	3	0.4835	0.5059	0.5065	0.7301	0.9409	0.8458
	4	0.5284	0.5497	0.5429	1.0974	1.3798	1.1963
	5	0.5634	0.5777	0.5657	1.4968	1.8235	1.5168
ORTEC-n450-k41	1	0.2604	0.2852	0.283	0.112	0.1397	0.1364
	2	0.4145	0.4285	0.4248	0.3874	0.4451	0.4305
	3	0.4928	0.5075	0.5036	0.7358	0.8254	0.7936
	4	0.5494	0.5586	0.552	1.1339	1.2421	1.1696
	5	0.5795	0.5883	0.5797	1.5422	1.6716	1.5428
ORTEC-n510-k23	1	0.2671	0.2904	0.2934	0.1263	0.1667	0.1579
	2	0.418	0.4449	0.4401	0.4021	0.5081	0.4726
	3	0.5105	0.5281	0.5248	0.7716	0.9276	0.8538
	4	0.5676	0.5782	0.5719	1.1706	1.3525	1.2371
	5	0.6047	0.6174	0.6047	1.6013	1.828	1.5794
ORTEC-n701-k64	1	0.2758	0.2878	0.2853	0.1226	0.14	0.1342
	2	0.4409	0.4519	0.45	0.4112	0.4507	0.4413
	3	0.543	0.5487	0.5531	0.7825	0.8595	0.8354
	4	0.6089	0.6176	0.6127	1.2133	1.3151	1.252
	5	0.655	0.6563	0.6539	1.6969	1.7697	1.6836

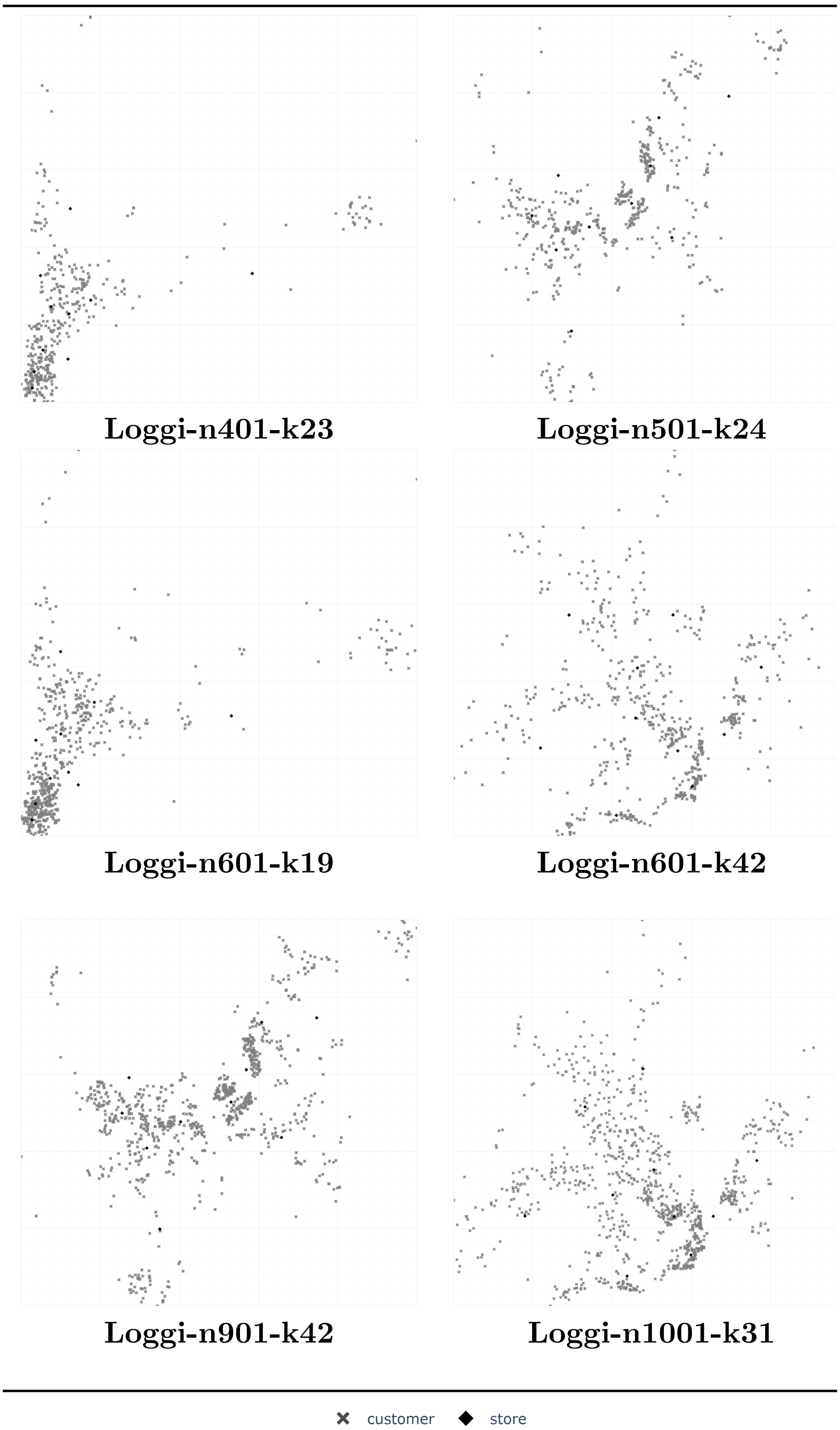


Figure 12: Customer dispersion patterns of the DIMACS (2021) (Loggi) instances mapped to a 500x500 Cartesian coordinate system

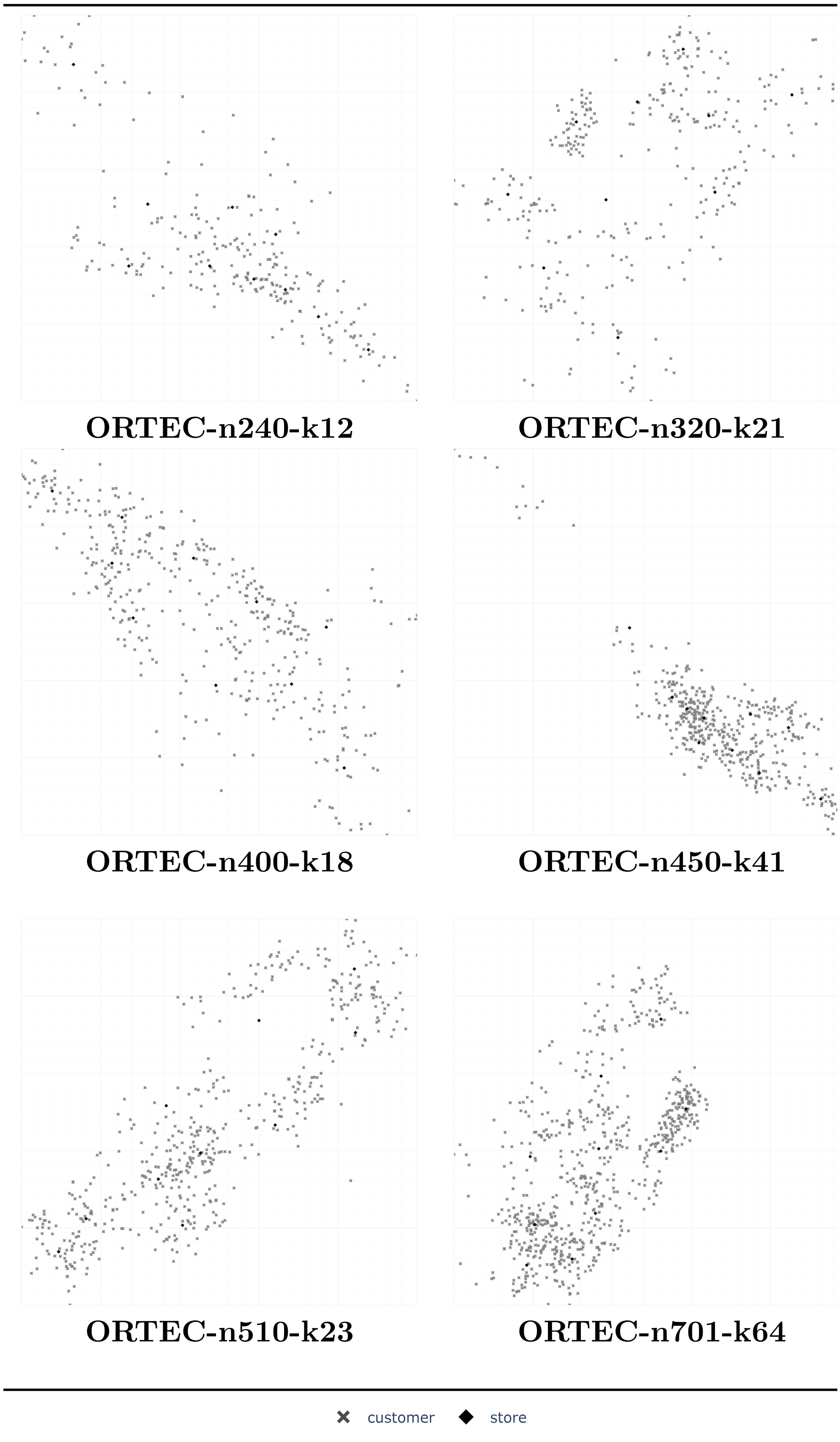


Figure 13: Customer dispersion patterns of the DIMACS (2021) (ORTEC) instances mapped to a 500x500 Cartesian coordinate system

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