MASTER

An agent-based model of downtown retail dynamics

Exploring the interaction between customers, retailers, and spatial setting

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Summary

The Dutch retail landscape is undergoing radical changes due to the growth of e-commerce, changes in customers' behaviour and macroeconomic disruptions like financial crisis and COVID-19 pandemic. These shifts have led to noticeable effects: reduced visitor counts, increased vacancy rates, and the necessity for adaptive reuse for retail locations, especially in major cities. While most research in the field of retail decay has been done in the major cities, there is a gap in the research about the effects of the changing trends in customers' and retailers' behaviour in small to medium-sized cities.

This study presents an agent-based pilot simulation system to examine the interactions between customers' and retailers' behaviour in Dutch downtown retail areas. The primary aim of the system is to develop a foundation for an advanced system that aims to provide stakeholders with realistic predictions that help create policies and decisions to revitalise and transform downtown retail areas.

An extensive literature review forms the foundation of the mechanisms integrated into the system. First, insights in retail trends are collected together with established retail theories and proven simulation methods and techniques are collected. The insights gained in customers' behaviour was that they are affected by store characteristics such as retail floor area (RFA) size, proximity to anchor stores, distance from customer to store and clusters of similar stores. Entry point placement determines the initial customer distribution. Unplanned visits/impulsive purchases also were found to enhance store performance. Retailers were found to evaluate their locations based on profitability metrics, including visitor counts, clustering with similar stores and also proximity to anchor stores. The profitability of their store in the model is determined by visitor count and RFA size, reflecting the insight gained in the literature that central locations, with more customer foot traffic, have higher rents. Underperforming retailers respond by adapting in terms such as relocating, closing or transforming their location into another function.

Agent-based modelling has previously been used effectively to replicate the dynamic interactions between customers and retailers, using a Multinomial Logit (MNL) model to evaluate customer preferences and Monte Carlo simulations to introduce probabilistic decision-making that accounts for spontaneous customers' behaviour.

The platform chosen to develop the agent-based modelling simulation system needed to meet requirements to effectively support the design and functionality of such a system. This choice was guided by the necessity to ensure compatibility with the demands of agent-based modelling, including flexibility, scalability, spatial modelling capabilities, and user-friendly features. The platform of choice is the NetLogo platform.

The simulation begins with a base scenario that serves as a benchmark for understanding the system's dynamics under standard conditions. Furthermore, the base scenario is a fictive retail area with representative composition of store types and numbers, as found in literature. Building on this foundation, subsequent scenarios are designed to emphasize specific factors of influence identified in the literature review. These scenarios are systematically tested to evaluate whether the insights from the literature are effectively replicated within the simulation.

From the base scenario, it quickly became evident that stores in streets located at the south of the shopping area were performing the worst, attracting the least amount of customers overall. Also most retail dynamics occurred in these streets, with the most retailers relocating out of these streets. With lasting vacancy, transformations resulted. Retailer decisions were affected by anchor store proximity and visitor counts, while the impact of clustering with similar stores was not clearly observed.

Most findings that impact customers' behaviour highlighted in the literature, were successfully replicated in the simulation system. Entry point placement, the distance from customer to stores, RFA size and unplanned visits were found to influence customer movement and/or store performance on a

consistent base. However, less clear were the effects of clusters of stores on customers' behaviour and anchor store proximity.

A refined version of the system would provide opportunity for urban planners, retailers, municipalities and real estate developers. Urban planners can use it to analyse the effects of new infrastructure developments on downtown retail and its stakeholders. Retailers can optimize their strategies for relocation and store performance. Municipalities can test policies to revitalize the area. Developers could predict the value of retail assets more accurately.

The system has its limitations. The first limitation is the simplified representation of customers' behaviour, excluding factors like shop window appeal, street furniture, crowding, and whether shoppers prefer lively streets. Parameter values are assumptions and lack dynamics over time limiting the predictive utility. The system does not account for temporal trends further limiting the system. Excluding the influence of e-commerce growth or societal shifts means that the system does not capture such evolutions over time.

Future studies should take into account the limitations mentioned above. In addition, the incorporation of various customers types, such as experience-based or discount-driven shoppers, would paint a more realistic picture of customers' preferences. Dynamic inputs, like variable rent could enhance the competitiveness of the retail market. Also the number of customer could adapt over time as response to environment changes, such as e-commerce growth or societal shifts, creating dynamics in inflow of customers. Finally, the application of actual GIS-data and machine learning could enhance the predictive power and real-time adaptability, rendering the simulation effective in analysing and forecasting retail patterns.

Abstract

This study presents an agent-based pilot simulation system to examine the interactions between customers' and retailers' behaviour in Dutch downtown retail areas. With the rise of e-commerce and the growing number of vacant stores, this situation is putting pressure on downtown retail. The research is guided by the central research question: "*How can downtown retail dynamics be simulated?*" The goal of the study is to lay the foundation of an advanced predictive simulation tool to aid the development of strategies that revitalize downtown retail areas. Based on an extensive literature review, the study identifies the various factors that shape retailing activity. By simulating various scenarios in the system, each emphasizing different influential factors, it was concluded that the majority of findings were successfully replicated by the simulation. Higher RFA weights emphasized the significance of store size. Distance from customer to store, even though the spatial areas was rather limited in the system, did affect customer preference. Effects of clusters of stores and anchor store proximity were less clear. These were implemented in the system by using the MNL model with an utility function in combination with a Monte Carlo simulation. Impulse purchases made the retail area flourish. Retailers were seen to be constantly trying to optimize their profitability through positioning in high foot traffic locations, and near anchor stores. Retailers were not observed clustering with similar retailers. The retailers however also have to make sufficient amount of sales in order to afford rent, leading to dynamic adaption such as vacancies or transformations when profit is not sustainable. Hinting the retail dynamics of the simulation system. Further, spatial factors like entry points also influence customer movement. Furthermore, the parameters used in the simulation, such as the weights of the utility function and rates of transformation are based on assumptions. Further research should validate and refine these parameters through empirical studies at greater depth. The prediction power could be enhanced if customers' behaviour models are improved, dynamics affecting retailers such as rent changes are being incorporated and GIS-based spatial data are being integrated into the system. With these advances, the simulation could become an effective and adaptable tool for urban planning and policy-making.

Keywords: Agent-Based Modelling; Simulation Systems; Retail Dynamics; Retail Real Estate Development; Adaptive Retail Reuse; Shoppers' Behaviour; Retailers' Behaviour

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1. Introduction

The retail landscape is evolving, customers' behaviour is changing, e-commerce is rising, all challenging the conventional way of retailing. Retailers must constantly adapt to these challenges in order to keep business going. To do this, it is necessary to understand what the preferences of the customers are, what retailers do or must do to adapt, and how the spatial setting should change to revitalize the downtown retail environment.

This research focuses on creating a pilot simulation system that captures these dynamics within Dutch downtown retail environments. By gaining insights from existing studies on customers' and retailers' behaviour, spatial setting influence, and interactions between stakeholders, this study aims to develop a foundational framework for a tool that is able to analyze the retail dynamics. The simulation system provides a basis for future work, with the ultimate goal of becoming a predictive tool for downtown retail development.

The sections of this chapter are structured in the following way: Section 1.1 provides the context and background of the research, giving insight into the underlying reasoning. In Section 1.2 the problem statement and goals are introduced. Section 1.3 highlights the societal and academic relevance, and Section 1.4 guides the reader through the structure of the entire report.

1.1 Context and background

Retail landscapes have undergone significant transformations in recent years, driven by the rapid rise of e-commerce (Dolega et al., 2021; Zhang et al., 2016), changing customer preferences (RetailSonar, 2020), and macroeconomic disruptions such as the 2008 financial crisis and the COVID-19 pandemic (Tangpong et al., 2009; Helm et al., 2020; Cushman & Wakefield, 2021). These shifts present unique challenges for traditional retail spaces, requiring them to adapt to maintain relevance amid rising vacancy rates and declining foot traffic (Evers et al., 2020).

These changes underline the urgent need for tools that can model and analyse the evolving dynamics of downtown retail spaces. By incorporating these insights into a simulation system, this research aims to bridge theoretical knowledge with practical applications, offering a structured framework for understanding and testing potential strategies in a controlled environment.

Since the turn of the millennium, there has been a notable surge in online purchases and sales, as highlighted by Dolega et al. (2021). Notably, in 2018, 20% of all transactions in the US and the UK occurred online (Van Leeuwen, 2018). The Netherlands experienced similar increases in online sales during that same year, with 64% of Dutch individuals aged twelve or older reporting online purchases. By 2022, this figure has risen to 74% (Statistics Netherlands, 2023). Recent insights from Statistics Netherlands (2023) reveal a prevailing trend, with online shopping being particularly prominent in categories such as clothing/shoes and meals, while personal care and beauty items are comparatively less popular choices among online customers.

The burgeoning e-commerce trend poses a challenge to traditional retail, potentially diminishing its attractiveness (Weltevreden & Rietbergen, 2007; Zhang et al., 2016). The shift can clearly be noticed in the relation of e-commerce with physical retail stores. Sales of commercial property has slowed down, while the vacancy rates of commercial property have surged, closely linked to the rapid growth of e-commerce. (Zhang et al., 2016). This correlation underscores e-commerce as a driving force behind the rise in retail vacancy.

The rise of online shopping has had a significant negative impact on the amount people spending in brick-and-mortar stores (Rose et al., 2012). The Dutch downtown retail landscape has been experiencing rapid changes over a longer period, with both the variety of stores and the number of shoppers noticing a decline, as highlighted in reports by Bouwinvest (2019). The 2008 financial crisis had a substantial impact on the retail landscape, leading to numerous brick-and-mortar store closures and the concept of the "Retail Apocalypse," as outlined by sources like Tangpong et al. (2009) and Helm et al. (2020). This trend gained even more momentum with the onset of the COVID-19 pandemic.

Governments aimed to stop the spread of the virus during the pandemic. It made mask-wearing compulsory, sealing of lockdowns and shutting of stores temporarily. These actions had a notable impact on the retail market, leading to a downturn in customer confidence (Koster et al., 2022). Throughout this period, RetailSonar observed distinct trends in shopping behaviour in both the Netherlands and Belgium. Notably, customers visited stores less often, but their individual spending increased. Furthermore, there was a noticeable uptick in local purchasing among customers (RetailSonar, 2020). While major city centres like Amsterdam and Rotterdam experienced a 21% decrease in sales, smaller towns saw a 12.5% increase (Haar & Quix, 2020). This divergence could be attributed to people's preference for the perceived safety of local shopping areas during the pandemic or the absence of tourists in city centres. RetailSonar (2020) highlighted the significance of strong traffic builders like hospitality, commuting, and tourism in determining a store's success during this time. Additionally, they noted a shift in customer preferences, with less emphasis on experiential shopping and a greater focus on convenience amid the COVID-19 period. These shifts in behaviour, compounded by the impact of implemented measures, prompted a notable increase in online purchases (RetailSonar, 2020).

To expand on the growing retail vacancy rates and the increasing presence of the hospitality industry in the Netherlands, recent studies reveal that the rise of online shopping continues to impact the traditional retail sector, exacerbating vacancy rates. According to Cushman & Wakefield (2023), vacancy rates in Dutch retail properties have been rising due to the rapid expansion of e-commerce, which is reducing foot traffic in physical stores and leading to closures, particularly in city centres. This trend, which began before the pandemic, has accelerated in recent years In parallel, there has been significant growth in the hospitality sector, especially in smaller towns and suburban areas. ING Economic and Financial Analysis (2023) indicates that the hospitality industry has bounced back after the COVID-19 pandemic, with a projected 3% growth in 2023. This growth has sparked the conversions of vacant retail spaces into restaurants, cafés, and hotels as a way to revitalize city centres. The rise in hospitality venues is seen as a response to the growing demand for experiential consumption, which complements shopping and boosts local foot traffic.

1.2 Research goals and problem statement

It was predicted that traditional shopping districts would become obsolete, much like forecasts that e-books would replace printed books. This prediction aligns with early views on the disruptive potential of e-commerce and digital media, which often underestimated the resilience of physical formats and spaces. For example, Burt and Sparks (2003) discuss how the rapid growth of e-commerce was initially seen as a threat to physical retail, drawing parallels to similar forecasts about the decline of printed books in favour of e-books. However, these predictions overlooked the enduring customer demand for physical interaction, both with retail environments and with tangible media.

This research represents the initial steps toward creating a digital simulation system aimed at supporting policy making regarding downtown retail in the Netherlands. As an early-stage pilot, this system simulates customers' behaviour such as store preferences and impulse purchases, and retailers' behaviour such as store closures, relocations, and transformations using basic insights concerning customers, retailers, property owners, and municipalities, setting a foundation for future improvements. By modelling retail dynamics, this study aspires to eventually enhance planning and inform policy development. In the long term, such a system could guide municipalities on actions like adding new entry points to a city.

The shopping needs of people are continually evolving due to macro-trends such as the rise of e-commerce and financial crises. As customer demands shift continually, the retail environment must adapt to remain efficient, including changes in store openings, closures, and relocations. Surprisingly, there is a lack of comprehensive analyses focusing on the Dutch downtown retail, despite these areas facing significant challenges in their retail structure, such as a decreasing number of physical stores (Statistics Netherlands, 2023).

However, the vacancy rate in the Netherlands is not unique; similar trends are observed in many other European countries, predominantly in medium to small-sized cities (Hallsworth & Coca-Stefaniak, 2018; Grimmeau & Wayens, 2020). In most of these cities, the primary customer is the local population, with limited tourism. It is anticipated that the composition and spatial arrangement of retail facilities will undergo notable changes in the upcoming years. Most studies regarding the shift in retail structure concentrate solely on large cities in North America, neglecting small to medium-sized cities in Western Europe, and more specifically, the Netherlands (Grewal et al., 2017; Dawson et al., 2008; Kent & Omar., 2003).

Previously conducted research on the spatial dynamics of retail in inner cities has predominantly focused on marketing and economic perspectives, as seen in studies by Grewal et al. (2017) and Evans (2011). Earlier studies from this point of view saw organizational retail changes as a cyclic phenomenon (Brown, 1987, 1993). However, recent research focusing on spatial planning reveals that the spatial pattern of retail is heavily influenced by recent macro-occurrences, such as the advent of the internet (Dolega et al., 2021) and the impact of the COVID-19 pandemic (Cilliers et al., 2021). These events trigger trends that challenge the traditional cyclical understanding of retail dynamics.

Therefore, this study aims to create the first steps towards a digital simulation of the future of Dutch downtown retail developments based on current and ongoing trends found in the literature. The central research question guiding this work is: "*How can downtown retail dynamics be simulated to develop a system that can predict the profitability of individual shops and shopping streets?"* The research question captures the outcomes of the choices made by the customers and retailers in the simulation, considering that viable shops attract more customers, hence increasing the number of customers in the street, making the street more attractive to other viable shops. The simulation system can be considered a decision support system for policy makers, retailers, and real estate owners/developers.

This inquiry prompts an exploration of sub-questions, however these will be formulated after gaining valuable insights from the literature review. These sub-questions will help identify the foundational elements needed to take the first steps toward developing a simulation system capable of representing future downtown retail dynamics. The literature review will provide critical insights into how the main research question can be approached, guiding the design and focus of the simulation system. By aligning with findings from existing research, this pilot system aims to reflect key aspects of retail dynamics, laying the groundwork for more comprehensive simulations in the future.

1.3 Societal and academic relevance

This research contributes to societal and academic insights into downtown retail by providing a pilot simulation tool. By examining research literature about patterns and factors affecting downtown retail, the paper collects the main factors of influence that have impact on the spatial structure and composition of retail. The ultimate goal is to lay a foundation for a simulation system that can predict realistic scenarios for exploration of the future Dutch downtown retail areas.

Socially, this study offers a preliminary tool for stakeholders, such as municipalities, retailers, and property owners to aid in their decision-making. However, as a pilot system, it is still a prototype and not a full-fledged decision support tool. Further advancements are required to create a fine-tuned simulation system that is capable of providing realistic outcomes. At this stage, the system aims to demonstrate the possibilities of its capabilities.

Academically, this study brings an analytical system for modelling the development of downtown retail. It extends existing literature by collecting insights in customers' behaviour, retailers' behaviour and factors of influence that impacts the retail dynamics and applies it in a pilot simulation framework. It is in the early stages, but the tool offers a visual way of thinking about how consumer demand or urban planning policies could impact the form of retail environments. The work provides a template to further explore these forces, but it also opens the door for further refinement and greater investigation, and calls for academic research in the future on downtown retail spaces and their myriad interconnections.

The research targets retail especially at risk of change in function due in shopping centres to see how they might function and survive in the future. The study contributes to academic research on downtown retail dynamics. The insights gained from it can inform future research into such scenarios or generalising to individual cases in the Netherlands or abroad.

1.4 Structure of the report

The report is structured to deliver a comprehensive exploration of downtown retail dynamics and results in the development and evaluation of a simulation system that captures literature findings of influence regarding these dynamics. Each chapter builds progressively upon its predecessor, guiding the reader along a logical sequence, from theory to simulation application.

An overview of the literature research on downtown retail dynamics is described in chapter 2. The insights gained are the main trends, theoretical views, and influences on retail. Customers' and retailers' behaviour, spatial dynamics like clustering and the impact of anchor store presence, adaptive reuse of vacant locations are among them. It also reviews several simulation techniques to determine whether they are appropriate for modelling complex retail dynamics and forms the basis for this particular simulation system.

In the methodology chapter, the research method and development of the envisioned simulation system using an agent-based platform is explained. It contains the conceptual framework with its components, the active actors in the system, the variables of influence and the assumptions integrated in the system. Additionally, the chapter contains sub questions that guide the research towards a well-defined answer to the main research question.

The simulation design and implementation are detailed in chapter 4. The focus of this chapter is to explain in detail how the system operates. It states how the variables of influence are defined into the parameters within the system, together with an explanation of their role in the system and how they interact. Important elements like customers' behaviour, retailers' behaviour and the spatial setting are discussed. The user interface with all adjustable components, as well as the initial assumed values given to them are described. And lastly, the reason and thoughts about the monitoring metrics in the user interface are made clear.

The results chapter discusses and interprets the results of the different simulated scenarios regarding downtown retail dynamics. Firstly, a base scenario is simulated. Next the influence of specific variables or settings will be tested in different scenarios. These scenarios range from adjusting weights that influence customers' behaviour, such as the influence of clustering and distance from customer to store to changing the spatial setting by adding an additional entry point. The outcomes are compared with the literature finding in order to check whether the simulation tool performs as expected.

The final chapter, the conclusion and discussion, summarizes the findings of the study and highlights what has been learned about the functioning of downtown retail in a simulation setting. It describes the limitations and shortcomings of the system in a critical discussion in all three components (customers, retailers, and spatial setting). The contribution and implications to urban planning and real estate is mentioned, along with recommendations to future research to refine the simulation system.

2. Literature review

2.1 Introduction

This literature review aims to give a broad overview of downtown retail dynamics, what drives retail today, and how it is changing. It seeks to find out what factors shape retail structure – customer preferences, location theories, and the effects of disruptive global events on retail areas. It is especially relevant for this study to understand how the impacts of a crisis, such as the financial crisis of 2008 and the COVID-19 pandemic changes the retail demand, shopping behaviour, and spatial structures over time. It also reviews previous work on retail simulation and collects approaches that can be applied to the simulation system for Dutch downtown retail areas of this research.

By considering both theories and findings, this chapter will highlight the intricacies of downtown retail and provide an explanation on the underlying aspects how customers move through retail areas, the considerations of retailers and the influencing factors to retail dynamics. These findings will, in the end, inform the foundation of the simulation system. Ultimately it will reflect the complex nature of retail operations and provide practical guidance to stakeholders in Dutch downtown shopping malls.

2.2 Trends in downtown retail dynamics

To begin the literature review, this section explores the current trends influencing inner-city shopping areas, particularly in small to medium-sized Dutch cities. These trends include the evolution of the retail mix, the impacts of e-commerce, and the effects of significant economic events on downtown retail spaces. Together, they shape the foundation of downtown retail dynamics.

Recent research by Smits (2023) highlights developments in retail mix of downtown retail areas. Certain trends follow a clear linear line, likely driven by the rapid growth of e-commerce and the rise of the experience economy. These trends suggest that brick-and-mortar stores are changing to meet evolving customer preferences, relying increasingly on immersive experience-based methods of retailing. Moreover, important events, like the 2008 crisis and the COVID-19 pandemic, created long-lasting variations on Retail Floor Area (RFA) configuration and customer spending habits in downtown retail (Smirnova & Lukianchuk, 2023). These disruptions highlight the importance of adapting retail models to account for external shocks and fluctuations in customer demand. One observable trend in the spatial organization of retail areas is the correlation between the number of facilities and their distribution over the shopping area. As the number of retail facilities rises, they tend to cluster more densely, reducing the mean nearest-neighbour distance and enhancing the agglomeration effect.

On the other hand, lower numbers in facilities lead to a more dispersed arrangement of retail outlets. This spatial relation is critical for the understanding of customer movement patterns, as clusters of stores tend to attract higher numbers of customers and engagement. It stems from Nelson's (1958) Agglomeration Theory which emphasizes the benefits of clustering similar enterprises. By sharing infrastructure and increasing customer convenience, these clusters encourage multipurpose trips and drive foot traffic to all stores on the street. This principle is further confirmed by Teller et al. (2008) and Passaro et al. (2016), that show clustering effects lead to better shopping experiences and make retail environments more successful. Variability in RFA by store type further illustrates the different demands for retail categories. For instance, leisure store types tend to spread out when the RFA increases so that they can focus on delivering a better customer experience. On the other hand, fashion and in/around the house store types generally see the advantages of clustering as stores with higher RFA in these categories correlate with closer distances, capitalizing on customer convenience and encouraging multipurpose shopping trips.

The composition of retail in Dutch cities is important for the development of a similar virtual environment, Table 1 summarizes the retail composition of the four largest cities in North Brabant (Den Bosch, Eindhoven, Tilburg and Breda). Important to note is that these numbers cover the whole of each city rather than the city centres. Furthermore, approximately 38% of the stores in Table 1 are located in the centre of the city, suggesting that retail is concentrated here (Province North Brabant, 2021).

The daily and non-daily retail outlets are distributed quite differently with non-daily stores in greater abundance. As far as daily retail stores go, specialty stores are most popular, followed by supermarkets and personal care stores. The most common category in the non-daily range is the fashion and luxury segment, which includes retailers of clothing and jewelry. The category is followed by the "in and around the house / hobby" segment, where retailers are focused on home-based products, such as animals, plants, domestic appliances, mobility, and craft supplies. Apart from “other” products, “leisure and hobby”-related stores form the smallest segment.

Table 1: Retail composition four largest cities of North-Brabant (Source: Province North-Brabant, 2021)

	Number of outlets	**Share**
Retail	**4076**	**100%**
Daily	**1165**	**29%**
Supermarkets	309	8%
Specialty stores	589	14%
Personal care	267	7%
Non-daily	**2911**	**71%**
Fashion and luxury	1351	33%
Leisure and hobby (specific)	305	7%
In and around the house / hobby	1006	25%
Other	249	6%

2.3 Retail location theories

Retail location theories are not directly implemented in the framework of the simulation system of this study, but these theories provide important insights into spatial and customer dynamics that can influence retailers’ behaviour and urban retail distribution patterns. This part covers classic theories including Central Place Theory, Bid-Rent Theory, the Principle of Minimum Differentiation, and Spatial Interaction Theory. These theories have more to do with the locations and distribution of retail stores at a regional scale than with the locations of individual stores in downtown areas. But aspects like shopping clustering, customers’ behaviour and the central location are still relevant. Analysing these theories, including the perspectives of Dawson (1980), Brown (1993) and Hirschman (1981), allows for a better understanding of retail agglomeration, customer movement, and impact of distance.

2.3.1 Central place theory

The central place theory first proposed by Christaller (1933) and Lösch (1940), summarized by Brown (1993) is the theory that predicts the size, density, functional composition and distance between shopping centres. The theory presumes equal population, economic wealth, accurate information and rational customers’ behaviour to maximise utility and minimise cost. It also assumes that goods are priced the same and transportation is subsidized in the same way, and that inner cities are equally accessible.

Customers typically gravitate toward the nearest central location for purchasing goods, especially for single-purpose shopping trips. Two key concepts underpin central place theory: thresholds and range. The range of a product refers to the maximum distance customers are willing to travel to purchase a given item, while the threshold refers to “*the minimum market demand necessary for a business to* *remain economically viable.*" (Lesger & Delaney, 2011). The theory predicts that expensive and less purchased products tend to have greater market sizes, while more common products have smaller ones.

Yet many of central place theory's assumptions are oversimplified. Studies have shown that population density, buying power, and shopping behaviour are all more complicated than originally thought. In low density areas, for instance, market areas are larger, and retail become more dispersed, while in high density areas, retail becomes concentrated (Berry & Garrison, 1958a & 1958b). Also, consumers make decisions on their shopping trips based on utility and convenience, rather than just the nearest location, and many shopping trips are multi-purpose rather than single-purpose as the theory originally predicted.

Though the central place theory does provide some insights, it is not as relevant for understanding the location choice of stores in downtown retail areas. The theory mainly addresses the broader hierarchical structure of retail locations. What is more applicable in the context of Dutch inner cities is the notion that they occupy the top position in this retail hierarchy. As a result, the most luxurious and high-end products tend to be concentrated in these central urban locations, which cater to higher spending customers.

2.3.2 Bid-rent theory

The bid-rent theory, as explained by Brown (1993), traces its origins to Haig's (1927) exploration of land use in New York City. The theory suggests that in a uniform landscape with equal travel accessibility, the central areas emerge as the most desirable and economically efficient locations. Central places are appealing because they are accessible to both labour and consumers. Diverse economic activities compete for those core areas, and the industries that could profit most from being central are willing to pay higher rents. This leads to a rent gradient in which the highest rents are in the centre, while gradually decreasing towards the edges (Brown, 1993).

Central locations are popular among retailers as they attract more customer traffic translating into higher sales. Hence the best places — the ones with the most exposure to consumers — have the highest rents. And in downtown centres, this pattern is especially pronounced. The most expensive rents are in the middle of the city, where usually the large retail chains that can afford those kinds of rents are located. The advantage of these locations is that the influx of customers will never cease, making these places the best spots in the city.

But, like central place theory, bid-rent theory also assumes a number of premises that might not always be true in real-world retail environments. This presumption of an uniform urban accessibility is, for example, incorrect in many modern cities. Accessibility is often much more influenced by infrastructure and transport. Also, the price of rents isn't always decreasing as one moves away from the city centre, as regional conditions can drive major rent differentials (Garner, 1966).

Bid-rent theory is useful for understanding the overall competition for central locations, but it is limited in the application when focused on small to medium-sized downtown shopping areas. Rather, the theory primarily highlights how large companies, like chain stores, are able to dominate the best locations in the city centre as they can afford higher rents than small businesses can.

2.3.3 Principle of minimum differentiation

The minimum differentiation principle outlined by Hotelling (1929) is based on the fact that profit-maximizing companies offering similar goods are clustered together in a market. In a linear market, where transportation costs are fixed and customers decide by distance, Hotelling inferred that companies that provide the same product will eventually coalesce into the centre of the market to get the largest market share. The central location allows them to get the largest number of customers, with the least amount of time for customers to get there.

Stores that are selling the same products will be in a cluster. The tactic takes advantage of customers' need to shop around, driving foot traffic and sales for all retailers in the cluster. While it might diminish product differentiation, clustering is an advantage that you get a bigger audience interested in multiple similar options, conveniently located in the same space. At malls, this yields "shopping destinations" for certain types of goods, such as fashion or electrical items.

2.3.4 Spatial interaction theory

Spatial interaction theory differs from central place theory in that it says that customers' decisions are not based on distance alone. It considers product variety, store attractiveness, and customer preference all to contribute to where customers shop. The Law of Retail Gravitation (Reilly's, 1931) is a foundational principle of this theory, underpinning that customers trade-off the size of a shopping destination against to geographical distance to that destination.

In shopping areas, customers do not always visit the nearest retail outlet, they might walk a little further for a better variety of products, cheaper price or better service. That makes the spatial interaction theory applicable to competition between retailers for customers on the basis of attraction, not distance alone.

The spatial interaction theory is helpful, but the real-world use is not without a challenge. Brown (1993) draws attention to some of the problem with the theory's assumptions, such as customers making single-purpose trips. In fact, customers and their shopping patterns are more nuanced — factors such as mobility options, the convenience of mobility, and simply how appealing a place is to customers are also determinants of where they will choose to shop. Furthermore, customers regularly make multi-purpose trips, which makes predictions harder.

Despite these limitations, the basic principle that a shopping centre becomes more attractive with a higher variety of products and a better location applies. The more options and the more diverse the retail mix, the higher the foot traffic and hence the attractiveness.

When it comes to mall design, this theory describes why certain areas of a mall that have a better mix of retail and/or have an anchor store are likely to attract more customers. These stores have more customer interacting and dwell time, since the customers experience greater variety and satisfaction of shopping.

2.4 Customers' behaviour

Retail environments are constantly changing, customers' behaviour is a large part of this. Therefore, it is essential to understand the factors influencing the behaviour, in order to develop a realistic simulation system that captures downtown retail dynamics. Learning the insights into how customers interact with retailers and the spatial setting, what preferences they have, all will have to be implemented in the simulation system. Factors like retail motives, impulse buying and environmental effects contribute to customers' behaviour in retail areas, affecting their routing, the time they spend shopping and to what extent of they engage with different retailers.

2.4.1 Shopping motives

Customers shop with a combination of utilitarian and hedonic reasons, which play significant roles in selecting what store to go to. Utilitarian shopping is a need-driven process – making use of a "shopping list" – in which customers prioritize meeting and satisfying needs effectively, without any emotional commitment (Babin et al., 1994; Holbrook & Hirschman, 1982). By contrast, hedonic shopping is based on sensory and emotional fulfilment: buyers want to feel and experience pleasure from the experience (Arnold & Reynolds, 2012; Kaltcheva & Weitz, 2006). Whereas utilitarian shoppers value convenience and low prices, hedonic shoppers seek exciting, active shopping experiences that stimulate the senses (Babin et al, 1994; Holbrook & Hirschman, 1982).

Shopping motives play an important role in influencing customer preferences about where to shop and how long they stay at a specific location. Utilitarian shoppers (usually "with a list") make quick focused visits, while hedonic shoppers visit more stores, spend more time, and pay more attention to what is happening around them. These multi-selective customers are attracted to the retailer mix, including store type, size, and location. Districts that contain a number of different stores that offer both functional and recreational options are appealing (Arentze et al., 2005; Dawson, 1983). The attractiveness of centres are heightened by features such as attractive designs, promotions and food courts, which are intended to serve both the utilitarian and the hedonic consumption of goods (Ibrahim & Chye, 2002). Moreover, in the Dutch market, a large floor space dedicated to specific items such as clothing and footwear, often is a deciding factor for shoppers when choosing a shopping district (Oppewal et al, 1997; Arentze et al, 2005).

Another contributing factor is multipurpose shopping, where customers like to fulfill different needs in a single trip. This behaviour renders larger retail environments – department stores, for example – particularly attractive because they provide one-stop shopping (Messinger & Narasimhan, 1997; Hanson, 1980). The combination of several retail facilities at one place not only helps customers save time but also drives them to spend more, making shopping centres with a diverse range of offering particularly attractive.

2.4.2 Impulse shopping

Impulse shopping involves unplanned purchasing due to feelings and desire, rather than intentional shopping (Dijkstra & Jessurun, 2013). These purchases are usually spontaneous, driven by the environment: eye-catching displays, promotions or sensory triggers, can get people to buy products they did not intend to buy initially. Impulse buying often begins with emotional reactions such as excitement or curiosity and may then be stimulated by factors such as decision fatigue, which increases over time. Decision fatigue lowers the ability to resist impulsive choices (Fici et al, 2024).

Non-impulse or planned shopping, on the other hand, is intentional. Non-impulse customers are those who come to the store with a set of needs, or a list of items, that they are hoping to fulfil (Dijkstra et al., 2009). This is the kind of customer characterized by logical decision-making because they shop for practicality and utility and are not influenced by an external trigger. Planned shoppers are also more inclined to compare products, prioritise their initial objectives, and purchase with a degree of thought and not on-the-fly emotional responses.

These two types of behaviours explain how customers' motivations and environments can influence their experiences in stores and both these types need different strategies to optimize store design and promotion. This difference is essential for retailers to design spaces for planned and unplanned behaviour, to improve customer experience and satisfaction.

2.5 Customer routing and entry points

Expanding upon customer motivations and patterns, customer routing and entry points also determine the dynamic of the shopping spaces. These spatial elements affect the customer distribution by influencing the initial engagements at the entry points, as well as foot traffic flow throughout the retail area. By affecting the accessibility and visibility of different stores, routes and entry points play a key role in shopping behaviour.

Customer routing describes how customers navigate through a retail area. These paths are largely driven by the perceived travel effort, entry point locations and store distances. As Borgers and Timmermans (1986) demonstrated, entry points function as physical and psychological anchors, defining the sequence and direction of customer flows. Their micro-level simulation system revealed that customers tend to take paths that require the least travel time, retracing their steps back to the point of entrance in a looped shopping path.

Borgers and Timmermans (2006) extended their earlier work by developing a model that simulates individual pedestrian route choices for downtown shopping areas. This approach assumes that the customers enter the shopping zone from a particular location (for example, railway station, bus stop, or car park) and exit through the same point. The model simulates the movement of pedestrians by choose consecutive links within the shopping network to complete their shopping trips.

The discrete choice model employed in this simulation predicts what path a customer is going to take. The choice is based on the physical features of the route, such as the variety of shops available, the distance already travelled and remaining to the exit, and the avoidance of backtracking or repeatedly passing the same links. This system, calibrated against real-world route choice data, offers a robust way to understand movement patterns, which is unique among other systems in having an endogenous, utility-based trip-completion mechanism. Such insights enable the detection of busy areas and help plan the location of stores and retail clustering.

Moreover, Brown (1992) reported that customers rarely venture into the whole shopping centre and rather visit only a small portion. Such a behaviour puts emphasis on strategically locating stores in high foot traffic zones and facilitating accessibility from key entry points. Brown's research reinforces the work of Borgers and Timmermans, noting that entry point placement and customer routing behaviour have significant effects on store visibility and success.

Oppewal and Holyoake (2004) analysed the effect of bundling and agglomeration on customers' choices by decreasing the cost of shopping and minimising the risks of product compatibility. Their findings are that customers prefer bundles of products in an attempt to cut down on search and transaction costs, yet competing stores within an agglomerated market de-merge, which is counterintuitive because they reduce single-store purchases. For example, if you have several alternatives customers will hold off on purchasing or buy the entire bundle from a single store. Other variables, like familiarity with the customer, timing, or having a shopping companion, balance these effects: familiar customer prefer to buy products individually, while the customer that are time-strapped prefer bundled products for efficiency.

2.6 Retailers' behaviour

Customer movement and entry points determine the initial flow and interaction in retail areas, retailer behaviour forms the second key factor of retail dynamics. The strategies of the retailers are directly related to the customer journeys and influence their own performance in the retail spaces. Understanding the retailers how they use clustering (agglomeration), bundling, and store evaluation strategies is required to develop an accurate system. This section explains the factors influencing retailers' behaviour.

2.6.1 Agglomeration and bundling

In studies conducted by Arentze et al., (2005) and Oppewal and Holyoake (2004), agglomeration (store clustering) and bundling (complimentary goods or services) has been investigated on the impact on customers' behaviour and the performance of retailers. Retail clusters — stores placed together in close distance benefit the customer through convenient shopping trips. This ease often means more foot traffic and sales.

Clusters of related retail can also act as anchors, triggering externalities that affect both the outside and interior stores. Nelson (1958) discovered that similar products perform better when placed in pairs because of consumers' needs for comparison while shopping. This tenet is seen in department stores, which are like shopping centres where customers compare items and brands in one location. Studies by

You et al. (2001) and Whyatt (2008) observed that stores, particularly commercial ones, tend to cluster together in order to capture comparison customers.

In the study of Arentze et al. (2005) it considers the purpose-adjustment effect, joint and cross-attraction effects of retail clusters. Customers tend to change their shopping purpose more often when they went to clusters that offered multiple store types. In a nested-logit model, they showed that large shopping malls with a diverse range of products not only attracts customers with multi-purpose trips, also customers on single-purpose trips, unlike isolated stores. The more attractive they are, the greater the market share that large agglomerations can command because the proximity to complimentary stores directly increases customers interest and spending.

These findings demonstrate that multipurpose shopping models are better predictive models than single-purpose models when it comes to analysing the performance of retail areas. Strategically, the purpose-adjustment and attraction effects of clustered areas can be exploited by retailers to unite customer demand and increase visits and cross-category purchases (Arentze et al., 2005). But even retailers that have few products to sell should consider the fact that the distance from multi-category shops can force customers towards one-stop shopping and decrease traffic to their own stores (Oppewal & Holyoake, 2004).

2.6.2 Store evaluation

According to Struckell et al. (2020), retailers continuously analyse their locations based on metrics like sales per square foot, foot traffic and net profit to decide if they should stay, relocate or close. These KPIs allow them to recognize weak spots and identify if a store meets or falls short of their goals, in case of falling short to their goals it is needed to reorganise for improved results. Retail giants, for example, Macy’s and Dollar Tree have recently sold or moved down failing stores and opened more successful ones (Commercial Property Executive, 2023).

Key performance indicators such as square foot sales and annual growth also help retailers balance profit with costs and make every store an asset to the success of the brand (Isarsoft, 2023; Veesion, 2023). If sales are not reaching targets, the store may be shut down, moved to a better location, or redesigned to increase customer attraction and conversion.

2.7 Anchor stores

Anchor stores play a central role in retail dynamics and the performance of shopping area. They are often large and iconic retail spaces, and they are magnets to attract customers, which in turn influence the behaviour of other retailers (O’Kelly, 1981). The concept of the anchor store has been around for a while, however is also susceptible to change as customer preferences and trends change. In this section the impact of anchor stores on shopping areas is described.

2.7.1 Definition and role of anchor stores

In the same way that clustering and bundling influences customer experience and retail success, anchor stores drive foot traffic and have their fair share of influence in retail areas. Department stores, like de Bijenkorf and Hema, have traditionally served as anchor stores in the Netherlands (Dallinga et al., 2009). But changing customer trends have expanded the definition, with a more diverse range of stores now serving as anchors, complicating the definition. While not much literature deals directly with the effects of anchor stores on consumers’ behaviour, a handful of studies do provide theoretically relevant data on their impact on shopping centres.

Konishi and Sandfort (2003) define an anchor store as a store whose brand awareness brings high foot traffic to the store. This draw is not only beneficial for the anchor but it also increases the sales and profit of nearby retailers. They explain, "*[...] an anchor store is a store that increases, through its name's reputation, the traffic of shoppers at or near its location*." In a similar vein, Damian et al. (2010) extended the definition of anchor stores by defining anchor stores as multi-location chains with brand recognition that can generate substantial foot traffic and cater to a diverse customer base. As Damian et al. suggest, an anchor store often has advantages (like a prime rental location) that reflect its strategic importance to the shopping centre.

Konishi and Sandfort (2003) and Damian et al. (2010) give conflicting opinions about what counts as an anchor store. While Konishi and Sandfort cater to single large-scale stores, Damian et al. take anchor stores as having clusters of three or more connected stores — essentially, a retail cluster. Ruiter (2004) adds a further nuance by classifying anchor stores according to their size, primary anchors exceeding 800 square metres catering to a wide range of customers, whereas secondary anchors cater to niche markets.
Over the past few years, new anchor stores have opened in the Netherlands beyond traditional department stores. Big (inter)national fashion chains, such as H&M, Zara, The Sting and Primark, have flooded Dutch shopping districts, and electronics mega-stores such as Media Markt have emerged as anchor tenants (Dallinga et al., 2009). These chains often exploit new development because there is limited space in existing retail districts, though it results in underperforming spots with limited product lines. Such stores may lack the capacity to perform the anchor function and potentially diminish a shopping district's competitive advantages as people move to other areas that provide broader products (Dallinga et al., 2009).

The department stores, though, such as de Bijenkorf, continue to be powerful anchors because they can house a wide range of tenants in one building. Borgers and Vosters (2011) reported that anchor type largely impacted shopping centre choice, with department stores being the most preferred option, followed by flagship fashion retailers, and large electronics stores falling behind, particularly among female consumers.

2.7.2 Anchor store impact on shopping area

Anchor stores influence the customer distribution within shopping centres by creating flows of pedestrian traffic. These stores tend to lure customer into places that once had low foot traffic and would turn these into more crowded locations (Hardin & Wolverton, 2000). Studies by Teklenburg et al. (1997) confirm that anchor stores like de Bijenkorf increase pedestrian flows and establish an association between anchor store positioning and retail activity. Ruiter (2004) also pointed out that anchor stores and nearby retail outlets were one of the most frequently accessed spaces within shopping centres and thus crucial in regulating pedestrian traffic.

Anchor stores are usually placed in strategic locations — either on the fringe of shopping centres to lure customers across retail streets or in the middle of the street at big intersections to draw traffic from entry points into the main commercial streets. Both methods are designed to ensure maximum foot traffic for stores within the area. According to Brown (1992), shoppers frequently walk by stores along these paths, providing exposure to anchor-facing stores or stores positioned at or near entry points to anchor stores.

Although anchor stores bring benefits to foot traffic, they also have impacts, both positive and negative — on adjacent stores. More pedestrian traffic generally does the trick, which results in increased store sales for those in the area (Brown, 1992). Stores depend on this passing foot traffic, and sales can often correlate to the number of people walking around and how much rent they charge (Borgers & Timmermans, 2005).

But it is not always beneficial to be located near an anchor store. Research by Yeates et al. (2001) found that when a main anchor store is shut down, it has the potential to significantly diminish sales for nearby retailers, demonstrating how crucial it is financially to keep anchor stores in place to attract shoppers to nearby shops. Similarly, Damian et al. (2010) found that the number of anchor stores in a mall directly affects the success of its sales, making anchor stores key to the success of shopping centres.

Another negative externality among anchor stores was observed by Konishi and Sandfort (2003): department stores might push customers away from specialty retailers because shoppers gravitate to the familiarity and convenience of big anchors. Second, retailers near anchors are frequently charged more for the positive spillover generated by anchors (Pashigian & Gould, 1998; You et al., 2001). Anchor shops are typically charged discounted rent because developers want to lure them because they add value to the shopping centre.

2.8 Adaptive reuse of retail space

The dynamics of retail real estate are undergoing significant transformations due to structural shifts in customer behaviour, the impact of e-commerce, and economic fluctuations. These changes necessitate adaptive reuse strategies to repurpose underperforming retail spaces for alternative functions, such as hospitality or residential use, in order to mitigate high vacancy rates and rejuvenate urban centres.

According to Ossokina et al., (2017), e-commerce plays a major role in the increasing vacancy rate. Consequently, retail real estate landlords must consider transforming the function of buildings into residential, hospitality, or cultural uses to address structural vacancy. Ossokina et al. (2017) found that most stores on the borders of shopping areas tend to cease operations. These vacant properties on the periphery can be more easily repurposed, provided there is sufficient demand for alternative uses. Furthermore, the probability of retail transformation is higher in larger shopping areas (25+ stores).

During the recession of 2008-2015, retail real estate vacancy increased by a factor of 1.6, despite a 20% decrease in rental prices for new contracts (Ossokina et al., 2017).

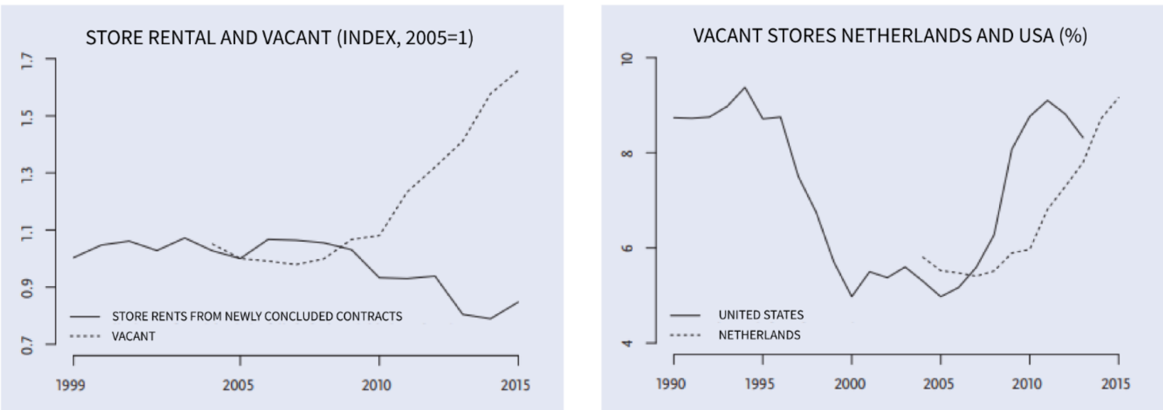


Figure 1: Fluctuations in rent and vacancy rates (Ossokina et al., 2017).

The average vacancy rate was 10% in 2016 (Planbureau voor de Leefomgeving, 2016), a significant figure but not exceptionally high. As Figure 1 illustrates, vacancy levels in the United States have previously risen to 10% before eventually declining, indicating that the retail real estate market experiences cyclical fluctuations.

In cases of a structural decrease in demand for retail space, some locations will no longer be profitable even with reduced rental prices (Ossokina et al., 2016). Transformation or demolition may be necessary to address this issue. Most shopping areas in the Netherlands are monocentric (Ossokina et al., 2017). Rental prices are highest in the centre and lowest at the outskirts, where vacancy rates increase. Figure 2 presents an empirical analysis of approximately 3500 store rental transactions between 2009 and 2015, illustrating that rental prices fall and vacancy rates rise with increasing distance from the centre of shopping areas (Strabo & JLL, 2016).

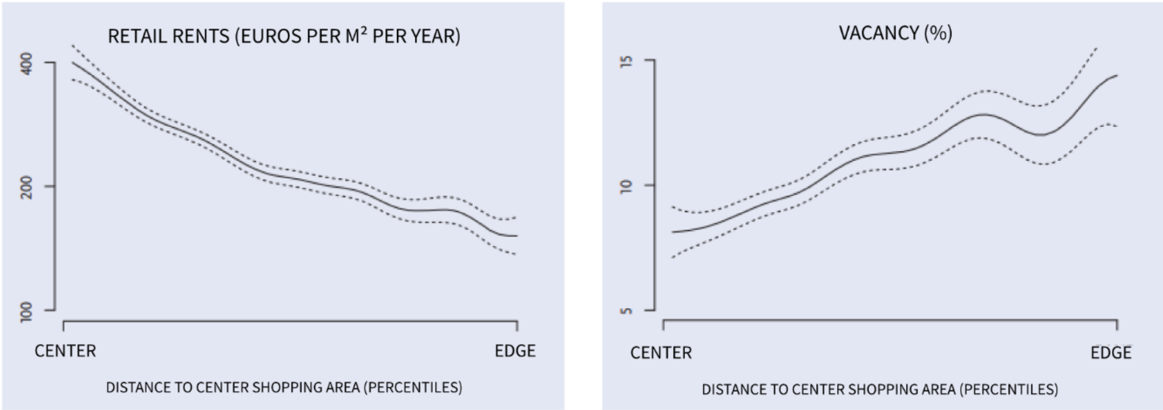


Figure 2: Effect of distance on rents and vacancy (Ossokina et al., 2017).

Teulings et al. (2016) developed a model describing the spatial dynamics of shopping areas, analysing the impact of revenue changes on rental prices and vacancy rates. For this model, the shopping area is situated in a residential neighbourhood. Figure 3 illustrates the relationship between the distance from the centre (x-axis) and plot prices (y-axis) for residential (green) and store (orange) functions. Plot prices are derived from rental prices. As distance from the centre increases, store plots become less profitable compared to residential plots. This distance marks the boundary of the shopping area. Stores near this boundary are at higher risk of becoming unprofitable during economic recessions and will likely become vacant as real estate transformation takes time.

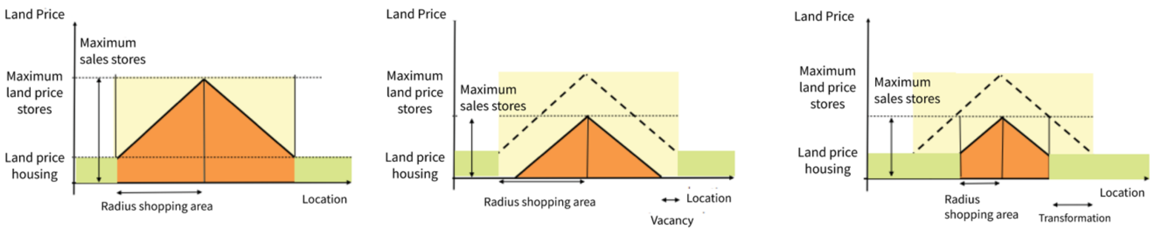


Figure 3: A spatial model of a shopping area (Ossokina et al., 2017).

Teulings et al. (2016) concluded that vacancy predominantly occurs at the borders of shopping areas, where transformation to other functions is easier. Vacant locations near the centre of shopping areas are more likely to attract new retailers due to their prime retail attractiveness.

In the Netherlands, the concentration of retail properties is highest in the centre of shopping areas, decreasing towards the boundaries where non-retail functions become more prevalent (Teulings et al., 2016).

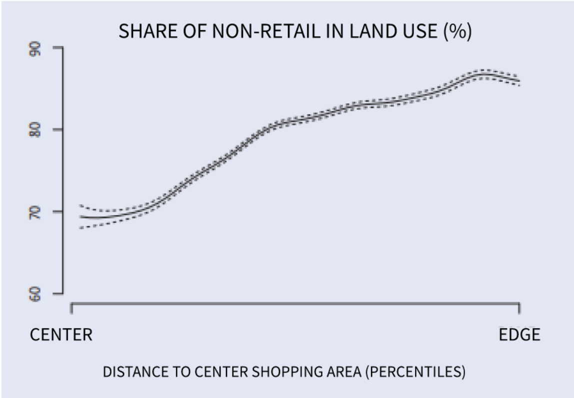


Figure 4: Share of non-retail in land use. (Ossokina et al., 2017)
The solid line represents a non-parametric estimate, and the dashed lines indicate the uncertainty margin around the estimate.

Ossokina et al. (2016) analysed 47 shopping areas in the Netherlands from 2010 to 2016, finding that 2.5% of retail properties transformed to other uses, primarily hospitality or residential functions, particularly near the shopping area boundary, as seen in Figure 4.

2.9 Methods of simulations

Research on the dynamics of retail and customer behaviours has been explored extensively, creating a valuable foundation of methods used to model such turbulent environments. The section explores these methods – such as Monte Carlo simulations, pedestrian-movement models, spatial simulation tools, and goes in-depth how human-like decision-making can be modelled. Each method offers something different: Monte Carlo simulations take care of ambiguities in customer flows and spending, pedestrian activity models analyse foot traffic driven by design and magnets, spatial simulations explore the effects of clustering, anchoring and location on customers' behaviour, and the BDI model is a framework to capture human-like behaviour in agents. The combined approaches contribute to the structure and functionality of the pilot simulation system that should provide practical information for retail planning.

2.9.1 Monte Carlo simulation

Monte Carlo simulation has been proven useful for retail studies when it comes to simulation of pedestrian movement and mall circulation in urban centres. Borgers and Timmermans (1986) applied this approach to a foundational study of pedestrian traffic flow in Maastricht, making predictions about how people would move through the area based on entry point locations, anchor shops and street attractiveness. The simulation gave probabilistic information about pedestrian flows, and the impact of spatial modifications (new mall developments or pedestrian zones) on the performance of shopping streets.

The combination of the multinomial logit (MNL) model and Monte Carlo simulations is an important development in this domain. The MNL model is used to compute probabilities of customers' choices among alternatives, depending on store preference factors, such as accessibility and clustering.
Combining it with a Monte Carlo simulation, it can be used to create probabilistic shopping scenarios by putting choice probabilities to simulated agents. This sync allows to manage complex and diverse variables, such as shopping patterns, preference for the type of stores, and routing modification without compromising randomness and customer variation.

Dijkstra, Timmermans, and de Vries (2009), for example, have demonstrated that this combination can be useful to simulate impulse and planned store visits, by capturing realistic decision-making process in pedestrian environments. The MNL model determines the probability of selecting specific shopping routes, Monte Carlo simulation adds randomness, which creates random behaviours of customer movement and interaction. This method is a realistic approach to simulate customer movement and shopping patterns.

2.9.2 Pedestrian activity models

Pedestrian activity models offer a complementary approach by focusing on customer movement within retail environments. Haklay et al. (2001) researched the influence of street design and attraction placement on pedestrian flow. Combining empirical measurements of pedestrian routes with models of micro-level interactions (e.g., navigating obstacles) and macro-level flows, these models give an integrated solution to modelling foot traffic in retail environments.

STREETS is an agent-based simulation system that captures pedestrian movement. STREETS uses entry points (transit stations, parking spaces) and adjustable entry rates, it simulate realistic entry and movement patterns, with adaptability to open urban areas. While originally developed for closed systems, the system can easily be adapted to model open environments by changing the entry points, allowing to use it as a flexible model for pedestrian movement. STREETS' modular framework permits sophisticated agent behaviours such as spontaneous decision-making and adaptive route planning, highly resonant with pedestrian behaviour. With the model, urban designers can forecast pedestrian flow and optimise layouts to distribute the flow and improve retail interaction.

Arentze et al. (1993) developed a model of multi-purpose shopping trip behaviour. In their studies, they observed how customer tailor shopping trips for maximum utility, involving a combination of uses based on factors such as store locations and the range of goods available. The model emphasizes the role of retail agglomeration in attracting customers who seek to shop efficiently.

2.9.3 BDI agents

In the development of systems that simulate human behaviour, it is important to incorporate frameworks that are capable of replicating the rational decision-making processes of individual in a complex environment. For example, the environment of a retail area where customers interact with retailers, navigate through the area, and make decision what shop to visit and what to purchase based on various factors. This behaviour is not only reactive, but also influenced by underlying goals and beliefs. The customers' behaviour must be predictable and modelled realistically.

One such framework is the BDI (Belief-Desire-Intention) model. The BDI model is designed to capture complex human-like decision-making of agents in a simulation. The model integrates three components: beliefs, desires, and intentions. Beliefs is the representation of an agent's understanding of the environment it is in, providing the necessary information to interpret and respond to what it encounters. Desires is the reflection of the agent's goals or objectives, driving its motivation and directing the behaviour. Intentions are the commitments the agent adopts to reach its desired outcome, forming its actions and guiding its decision-making process (Rao & Georgeff, 1995).

This framework allows for a flexible and adaptive system, where agents can change their plans based on new information of environmental changes. The BDI model is particularly effective in complex, real-world scenarios where decision-making is influenced on both long-term goals and short-term situations (Rao & Georgeff, 1995).

2.10 Conclusion

The literature review gave insight in how the growth of e-commerce has reduced physical shopping, creating more vacancies, especially at the edges of retail areas. Adaptive reuse strategies, such as the transformation of retail into functions such as residential, are essential for revitalizing downtown retail areas.

Furthermore, it provided useful insights to understand customers' behaviour, retailers' behaviour, and the spatial setting. Customers are primarily interested in RFA, anchor store location, grouping of stores, and proximity. Often customers make unplanned visits/impulsive purchases based on appealing designs or promotional stimuli. These factors influence the behaviour and preferences of the customers in downtown retail areas.

Retailers prioritize locations with high clustering, proximity to anchor stores, and high foot traffic to maximize revenue. Their choices, based on performance such as profitability and visits, often include a decision to stay, relocate or close their store. Following closure, vacant store locations may host other retailers or transform into another function. Also rent is higher in central locations, where foot traffic is high.

Within the spatial setting it is found that anchor stores are magnets that attract customers and help local stores in their proximity perform better. Entry points influence the customer distribution and their initial engagements. Entry point placement helps establish foot traffic patterns and creates visibility of stores. The retail composition in Dutch downtown shopping areas consists of a mix of daily and non-daily stores. Supermarkets, specialty and personal stores are the daily store types. Fashion & luxury, leisure and in/around the house are non-daily stores.

By examining several simulation systems of customer movement in retail areas, it was concluded that agent-based modelling suits this topic well, together with the integration of a combination of the MNL model and Monte Carlo simulation. The behaviour of the agents can be modelled using the BDI model.

3. Methodology

3.1 Introduction

This chapter provides an explanation of the methods used to start the development of the simulation system of downtown retail dynamics. First, the approach to find an answer to the main research question is described, in here the main research question is divided into several sub-questions based on the findings of the literature review. Sub-questions emerged on how to tackle and integrate the components, shaping a structure for the development of the system.

It also describes the stakeholders and the spatial setting of the system, together with a brief description of the validation against the literature review findings. Choosing the correct tool for programming is very important, by demanding strict requirements an agent-based modelling tool is selected.

The conceptual system is also presented which provides a description of the interaction between the components in the system. This framework links the research concept, input data parameters and methodological choices to the simulation's development and testing. The chapter ends with some sub questions answered.

3.2 Approach

This study develops a pilot simulation system to explore downtown retail dynamics. It combines agent-based modelling with the findings captured for downtown retail and focuses on the development and replication of the basic patterns rather than detailed predictions. The goal is to investigate customers' behaviour, retailers' behaviour and the spatial setting in Dutch downtown retail landscapes.

3.2.1 Guiding framework

The sub-questions are based on the insight gained from literature review, made up to guide the development of the simulation system. Each sub-question addresses a specific aspect of downtown retail dynamics, shaping the design and functionality of the simulation:

1. What are the main mechanisms affecting customer behaviour in downtown retail environments?
2. How can the performance of individual stores be assessed?
3. What are the main mechanisms affecting retailer behaviour in downtown shopping centres?
4. How can the above-mentioned mechanisms and indicators be implemented in a simulation tool?
5. How can policy measures be evaluated by means of the simulation tool?
6. How can the performance of the simulation tool be assessed?
7. What are the requirements regarding the simulation tool, and which simulation tool is most suitable?

3.2.2 Simulation setup

The system simulates the key features of a downtown shopping district in a 2D spatial grid. This grid represents streets, stores, and entry points, such as transit stations and parking garages, trying to replicate a simple but realistic spatial setting where customer and retailer interact.
The actors in the system are called agents, there are customers and retailers. The customers are given a certain shopping behaviour based on preferences and interact with the retailers. The retailers will display their own behaviour, based on the choices of the customers where they walk and shop. Retailers react by either staying on their current location, relocate, or close their store. It also is possible to transform their store location into another function. The simulation features a range of stores types: daily, fashion & luxury, leisure, in/around the house, speciality, hospitality, cultural & recreation, representing the variety of downtown retail areas. The goal is to replicate the findings of the literature about the

interactions between the agents into the simulation system. Creating a foundation for a predictive simulation system that analyses the fundamental dynamics in downtown retail.

3.2.3 Scenario evaluation

Scenario evaluation is a key part of the research to evaluate the system's ability to replicate the findings of the literature. By changing parameter settings, the simulation analyses the effects on customers' behaviour by adjusting entry points, retailer clustering and other influencing factors. This approach allows to explore the relationships between customers' behaviour, store positioning and downtown retail dynamics. The simulation outputs, including vacancy rates, foot traffic distribution and store metrics are analysed to assess whether the simulation results represent the expectations from the literature.

3.3 Requirements and overview of the simulation Tool

This section outlines the demanded requirements for a simulation tool to model the complexities of downtown retail dynamics effectively, followed by an overview of the selected tool for this research.

3.3.1 Requirements for the simulation tool

An agent-based simulation system with complex interplay between actors demands for strict requirements. The requirements include:

- **Agent based modelling capabilities:** The tool needs to be able to model individual agents (such as customers and retailers) with different behaviours and interactions.
- **Spatial modelling:** It must incorporate (simple) geographic layouts and spatial relationships in order to mimic actual downtown shopping areas.
- **Flexibility and extensibility:** The tool should allow customization of the behaviour, variables, and mechanisms of the agents.
- **User accessibility:** An easy-to-use user interface and smooth learning curve.
- **Visualization:** The capacity to provide transparent, real-time visual representations for analysing agent actions and reporting outcomes.
- **Scenario testing:** The tool should allow policy changes, parameter adjustment and mechanisms to be evaluated against one another to understand how they affect downtown retail spaces.
- **Scalability:** the tool must be able to handle various levels of complexity, from pilot system to enhanced model extensions in the future.

3.3.2 Overview of NetLogo

The chosen program of choice is NetLogo to develop the simulation tool for this study, because it fits perfectly with the above requirements.
NetLogo is a versatile multi-agent simulation program which is highly suitable for representing spatial interactions between agents. It enables users to model single entities – for example, customers and retailers – with individual rules and behaviours, and it is suitable for modelling downtown retail interactions (Heppenstall et al., 2016).

The tool's spatial modelling ability allows the creation of geographical environments, capturing factors such as store distance, customer foot traffic, and clustering effects. This aspect is important when analysing spatially dependent behaviours and outcomes in shopping centres.

NetLogo's user-friendly design – both graphical and textual programming — making it accessible to a wide variety of users. This availability facilitates collaborative research and iterative model building. Also, NetLogo's vast array of pre-designed models and extensions make it easier to add custom features or mechanisms (GIS Agents, 2023).

Visualization is another NetLogo strength. It allows for easy tracking agents' actions and interactions over time, and produce insights that can be communicated to stakeholders or used to improve the model (Gaur & Singh, 2023).

The tool has been applied in a wide range of urban research, from modelling urban sprawl to examining retail competition. It is proven to be effective in estimating customers' behaviours, retailers' behaviour, and competitive relationships which validates its use for this research (Ligmann-Zielinska & Jankowski, 2014; Heppenstall et al., 2016).

3.4 Simulation system design

In this section, the conceptual framework and design of the simulation system is presented, exploring the dynamics of downtown retail. The conceptual framework of the simulation details the key components – customers' behaviour, retailers' behaviour, and spatial setting – and how they are expected to affect the retail dynamics. Then it is speculated how these components interact within the system in order to provide a picture of what potentially happens in the downtown retail environments. Finally, this section discusses what is required to build a realistic and flexible simulation as a basis for testing and validating the system by means of scenarios.

3.4.1 Conceptual framework

The conceptual framework displays the simplified interactive nature of the components in the system. Customers, retailers, and the spatial setting, in the form of a 2D grid, are the primary components of the system. Basically, customer foot traffic drives store profitability which in turn impacts store relocations or closures. Assumed parameters are added to the system to enable scenario-based analysis.

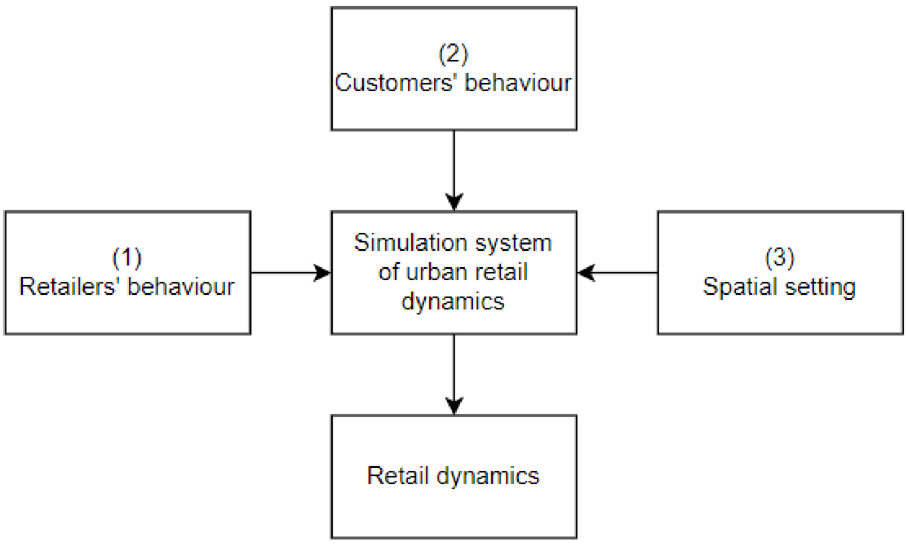


Figure 5: Conceptual framework for a simulation system to explore downtown retail dynamics

As shown in Figure 5, the simulation system integrates key components—customers' behaviour, retailers' behaviour, and spatial setting—to reflect how these components interact within downtown retail environments. Together, these components influence the system's outputs, which provide insights into retail dynamics.

Within the system the components' behaviour do differ in time scale. Each customer is simulated to make a single shopping trip, with new waves of customers entering the shopping area in three shifts throughout the day. The length of a day is adjustable by the user of the system. The time scale of retailers is much longer as their decisions are closing, relocation or transforming their stores according to their stores performance. The evaluation and decisions of the retailers are done after a month, during the period there are no customers active in the shopping area. The system allows the user to extend the evaluation period of retailers.

Customers' behaviour

Customers' behaviour encompasses shopping habits, preferences, and movement patterns within the shopping area. The customers' behaviour should be flexible and adaptive within the system, so that the decision-making process of the customers can change and adapt based on new information or environmental changes. To accomplish this, the BDI (Belief-Desire-Intention) model is integrated in the system. The customers' beliefs in the simulation concern the understanding of the layout of the shopping area, including the streets, and the locations of the stores and types of stores. The customer is also aware of the characteristics of each store, such as the distance to themselves, size, proximity to anchor store and clustering. Their desire is their goal, which is to complete their shopping list. The intentions are specific plans or commitments the customers make to achieve their desires. The customer selects a store to go to based on the store characteristics and plans a route to this targeted store by moving from intersection to intersection in the shopping area. In order to complete their goal, customers attempt to make purchases upon entering stores. They may also adapt their routing when influenced by unplanned store visits.

The customer's choice of stores is central to the system, customers enter the area at designated entry points. Each customer is equipped with a shopping list, although recent literature indicates that customers are often influenced by environmental factors beyond their initial shopping lists (Borgers & Timmermans, 2015). Stores carrying items from the shopping list of the customer are more likely to attract visits, but other factors—including distance from customer to store, proximity to anchor stores, clustering with similar stores, and store size—also shape customers' choices. Each of these factors play a weighted role in directing foot traffic, as illustrated by Borgers and Timmermans' model (2015), where entry points and store placement induce shopping routes. Customers will move towards their targeted store, based on the attributed mentioned above. They make their way towards their targeted store by 'hopping' from intersection point to intersection points, based on the distance from the target store to the intersection and the distance from themselves to the intersection. When moving through the shopping area the customers visit stores, either planned or unplanned. In the stores they attempt to make a purchase (a customer either fails or succeeds at making a purchase in a store). By setting the parameters related to the variables carefully, the simulation can predict foot traffic and sales.

Retailers' behaviour

Retailers' behaviour refers to relocations, closures and transformations — which are all driven by the customers and the store's market position. The most desirable locations in the city centre – with the highest rents – attract more customers, but at a greater operational cost. Each store records visitor traffic and sales over time and the results dictate whether it stays, relocates or closes (Commercial Property Executive, 2023; Isarsoft, 2023). Retail adaptive reuse is the transformation of stores; when a store no longer can become profitable, it could be repurposed into another function, further fostering the economic flexibility of the area.

Spatial setting

The spatial setting refers to the organization and layout of the shopping area, including entry points, anchor stores and store clusters. Retailers use the stores, customers come to the stores to shop. The layout and organization influences the customer movement. Entry points placed at strategic locations become determinants for customer distribution. Anchor stores act as magnets, driving traffic to the benefit of nearby retailers. Secondly, grouping similar stores generates points of interest for certain products, which can impact customer preference and make specific areas more attractive for multi-purpose visits. By adjusting the parameters of such variables, the simulation can replicate various shopping behaviour of the customers within the shopping mall.

The components— customers' behaviour, retailers' behaviour, and the spatial setting — are all incorporated into the simulation system. This will control how each component will behave, so different cases can be simulated. The parameters and variables associated with these components, the parameters are discussed in more detail below. The different scenarios are built, for example, around changing entry points or creating large clusters, to explore how these adjustments could affect foot traffic, store sales, and the reaction of retailers.

Retail dynamics

The simulation system is designed to replicate the actions and interactions of customers, retailers, and spatial setting, together to influence downtown retail dynamics. As Figure 5 demonstrates, these three components interact within the simulation, and the result consist of changes in the dynamics of retail, such as closings, relocations and transformations. Rather than having accurate predictions, the system attempts to illustrate the mechanisms involved in retail development and how these shifts are produced by the interactions between the components. By demonstrating these dynamics, the simulation offers an pilot tool to help shape future policy that can function as the foundation of a more advanced system, allowing planners and decision makers to better appreciate how varying downtown retail configurations will affect them.

3.4.2 Input data

The functions modelled in the simulation are based on common retail functions identified in existing literature, as discussed in the literature review. The store functions namely are: daily, fashion & luxury, leisure, in/around the house, speciality, hospitality and cultural & recreation. While studies on city retail compositions provide valuable insights, they often address these functions in broad terms. However, recognizing that downtown retail compositions at the city level differ significantly from those in downtown areas, this simulation focuses specifically on the unique characteristics and dynamics of downtown retail environments to create a more representative retail setting.

This research aims at establishing a foundation for modelling downtown retail dynamics through an agent-based simulation, focusing on main findings from the literature. Instead of utilizing detailed datasets, this approach applies general principles derived from literature. The constructed retail area, therefore, reflects a simplified retail environment, possibly representing the structure of a medium sized Dutch downtown retail area.

Parameters

Most of the parameters used in the simulation cannot be fully supported by literature, as they vary significantly depending on time and location. Therefore, parameters related variables have been set based on common sense and testing. Examples of such parameters are the probability of successfully purchasing an item per store type, the rent to be paid by retailers, the weights in the utility function of choosing a particular store to visit, and the weights of the factors influencing retailers' relocation decisions are based on assumed values. However, the probability increase in the eagerness to purchase over time is backed by Fici et al., (2024), as are the increases in the likelihood of going home and the occurrence of unplanned store visits (Dijkstra and Jessurun, 2013). Importantly, almost all parameters in the system can be adjusted by the user, allowing for flexibility and customization based on specific scenarios or assumptions.

3.5 Conclusion

This chapter introduced the approach to the agent-based simulations of downtown retail interactions — including customers, retailers, and spatial setting. Using NetLogo, different scenarios with alterations can be tested whether the literature review findings can be seen replicated into the simulation system.

Some of the sub-questions raised at the start of this chapter are already answered partially:

The simulation integrates factors that influence customers' behaviour mechanisms, such as distance from customer to store, clustering, anchor store proximity of the store, and RFA size, to predict customer movement and shopping preferences. Store performance is measured using factors such as sales, profitability, and vacancy rates. Retailers' decision are based on the profitability of the store, visitor numbers and anchor store proximity, shaping potential adaptive reuse.
These processes are built into NetLogo's multi-agent framework, leveraging its spatial modelling and visualization tools. NetLogo was selected for its ease of use, its scalability and its proven effectiveness in urban studies. In later chapters more details are discussed and additional sub-questions are answered.

4. Simulation design and implementation

4.1 Introduction

This chapter presents a detailed description of the functioning of the simulation system to model retail dynamics in a fictional environment. The system replicates various interactions between customers and stores within a spatial setting, offering insights into how the retail environment evolves over time.

Figure 6 below provides a simplified diagram of the simulation system, offering a brief overview of its key components and structure. This visual introduction serves as a reference point before moving into a detailed explanation of the system's design and functionality.

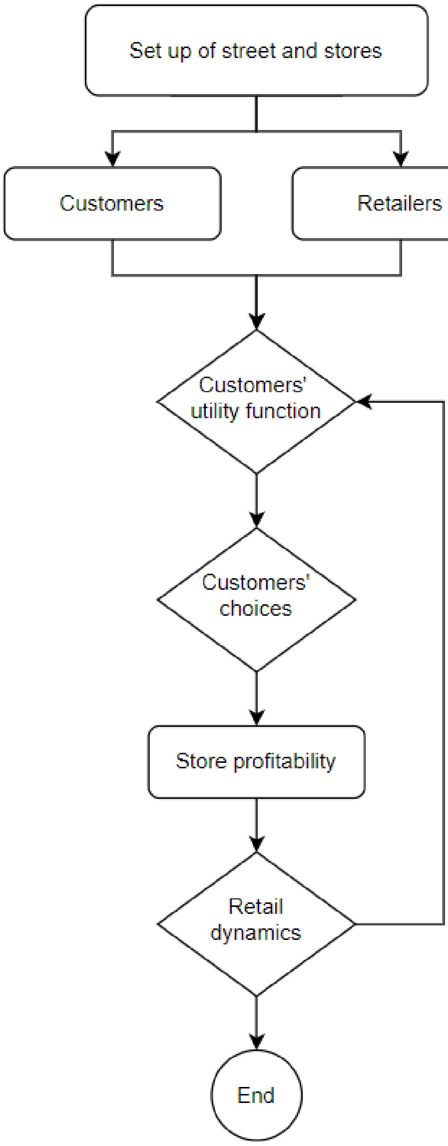


Figure 6: Simple diagram of the simulation system

Setup process

The simulation starts with the creation of the virtual environment. The spatial environment consists of patches, which are square spaces that resemble different functions such as stores, residences, streets and entry points. A patch cannot change its position; it only changes its function. These patches are given information values such as type and size. Moreover, agents are the customers and retailers with behavioural characteristics. The customers each have a shopping list and enter through the entry points. Retailers are generated in stores and are given a retail function (fashion & luxury, daily, leisure, in/around the house, specialty, hospitality and cultural & recreation). These retail functions are colour coded to make them clearly identifiable. The store-patches adopt the colour of the retailer that currently is in the store. The customers are sensitive to different store attributes, these attributes are the respective distance from customer to the store at the given time, the store's distance to an anchor store, clustering of similar stores and the RFA size. This impacts how they engage with stores. Every customer acts independently, attempting to finish their list. But it is also possible for the customer to make unplanned store visits.

Customers' Utility function

The utility function is the core module of the customers' behaviour in the simulation, governing the interaction between customers and retailers. When a customer enters the shopping areas, the customer considers each store as a potential target store, the target store being the store the customer will move towards. This utility function is shaped by the variables mentioned above. Each variable given a weight in proportion to its significance. The output will be a list of stores, sorted on their utility and corresponding probability. Higher utility stores are likely to be chosen more often, replicating customers' behaviour. Once a store is visited, the utility for all stores is recalculated based on the location of the customer and he/she will go to the next store. The utility function will be explained in greater detail in section 4.2. It is important to note that the order of the shopping list is of no influence in the current state of the simulation system, as customers either checks if a store has an item from their shopping list yes or no.

Store profitability and dynamics

After all customers are done shopping and have gone home, the system calculates store profitability. The sales made by the store during each cycle are tracked. Stores that do not generate sufficient sales required to afford rent are marked as unprofitable. Rent is determined by visitor count on the street in front of the store and its RFA, in Section 4.2, this is explained in more detail. If a store stays unprofitable for several consecutive cycles, the store will go bankrupt and its location becomes vacant. If no other store decides to move into the location, the location will be transformed into another function. Another retailer might relocate into this location, depending on the visitor count in front of the store, distance to an anchor store and clustering with similar stores in the street. The rent retailers pay depends on how many visitors the street in front of the store had this cycle and RFA size, which means that locations with higher foot traffic bring more expenses.

Key system outputs

The system creates a series of outputs that describe the status of the retailers and the interactions with customers. It tracks store performance such as profitability and failure rates. The customers' movement and preferences are also tracked in terms of visits, providing insights in store popularity.
Moreover, the system captures the retail dynamics over time, with store closing, relocating, or transforming based on the profitability.

In the following sections the system's architecture is described, detailing the structural and functional components. This includes a description of the actors, spatial setting, and processes that make customer and retailers interact.

Section 4.3 details the user-configurable parameters and monitored metrics, illustrating the system's adjustable capabilities and evaluation options. Section 4.4 is a technical explanation of the user interface. Section 4.5 concludes the chapter by summarising the results and answers to sub-questions.

4.2 System architecture

This section defines the architecture of the system in terms of the structure and components that are the foundation of the simulation. It describes how the spatial environment is generated, the role of the agents, and the mechanisms of the customers and retailers.

Setup

Firstly, the system runs on a fixed random seed to ensure consistency in results across different runs to keep the initial spatial setting unchanged across different scenarios. The simulation system starts with the setup, generating a fictive spatial retail environment that is not based on a particular case, which is filled with streets, intersections, residents, stores, and customer entry points. Streets are represented as grey patches in the simulation, forming the infrastructure for the customers. Intersections have a crucial role in customer movement, as the customers move from intersection to intersection. The technical benefits of this are detailed further below. Along the streets, stores are setup, with an option to have some stores deliberately left vacant. In total there are 60 stores divided into 7 different functions, based on the insights of the literature review: daily store, fashion & luxury, leisure activity, in/around the house, specialty store, hospitality and cultural & recreation (see Figure 7). The retail composition, as derived from the data, attempts to reflect the composition according to the Province of North Brabant (2021). Culture & Recreation accounts for 3.6%, Daily represents 9.5%, Fashion & Luxury constitutes 35.4%, Hospitality comprises 16.3%, In/Around House makes up 18.4%, Leisure accounts for 8.1%, and Specialty represents 8.7%. In the middle of the virtual retail environment two large size anchor stores can be seen, as these are represented by 4 patches each.

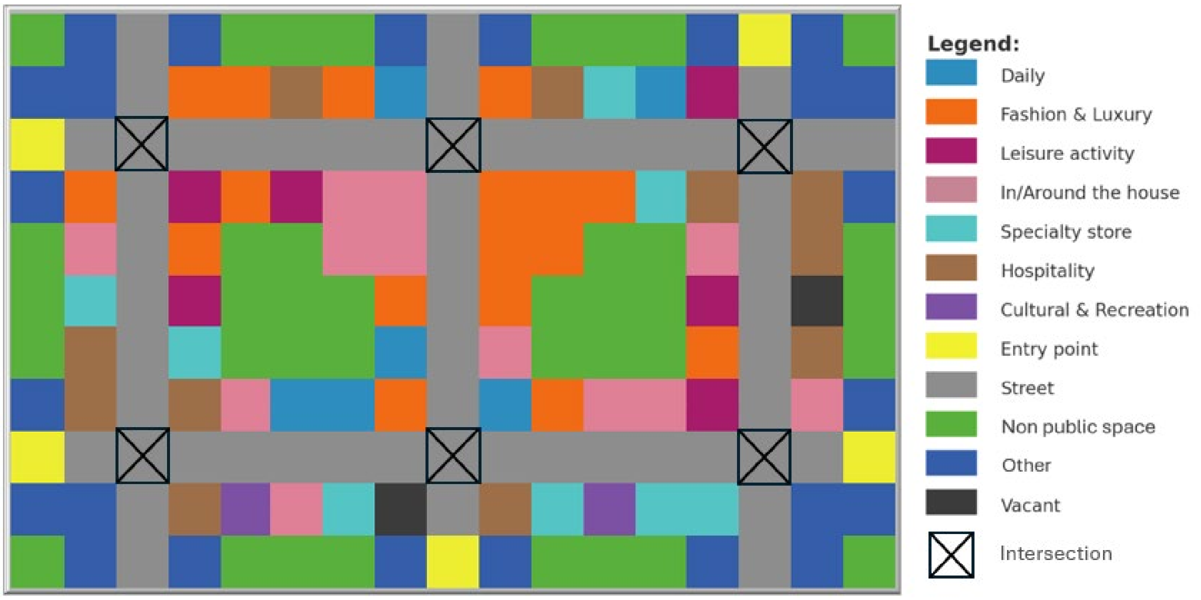


Figure 7: Generation of spatial retail environment setup

At setup, a Retail Floor Area (RFA) size is set for each store, this influences the customers' preference. Additionally, the first type of agents is generated, the retailers. These take place into the stores and are given a function. All retailers only sell one kind of product, that is based on their function. These items, therefore, are merely titled by their corresponding function, while store patches are given the respective colour: 1) Daily (sky), 2) Fashion (orange), 3) Leisure (magenta), 4) House (pink), 5) Specialty (cyan), 6) Hospitality (brown), and 7) Culture (violet). All stores have an infinite supply. The anchor stores have an in/around the house and a fashion & luxury function.

The second agent type are the customers. Every customer has a shopping list with items he/she will look to go home with. A shopping list example would be like this: [[4 1] [3 1] [6 1] [2 1]]. In this example, the first number indicates the product ID that matches the store function. For clarification: 1 resembles an item of fashion & luxury stores. The second number indicates the quantity, however this cannot be higher than 1, when an item is purchased by the customer and it was on their list it will be set to 0 and in turn removed from their shopping list. Users of the system can adjust the maximum length of the shopping list. For example, when set to maximum 6, the lists will vary from 1 to 6 items on the list. Customers will prefer stores that have items on their shopping list, a detailed formula can be seen below in the Customers' behaviour section. The shopping list also has an important function in the decision of the customer when going home, if a shopping list is empty he/she will go home. Customer will be shopping during the "shopping period", this is an adjustable time period. After the shopping period is over, the customers are forced to go home.

Customers' and retailers' behaviour

Figure 8 illustrates the steps and decisions of the customers and retailers in the simulation. The figure gives a systematic representation of the processes. Each decision, action and interaction variable is explained below, step-by-step, giving insights and understanding into the underlying thoughts of the agents.

Customers' behaviour

So far the generation of the virtual environment, the retailers and customers have been explained. At first, the time period for how long the customer are shopping is setup by the user. To keep track of time, the system counts so called 'ticks'. In the system, a tick represents a single unit of time or step in the simulation, during which all agents (e.g., customers, retailers) update their state according to the rules of the system. Retailers will have an evaluation at every 1500 ticks (representing a 'month'), this evaluation is explained in more detail below in the section about the retailers. To fasten the simulation, a 'month' consists of 10 'days' (150 ticks per day) and every 'day', customers will be fed into the retail environment in 3 shifts (at 0, 50, and 100 ticks). The user can set a maximum number of customers that can appear each shift. To simulate population peaks and drops, the actual number of customers for each shift is randomly chosen between 50% and the full set maximum. The first decision-making step in figure 8 is based on the utility function. For each customer, the utility function determines the probabilities for each store to be targeted next.

Each store has an unique attractiveness score for each individual customer, which influences the likelihood of a customer choosing to visit that store. This score is derived from several factors: whether the corresponding type of store in on the customer's shopping list, the distance from customer to the store, the size of the store, the distance from the store to the nearest anchor store, and whether the store is part of a cluster of similar stores. The clustering effect enhances attractiveness by grouping similar stores in the same street, creating an agglomeration that increases overall appeal.

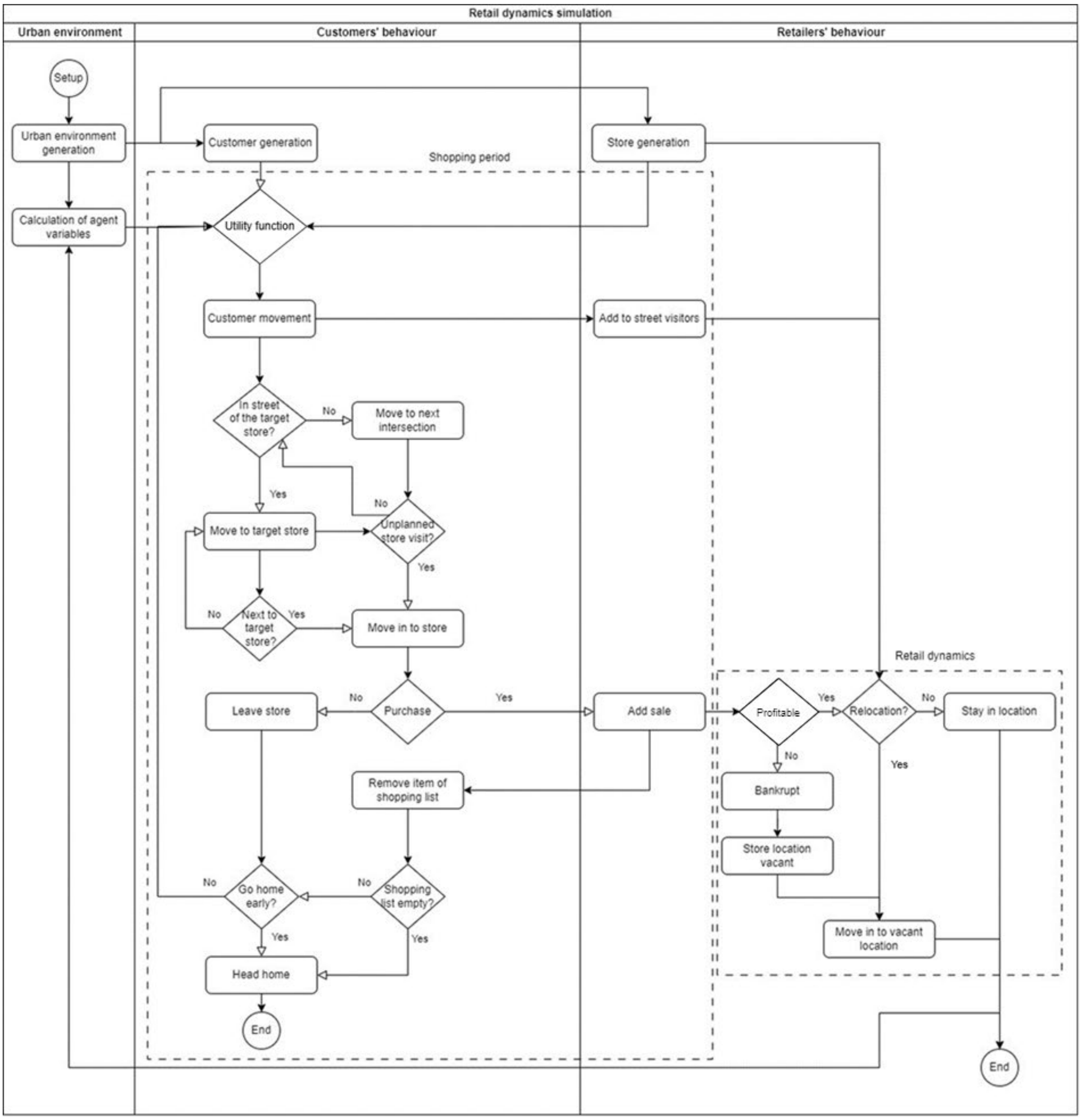


Figure 8: Detailed overview of simulation system

The variables are integrated into a utility function, where they are assigned weights based on their relative importance, with the distance variables influencing the utility negatively and the size and clustering variables positively. Size and clustering are fully taken into account if a store sells an item from the customers' shopping list; if not, they only count partially or not at all. An example will be provided below. The weights can be determined by the user in the interface. The result is a list of utilities, with the highest utility indicating the store that is most attractive to the customer. Subsequently, Multinomial Logit (MNL) choice probability are calculated using the utilities of the stores (detailed explanation in Appendix B), reflecting the likelihood of the customer choosing each store. Given these probabilities, a store will be selected by means of Monte Carlo simulation (see Appendix D), after the creation of a cumulative distribution of the MNL outcome (see Appendix C).
It is important to note that each customer keeps track of the stores they have visited, these stores are not included into the list of potential target stores anymore.

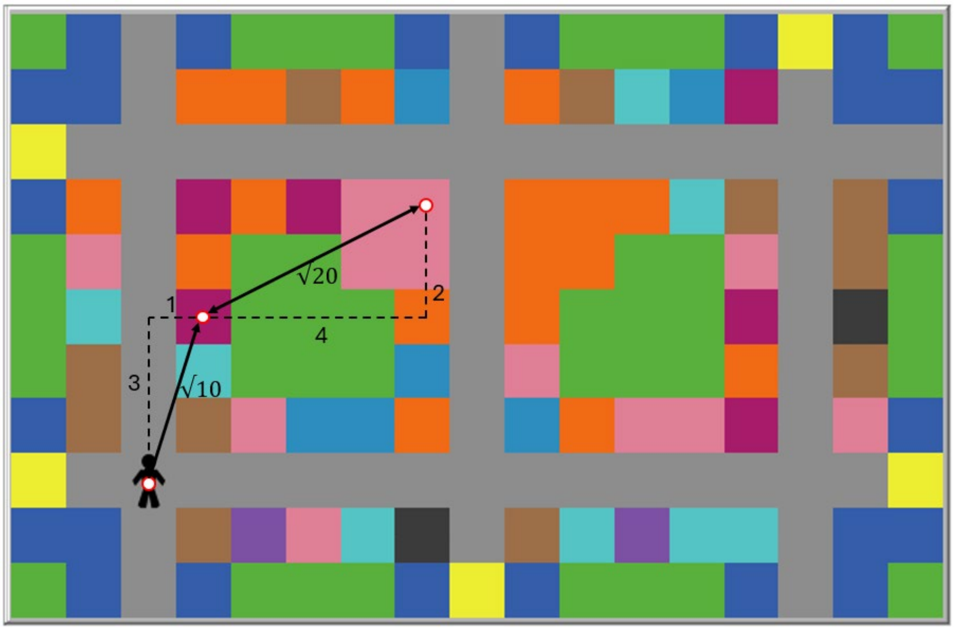


Figure 9: visualisation of distance measurement

Assume the situation shown in figure 9. The customer's shopping list contains an item of 'Leisure'. The distance to the nearest Leisure-store is 3 patches to the north and 1 patch to the east, based on the Pythagorean theorem, making the direct distance towards it √10 ≈ 3.2. The distance from that leisure store to the closest anchor store is √20 ≈ 4.5 units. The size (RFA) of the leisure store is 500 square meters. All store size information can be found in Appendix A, along with other hard-coded data. Regarding clustering: there are more Leisure-stores in the same street. Important to note is that the distances are measured directly.

The scores of the various variables are used to calculate the utility of each store, ultimately representing the final score for selection. The utility function is expressed as:

$$V_i = (w_1 \times RFA_i + w_2 \times Clustering_i) \times S_i - w_3 \times DistanceCustomer_i - w_4 \times DistanceAnchor_i$$

Here, S_i is a binary variable that reflects whether the store sells an item from the customer's shopping list:

$$S_i = 1 \; if \; the \; store \; sells \; an \; item \; from \; the \; shopping \; list, \; and \; S_i = 0 \; otherwise.$$

If the value of w_1 to w_4 increases, the corresponding variable has a greater impact on the utility. The Retail Floor Area *(RFA)* and *Clustering* have a positive effect on the utility, while the distance variables (*DistanceCustomer* and *DistanceAnchor*) have a negative effect.
The binary nature of S_i ensures that the RFA and Clustering factors only contribute to the utility of a store if it sells an item from the customer's shopping list ($S_i = 1$). When $S_i = 0$, these factors have no impact, reflecting that stores not on the shopping list are significantly less attractive.

Depending on the store's function, the importance of RFA (Retail Floor Area) size varies, as different types of stores may differ in attraction per m². Users can assign weights to various factors, including the distance to each store for the customer and the distance to the nearest anchor store. In the spatial setup, the customer-store distances tend to be greater on average (mean 9.4, maximum 14.8) than distances to anchor stores (mean 5.0, maximum 6.4), the relative importance of these distances can be adjusted by the user to fit specific scenarios.

V_i (utility of store) represents the attractiveness utility of a single store *i*. In an example (see Figure 10) the utility for the marked store is calculated. In Figure 10 the location of the customer can be seen as well. The RFA_i-variable represents the value for the retail floor area of store i, and so on. The w_1-

variables represent the weights for the variables, being 0.00192 for RFA (Daily store), 0.1 for clustering, 0.04 for the distance from the customer to the store, 0.04687 for the distance from the store to the nearest anchor store and 0 for not being on the shopping list.
The RFA of this store 340 square meters, the clustering is 1 as there is one similar store in the street, the distance from the customer to the store is about 10.3 and the distance from the store to the nearest anchor store is 4. Filling in the formula in provides a utility score of ≈ - 0.5993. Since the store does not carry an item from the customer's shopping list, it does not attract the customer. The final calculation is therefore:

$$0 \times (0.6528 + 0.1) - 0.4118 - 0.1875 \approx -0.5993$$

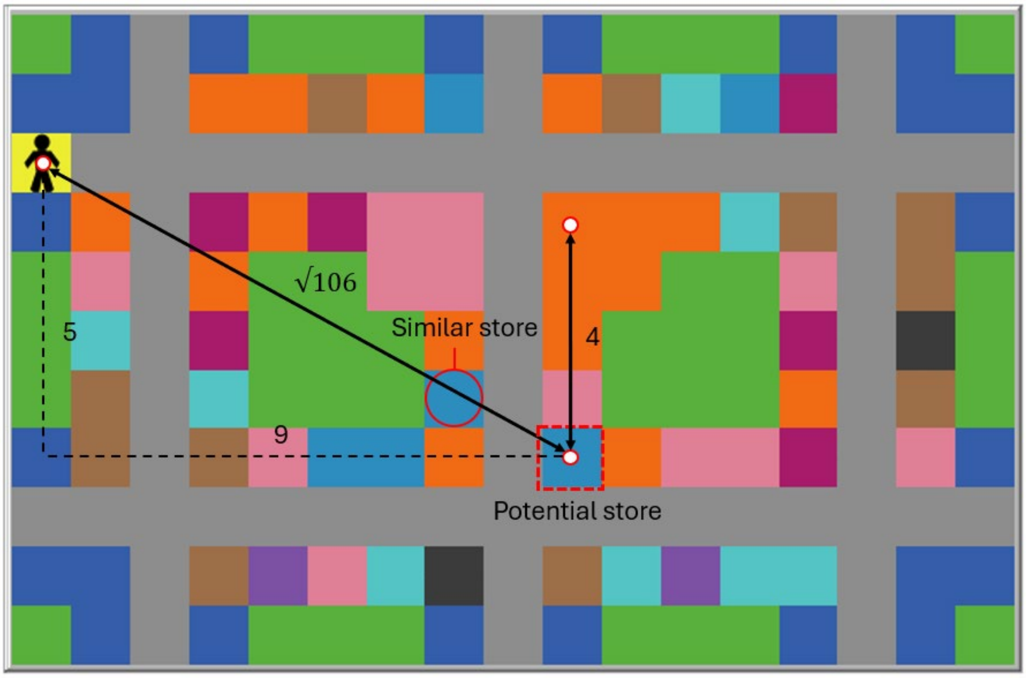


Figure 10: Example calculation for store utility

This utility score must be calculated for each store in the retail environment. According to the Multinomial logit model (see e.g., Hensher et al., 2015), the exponent of each store's utility is standardized over all stores, resulting in a probability for each store to be chosen. So, there is no designated choice set for store choice, however the probabilities of store that do not have an item from a customer's shopping list are significantly lower than stores that have. A random number is then drawn between 0.00 and 1.00 to identify the selected store (Monte Carlo simulation). According to the MNL model, the exponent of the utility scores is taken to calculate probabilities. Therefore, the range in utilities should be kept limited. The initial weights given to the variables in the utility formula are carefully selected so that the utility of the best scoring store (mostly the fashion & luxury anchor store) will be around ± 2.5.

However, mostly the customer will not have the selected store as their main and only target. This selected store becomes the main target of the customer, but will not go there directly. Only when the customer is in the street of the targeted store, the customer will move directly towards it. However, if the customer has not reached that street yet, the customer will moves to this street by moving from intersection to intersection. At each intersection, the customer will list the closest intersections to the target store. Due to the form of the retail structure, this means all intersections within a radius of 6 patches to the customer. Following this list, two distances are measured with the intersection as its middle point: the distance from the store to the intersection and the distance from the customer to the

intersection. In Figure 11, the customer has a choice set of two options, both optional intersections are 6 patches away from the customer. Option 1 however is only √41 ≈ 6.4 patches away from the target store while option 2 is √125 ≈ 11.2 patches away. Option 1 therefore provides the shortest distance, and the most likely route for the customer to get closer to the main target.
However, the distances of both options are standardized and with the MNL model a chance distribution is made, giving the best odds relative to each distance. Again, the distances from the intersections to target store are measured directly to ease calculations.

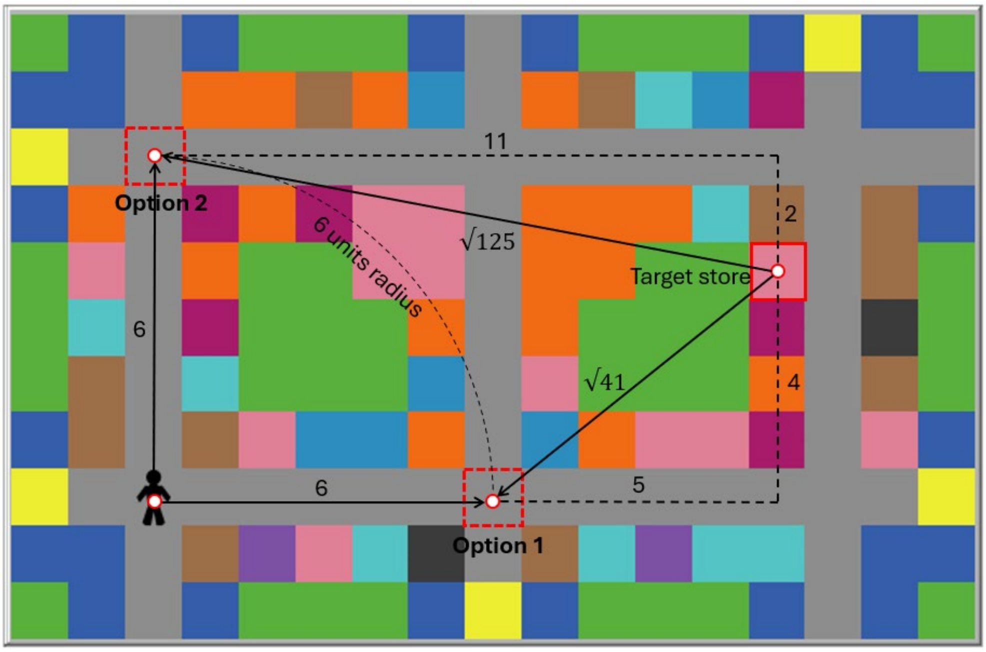


Figure 11: Example of route determination to the target store

Suppose, the customer now has chosen option 1 and moves towards it. During the travel from the initial intersection to the intersection of option 1 it is possible for the customer to make an unplanned visit according to a preset probability, set by the user. Every time the customer passes a store, there is a chance he or she makes an unplanned visit.

Once arrived at the intersection, it is determined whether the customer is not yet in the street of the target store. The process of selecting and moving to the next intersection is initiated. This time there are three options. However, option 3 already was visited during the journey of the customer towards the target store and, therefore it is no option. In figure 12 it is once again option 1 that is closest.

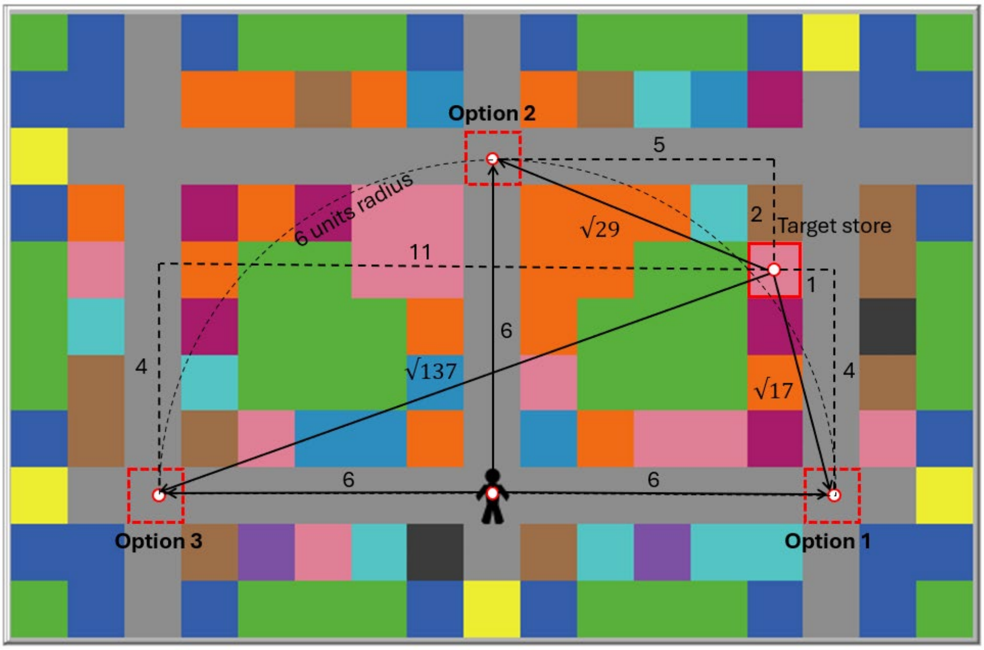


Figure 12: Advancement of figure 11

If the customer would choose to go for option 1 again, at arrival at the intersection it will be determined that the customer is in the street of the target store. A different movement system now is used, and the customer will always move towards the target retailer. It still is possible to make an unplanned visit however.

Arrived at the target store, the customer adds the retailer to its visited list, to ensure it will not visit it again. Then the customer will either successfully make a purchase or it fails to, the initial success rates are set by the user. When failing to make a purchase the customer adds a +5% (+0.05) to the purchase success rate to this particular store-function, as the customer is eager to buy something. If the purchase was successful, the retailer gets added a sale, and the item will be removed from the shopping list (if the item was on the shopping list). For either option the customer also increases its probability of going home before finishing their shopping list by 5%, as the customer gets exhausted over time. In addition, as customers also get exhausted over time by walking, at each tick/step the probability of going home is increased by 1%. Customers can only decide to go home when leaving a store. In extreme cases, a customer may not visit any store, which can occur only if the customer is forced to go home because all stores have closed.

In the literature, it was found that, on average, each customer makes one unplanned visit during their shopping journey (Dijkstra and Jessurun, 2013). By analysing the average amount of stores passed by of each customer's shopping experience, this factor was determined to replicate this behaviour within the system. If a customer passes by a store, it always checks if he/she will make an unplanned visit by using the Monte Carlo simulation. If a customer is in between two stores, the percentage of an unplanned visit still equals the percentage set by the user. So it does not double, however if the customer decides to make an unplanned visit in this situation, another Monte Carlo simulation determines which store will be entered.

When leaving the store, the customer is placed at the most recently visited street patch, to ensure it enters and leaves the store through the same entrance. At leaving the store the customer checks if he/she is not exhausted and if there are still items on its shopping list. If the customer feels exhausted he/she will automatically empty their shopping list, this in turn will indicate the path finding movement system to directly move towards its initial entry point. If not, the next target store will be chosen and the customer will move towards that store.

Retailers’ behaviour

The rent is dynamic, and is determined by the store’s size and the amount of pedestrian visitors on the street patch in front of the store. Important to note is that for the traffic only the amount of actively shopping customers is tracked, as soon as customers are determined to go home these do not count for additional visitors on the streets. This makes sure larger, and more popular retailers have to generate more sales to stay profitable. The formula for rent is:

$$Rent_i = RFA_i \times 0.01 + Visitors_i \times 0.01$$

For example, if a store has 500 m^2 RFA and the street in front of the store had 1200 visitors that month, the rent will be: 500 x 0.01 + 1200 x 0.01 = 17. Therefore 17 purchases need to be done by customers in this store to be profitable. In future refinements of the model, this mechanism can be replaced by a monetary system.

To evaluate the profitability of the stores, the number of visits, the number of sales per store, and the number of customers per street patch will be stored. This information is relevant for the retailer as the retailer might consider moving the store to another location, or worse still, has to close down the store. After each ‘month,’ the system checks for each store whether the sales exceed the rent the retailer has to pay. If not, the store is labelled as unprofitable, and the store’s unprofitability count is raised by one. If a retailer is profitable in the designated time period, the unprofitability count will be reset to 0, allowing the retailer to continue operating without risk of being flagged as unprofitable.

If the unprofitability trend of the retailer keeps going for 3 time periods (the amount of time periods can be determined by the user), eventually the retailer is forced to move out of the store. The store will become vacant; if it stays vacant for 5 time periods, the owner of the building will transform it into another function (such as residential, an office, or societal service). Again, this can be determined by the user of the system. However, before vacant stores are transformed, it is possible for other retailers to relocate into one of the vacant stores.

There are three variables a retailer considers before relocating his/her store. First, the retailer checks whether the amount of customers in front of the vacant store exceeds the number of customers in front of the retailers current store. This may increase the retailer’s sales. Secondly, the retailer considers the agglomeration effect: are there more retailers with similar function in the street of the vacant store location compared to the current location. Lastly, the distance to the anchor store, as in turn this would generate more traffic flow to the store. For the user it is possible to setup how many of these criteria have to be satisfied for a retailer to decide to relocate. If this amount is met, the retailer with the largest difference in numbers, therefore most eager will match with the vacant store location and the retailer moves to the new store patch(es). In the figures below the store dynamics can be seen, with the retailers visibly relocating.

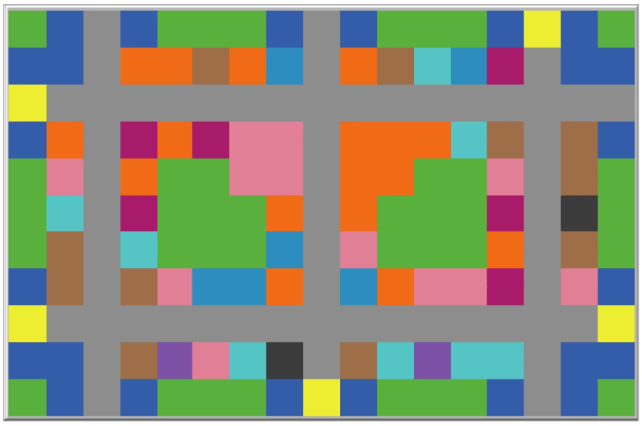


Figure 13: situation 1

In situation 1 (Figure 13), two store locations are vacant within the shopping area (the black patches). Additionally, two retailers in other store locations have found their current locations less desirable compared to the newly available vacant spots.

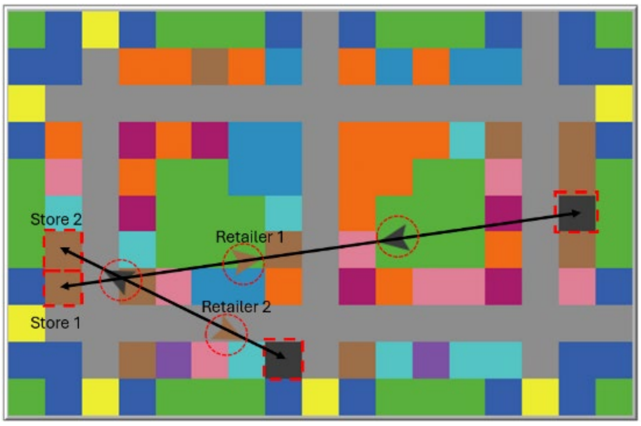


Figure 14: situation 2

In situation 2 (Figure 14), the retailers are observed relocating to the available vacant store locations and the vacant stores 'move' to their original locations.

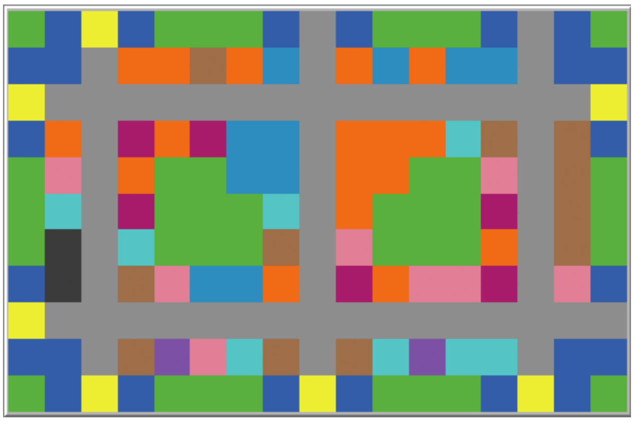


Figure 15: Situation 3

In situation 3 (Figure 15), the shift in retailers has been completed

After the relocation is finished, a new cycle of customers is ready to shop again. The values for visitors and sales all are reset. The unprofitability is kept track off, the clustering value, and the distance to nearest anchor store is recalculated based on the new retail environment.

4.3 Description of agents and environment

This section explains the simulation settings adjustable for the user, detailing how these inputs influence customers' and retailers' behaviour within the system. Firstly, the adjustable parameters are discussed in 4.3.1, followed by an overview of the metrics tracked by the system in 4.3.2.

4.3.1 User-configurable simulation parameters

This subsection introduces the components of the user interface, together with the initial settings of the adjustable parameters for both customers and retailers. Figure 16 illustrates the layout of the user interface, identifying the components in clusters.

System setup settings

Users can set the simulation in motion using the setup button, which generates the hypothetical retail environment. The system progresses through time via the go or step buttons. The go button always runs the system continuously, with a maximum of 1000 ticks, whereas the step button runs the system one 'tick' further. Lastly, there is a button that allows the simulation to run continuously until it reaches the designated evaluation time.

Feeding points (in yellow) along the edge of the map in Figure 16 show where customers can enter the system, these can be turned on and off by the user around the display at the corresponding location.

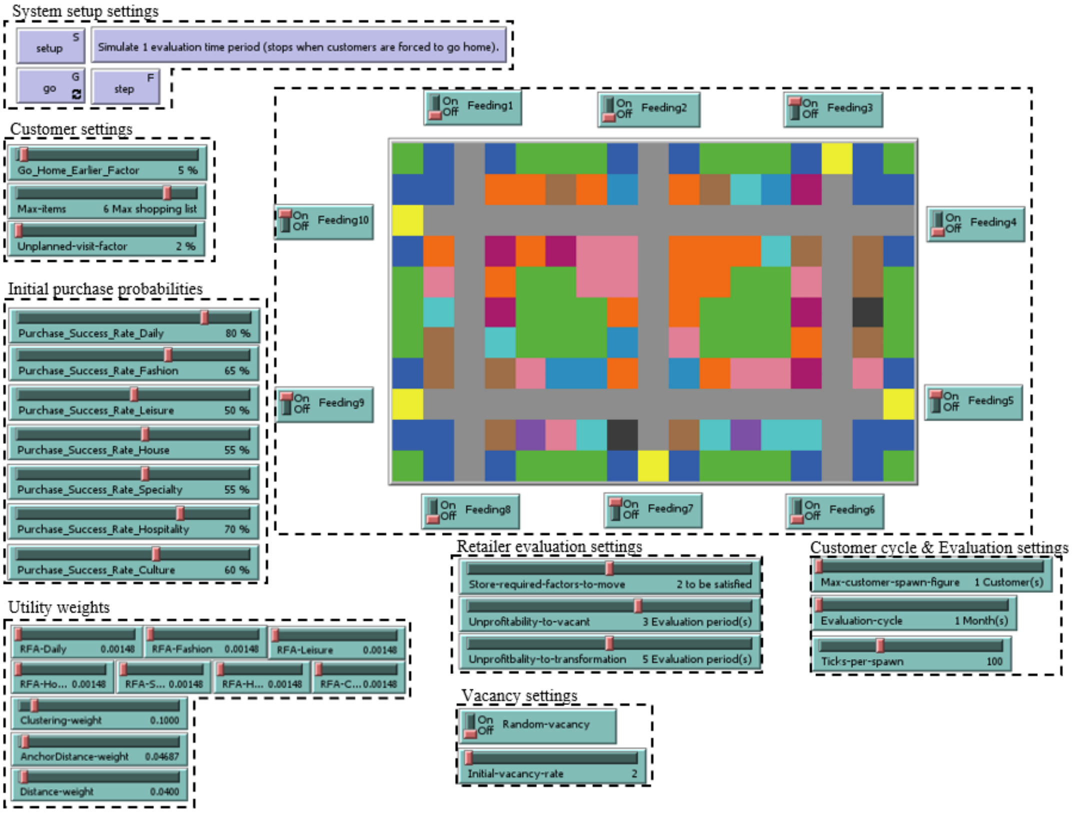


Figure 16: Different components of the user interface

Customer related settings

Customer settings

These factors focus on customer behaviour in the simulation. It includes the following parameters: **Go_Home_Earlier_Factor**, influencing the likelihood of customers leaving early (before finishing their shopping list). **Max-items**, which sets the maximum number of items on the customers' shopping list, and **Unplanned-visit-factor**, which determines the probability of customers making unplanned visits to stores during their journey. The initial values:

- Go_Home_Earlier_Factor: 5%
- Max-items: 6
- Unplanned-visit-factor: 2%

Initial purchase probabilities

These parameters allow users to define the likelihood of customers successfully purchasing from different types of stores. These values are set for various store categories. Each store type has its own success rate determined by the user, influencing customer shopping outcomes. The percentages are the chance of a customer making a purchase yes or no, based on a Monte Carlo simulation. As there was no literature found these figures are assumptions. The initial values are:

- Purchase_Success_Rate_Daily: 80%
- Purchase_Success_Rate_Fashion: 65%
- Purchase_Success_Rate_Leisure: 50%

- Purchase_Success_Rate_House: 55%
- Purchase_Success_Rate_Specialty: 55%
- Purchase_Success_Rate_Hospitality: 70%
- Purchase_Success_Rate_Culture: 60%

Utility weights
This interface component allows users to assign weights to various factors that influence store attractiveness to customers. These include **RFA-weight** (Retail Floor Area), **Clustering-weight** (whether similar stores are nearby), **AnchorDistance-weight** (distance to an anchor store), and **Distance-weight** (distance between customer and store). These weights are used to calculate the likelihood of a customer selecting a particular store during their shopping trip. **Shopping list** is either 0 or 1 as an item is on the list or not.

The initial values:

- Shopping list: 1 or 0
- RFA-weight:
    - RFA-Daily: 0.00192
    - RFA-Fashion: 0.00148
    - RFA-Leisure: 0.00104
    - RFA-House: 0.00133
    - RFA-Specialty: 0.00089
    - RFA-Hospitality: 0.00074
    - RFA-Cultural: 0.00059
- Clustering-weight: 0.1
- AnchorDistance-weight: 0.04687
- Distance-weight: 0.04

Retailer related settings

Vacancy settings
The simulation includes a mechanism where two vacant stores are set at the beginning to allow all mechanisms within the system to be visible. The vacancy is an assumption: users can enable or disable **Random-vacancy**, which will randomly select stores to become vacant, the amount can be adjusted by the user. In this case it would be 2. The **Initial-vacancy-rate** defines the starting number of vacant stores at the beginning of the simulation if the **Random-vacancy** is turned on, allowing users to simulate environments with different levels of store availability. If the **Random-vacancy** is turned off, two preselected stores become vacant.

- Random-vacancy: off

If turned on:
- initial-vacancy-rate: 2 stores

Customer cycle & Evaluation settings
Users can set parameters for the passage of time in the simulation. The **Evaluation-cycle** slider controls how long one cycle lasts before retailers evaluate (e.g., one month), while the **Ticks-per-spawn** setting defines the intervals between customer spawns in the system, as mentioned previously this interval contains three shifts. Users can also control the number of customers entering the environment during each evaluation period. The initial values:

- Max-customer-spawn-figure: 100 customers per shift

- Evaluation-time: 1 month
- Ticks-per-spawn: 100

Retailer evaluation settings
This part of the interface determines how and when retailers decide to relocate. Users can adjust settings like the number of **Required-factors-to-move**, which controls how many relocation criteria must be met (1, 2, or 3), **Unprofitability-to-vacant** (number of periods of unprofitability before a store becomes vacant), and **Unprofitability-to-transformation** (number of periods before a vacant store is transformed into a different use, such as residential or a societal service use). The initial values:

- Required-factors-to-move: 2
- Unprofitability-to-vacant: 3 evaluation periods
- Unprofitability-to-transformation: 5 evaluation periods

4.3.2 Monitored metrics

Figure 17 presents the key metrics, including total and current cycle figures for customers, sales, and store visits. One cycle represents a single time period elapsed, and one time elapse represents a month. These numbers can be analysed to gain insights into the changes in customers' behaviour and overall store performance in terms of sales and visitor frequency, helping users evaluate the impact of different scenarios.

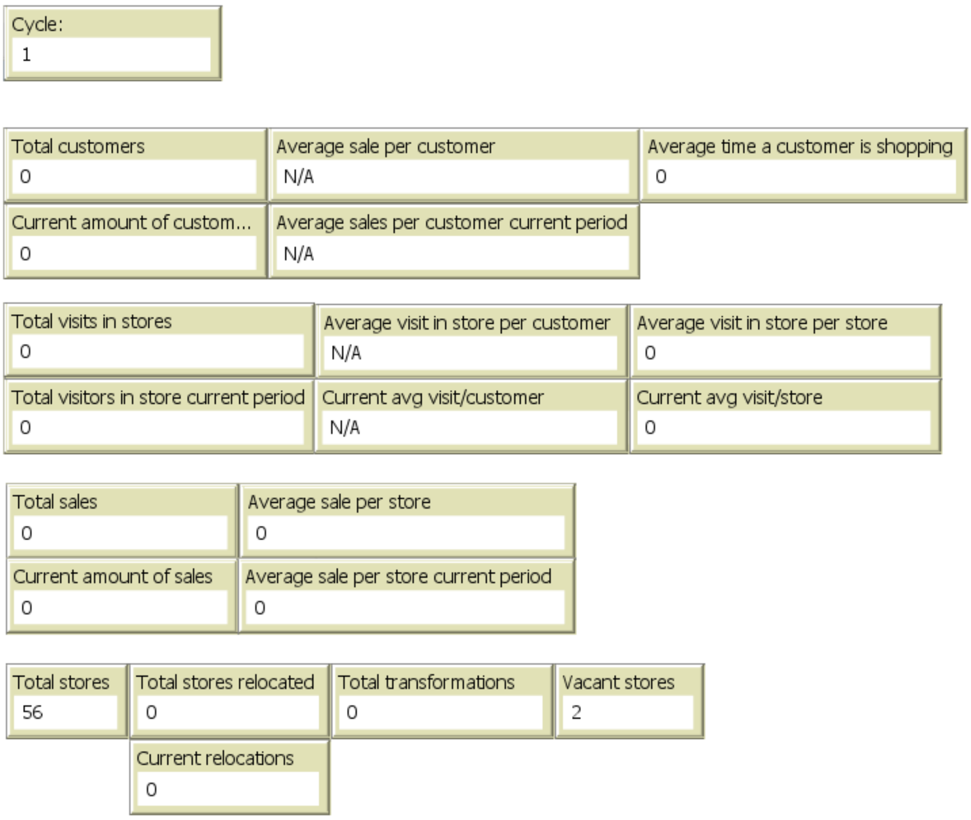


Figure 17: Outcomes of monitored metrics displayed in the user interface

As previously mentioned the Cycle stands for the current time period the simulation is in.

The Total Customers number represents the amount of customers through all cycles. Similarly is the Total Sales and Total Visits in Stores. Stores Relocated shows how many stores have relocated. Then the Current Customers, Sales, Visits and Relocations track the amounts of the current cycle.
The Average shopping time reflects how long each customers spends shopping; this is measured in ticks (ticks are the unit of time).
The Total Stores number shows the current active numbers of stores. Unactive stores will either be vacant, or already transformed into another function.
The averages of all metrics are also displayed for both total and current numbers, for both customers and sales.

During a cycle, customer behaviour is shown with the number of sales per store (Figure 18a). At the end of a cycle, numbers of customers per street-patch are shown (Figure 18b) as well as the number of unprofitable months per store, if any (Figure 18b).

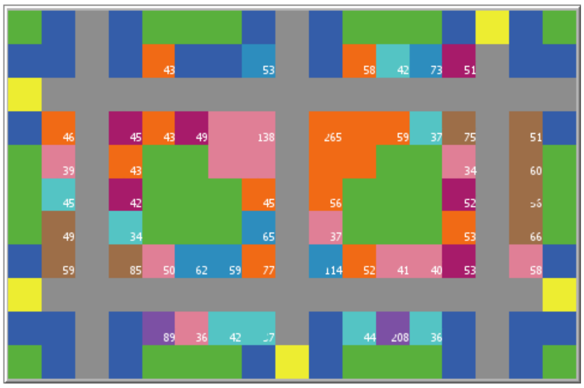


Figure 18a: Number of sales per store

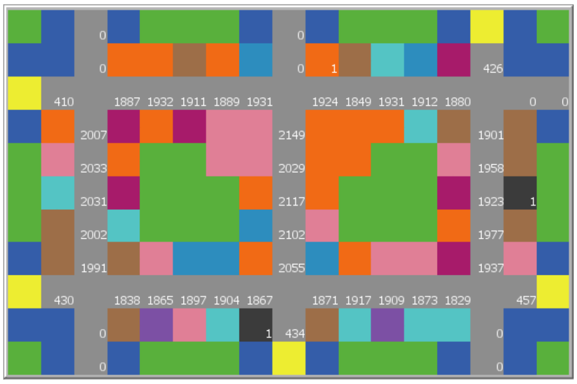


Figure 18b: Number of visitors per patch

4.4 Conclusion

This chapter outlined the development and structure of the simulation system. The initial setup, customers' behaviour, retailers' behaviour and each mechanism have been described. The mechanisms incorporated are findings from the literature review replicated into the system. The adjustable parameters of the mechanisms have been explained, together with the initial settings. Lastly, the components of the metrics to analyse the outcomes were explained.

Some sub questions are answered, or their previous answers have been extended:
Customers' behaviour is modelled using an utility function based on retail floor area (RFA), store clustering, distances to stores and store proximity to anchor stores, as well as items on the customer's shopping list. Weights determine the importance of the utilities, directing customers to stores with higher utilities. Unplanned store visits, purchasing success rates and customers leaving early are chosen by a Monte Carlo simulation, with success rates and leaving early having increased chances over time.

Store performance is measured by profitability, comparing sales to rent, which is based on RFA and visitor counts. Unprofitable stores become vacant after repeated failures, allowing other stores for relocation or transformation over time.
Retailers consider vacancies to relocate for better visitor counts, clustering, or proximity to anchor stores. Long lasting vacant stores are transformed, reflecting retail adaptability.

The mechanisms of the customer are implemented by using an utility function and a Monte Carlo simulation. The mechanisms for retailers to become vacant or transform are time dependant. If a store would relocate it is simply a mechanisms of comparison. Spatial rearrangement of entry points can easily be done by pressing the correct buttons in the user interface.
The tool can be used to evaluate policies by adjusting parameters like entry points or utility weights. Real-time outputs show impacts on visitor patterns and profitability.

5. Results

5.1 Introduction

In this chapter, different scenarios are simulated, exploring how various factors influence the dynamics within a shopping area. The base scenario tried to simulate a regular situation. The subsequent scenarios have alterations in parameters that emphasize attributes of influence found in the literature review. The goal is that the system can replicate these findings, ensuring that the findings are incorporated with confidence. The scenarios are discussed in the next section, followed by a concluding section.

5.2 Scenarios

Through a series of scenarios, the impact of entry points is examined, along with alterations in the customer settings, and the retailers' behaviour. The base scenario serves as a starting point. After the initial base scenario, seven scenarios with alterations are run to find out what the impact of each adjusted parameters is. These alterations include changes in the spatial setting, increasing the customer inflow and emphasizing weight of specific factors. Each scenario provides insights into the mechanism driving a specific aspect of the retail dynamics. The outcomes are compared with findings from the literature.

Most figures presented are outcomes of a scenario after running 12 cycles (months), unless otherwise stated. The visualizations are captures of the simulation systems' metrics and display. The figures are compared to the base scenario and are used to explain the impact of the alteration.

5.2.1 Base scenario

In the base scenario, the initial settings (see section 4.3.1) for the retail environment are currently active. These settings reflect the basic assumptions about customers' behaviour, store performance, and foot traffic distribution. No additional entry points or adjustments to customer behaviour have been introduced. The simulation begins with a fully occupied shopping area, where retailers and customers interact according to predefined rules of foot traffic, store distance, and customer preferences.

Over the course of 12 cycles (or months), the dynamics of the area evolve naturally, without any external interventions. In Figure 19 the initial composition can be seen. Throughout these cycles, several key patterns emerge that highlight the challenges and opportunities faced by retailers in this environment. For the base scenario, the process will be illustrated over time by discussing results for each month (cycle) through the year.

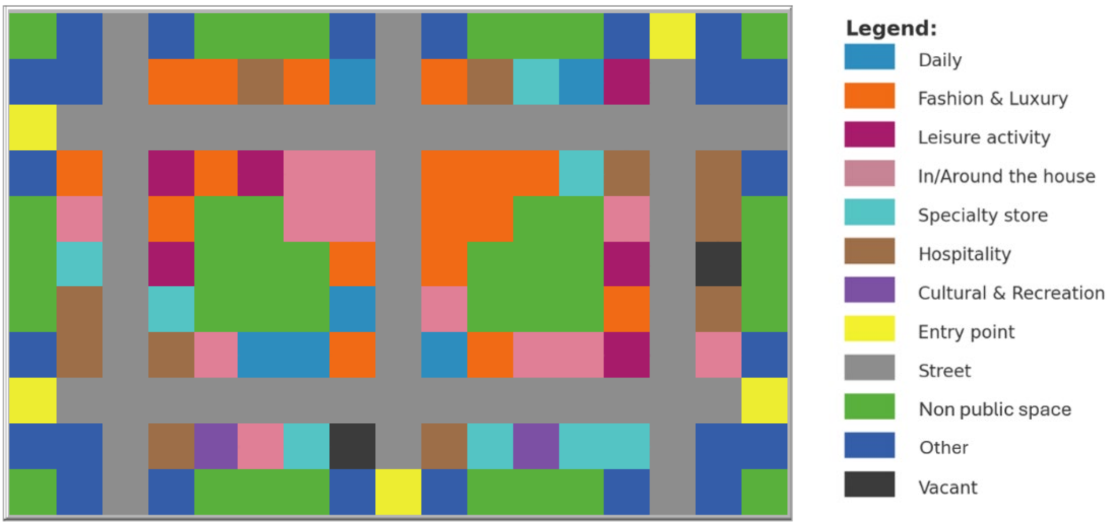


Figure 19: Initial composition

Cycle 1 to 3 (Figure 20): The initial cycles of the simulation provided insight into customer distribution and preferences in the retail area, showcasing the popularity of the different streets. Three relocation events occurred and some other retailers struggled to maintain profitability, and one store eventually became vacant. The dynamics of these changes are summarized as follows:

In Cycle 1, a Hospitality retailer decided to relocate in the same street from its original position with 1,716 visitors to a location closer to an anchor store and achieving a minor increase in visitors to 1,736. The west and middle streets are most popular during the cycle. Both southern streets have the least amount of visitors.

By Cycle 2, a Specialty retailer relocated to a location closer to an anchor store, moving from a position with 1,760 visitors to one with 1,816. The relocation broke the strength of the previous cluster, but demonstrated the retailers' preference for distance to high-traffic anchors in combination with higher foot traffic. During this cycle the middle street kept its popularity relative to the other streets. The distribution among other streets, with the exception of both southern streets, were equal.

After Cycle 3 a Fashion & Luxury retailer in the northern area of the shopping centre went bankrupt, despite having a high traffic location together with 250 square meters RFA. Interestingly, the vacant store was subsequently filled by another Fashion & Luxury store retailer relocating from the west, increasing its visitor count from 1,823 to 1,925 together with a closer distance to the anchor stores. Overall, the amount of visitors increased from the previous cycles. The distribution kept the same.

The street hosting anchor stores and the highest retail floor area (RFA) per store consistently attracted the highest customer traffic, emphasizing its central role within the shopping area. Relocation behaviours demonstrated a clear prioritization of shorter distance to anchor stores over clustering with similar stores.

The two northern streets demonstrated strong clustering of Fashion & Luxury retailers, attracting plenty of foot traffic. The street to the east scored well on clustering due to the concentration of Hospitality outlets and being close to two entry points.

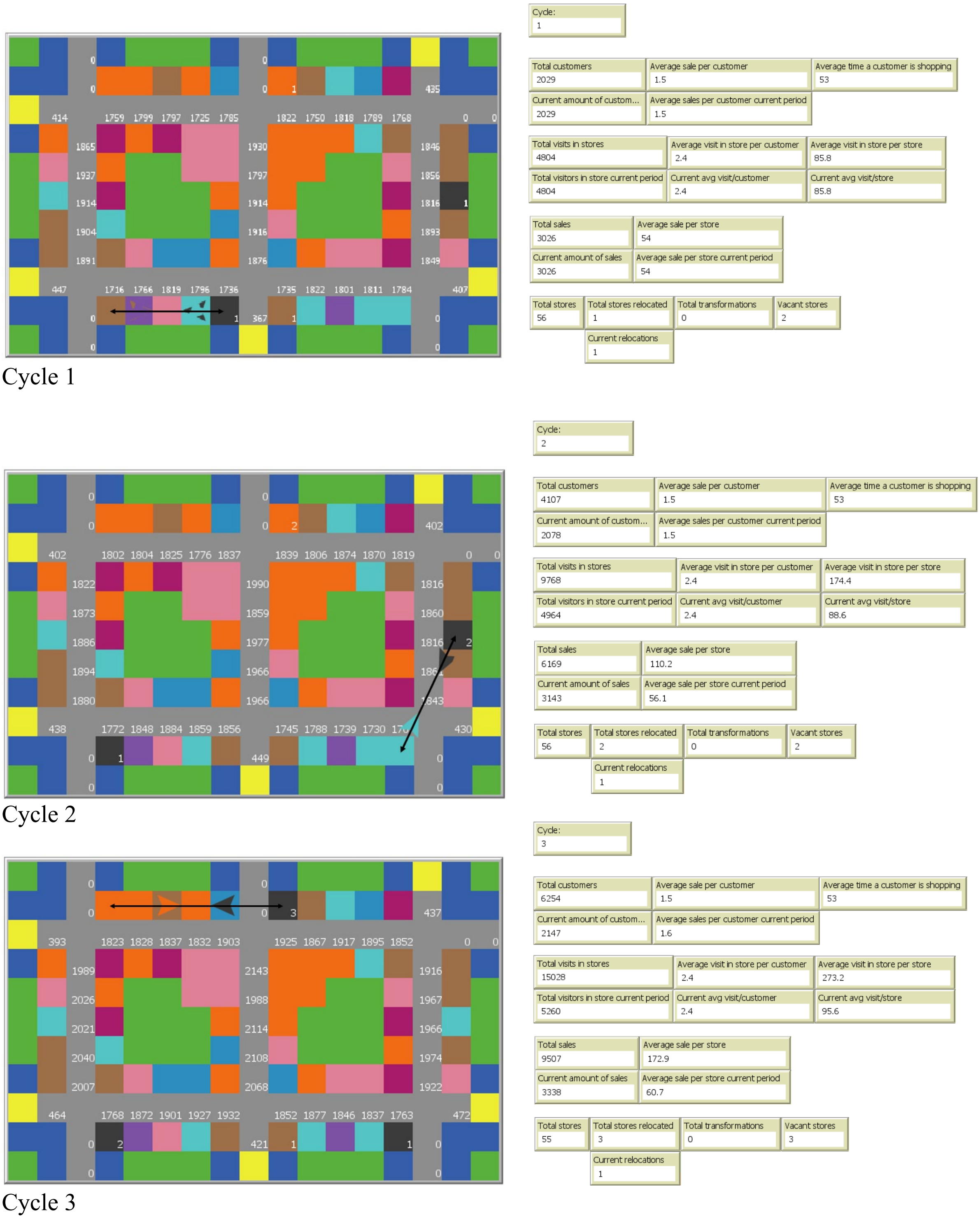
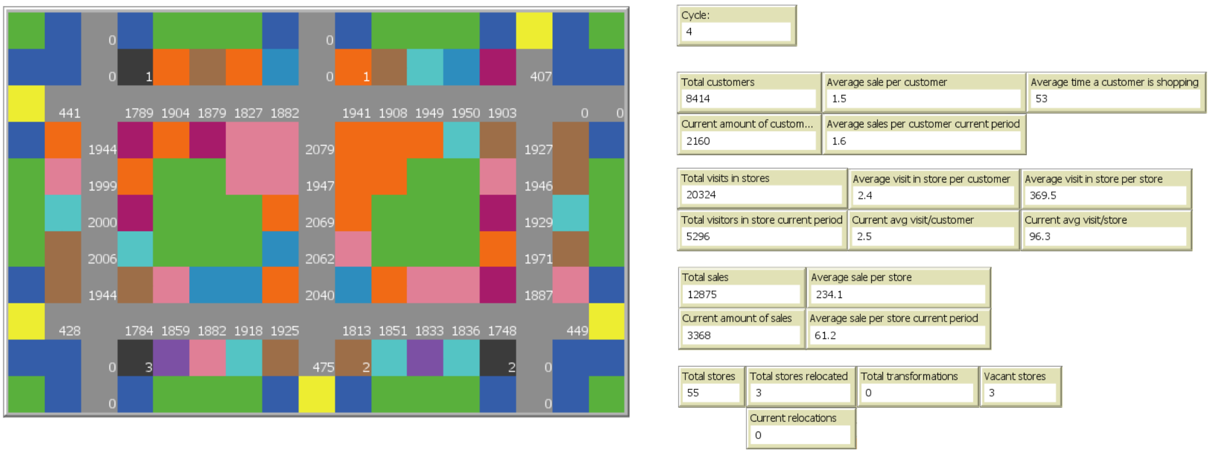


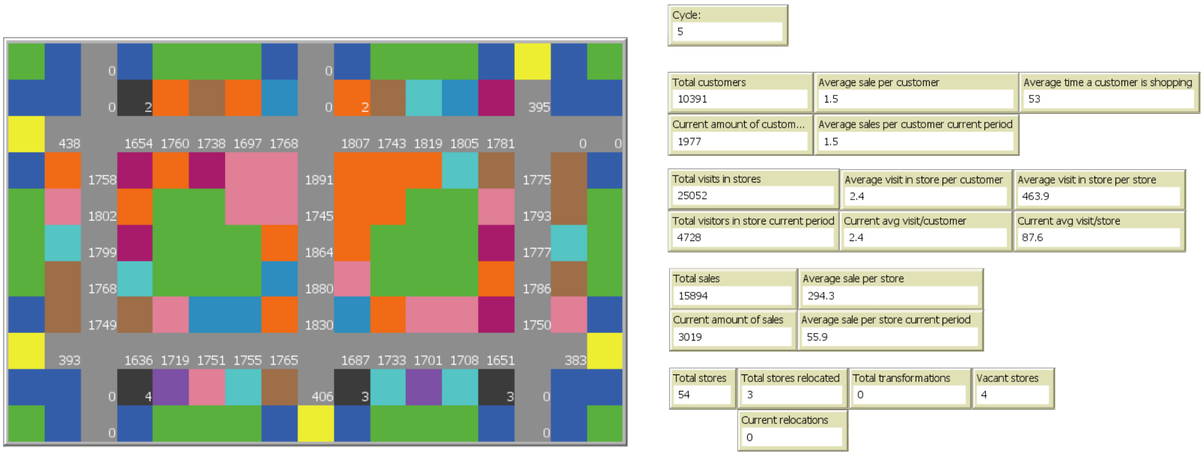
Figure 20: Retail dynamics and metrics across cycles 1 to 3.

Cycle 4 to Cycle 6 (Figure 21): At the start of Cycle 4, the overall relocation activity stagnated as the current vacant locations were not considered attractive to other retailers. All three vacant stores were located in different streets, and interestingly enough on the outskirts of the retail area.
By Cycle 5, another store became vacant in the southeast street and in Cycle 6, the Fashion & Luxury retailer that relocated its store in Cycle 3 also was not profitable for 3 consecutive cycles and became vacant. Another Fashion & Luxury from the street to the west relocated into this location, to improve its distance to the anchor store and visitor count from 1,736 to 1,844. However breaking a strong cluster.

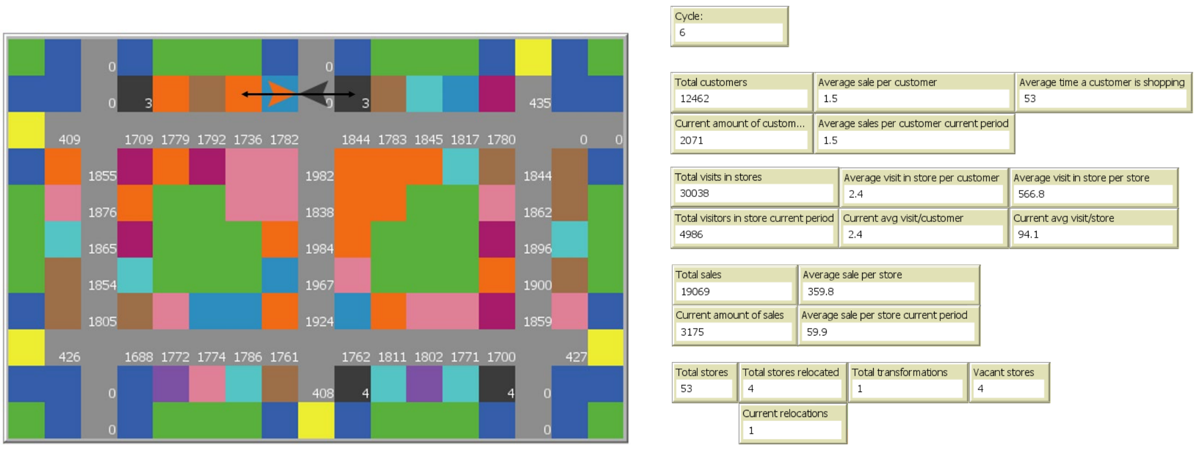
Also the southeastern street had its first store transform into another function. With two stores on the edge of being transformed as well.



Cycle 4



Cycle 5



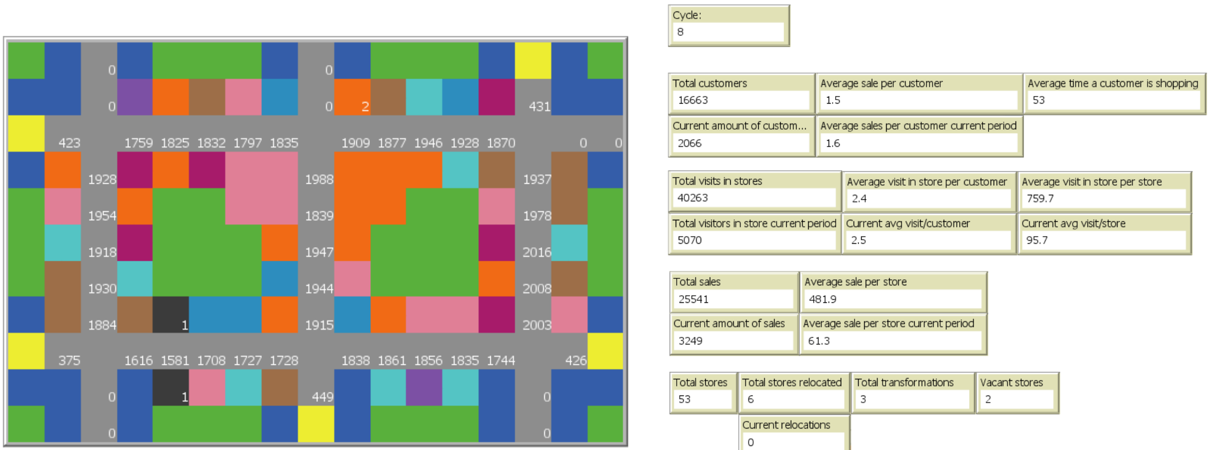
Cycle 6

Figure 21: Retail dynamics and metrics across cycles 4 to 6.

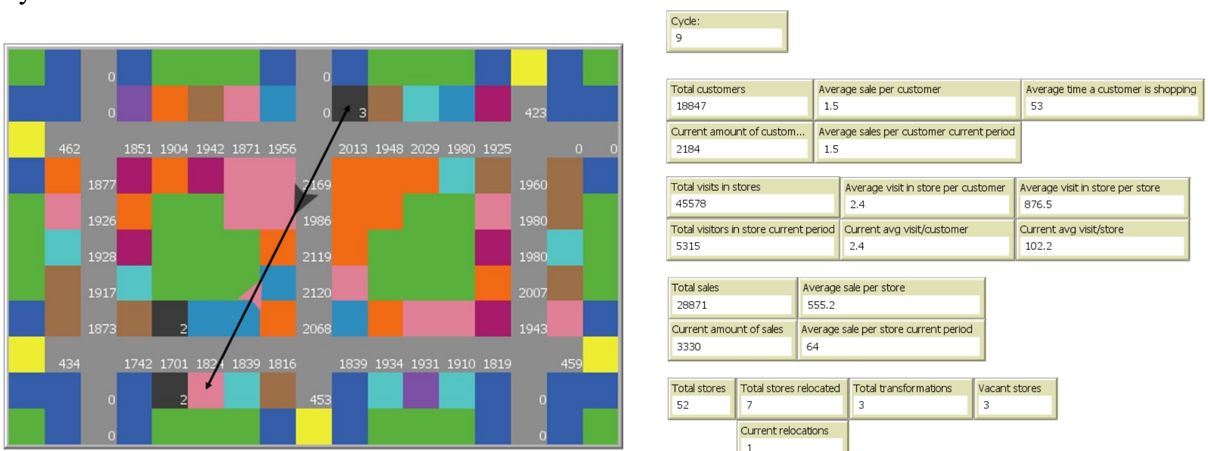
Cycle 7 to Cycle 9 (Figure 22): At the end of cycle 7 two retailers from the southwest street decided to move to the street to the north. Leaving behind a street lacking visitors. Both retailers moved based on an improvement in visitor count and proximity to anchor stores.
During Cycle 8 it became apparent that the street on the southwest was struggling, as it was seen with the lowest visitor counts in all cycles so far. These visitors distributed themselves evenly over the rest of the streets with no distinctive main street forming.

Cycle 9 worsened the situation of the southwestern street with a In/around the house retailer moving out for similar reasons as the other retailers did. The vacant store was again from the Fashion & Luxury retailer that moved in there three cycles ago. Furthermore, the middle street was the main street once again, with an evenly distribution over the other street.

Cycle 7



Cycle 8

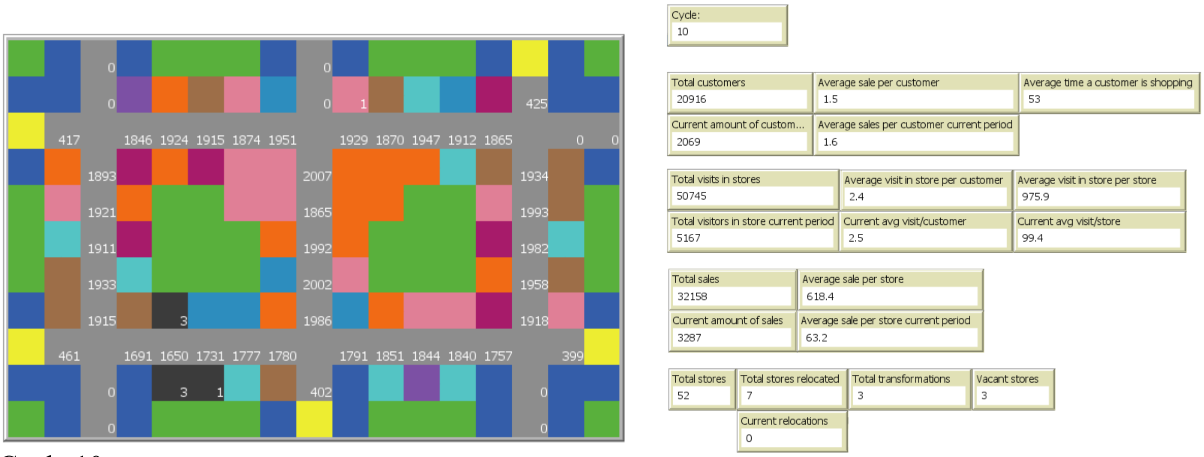


Cycle 9

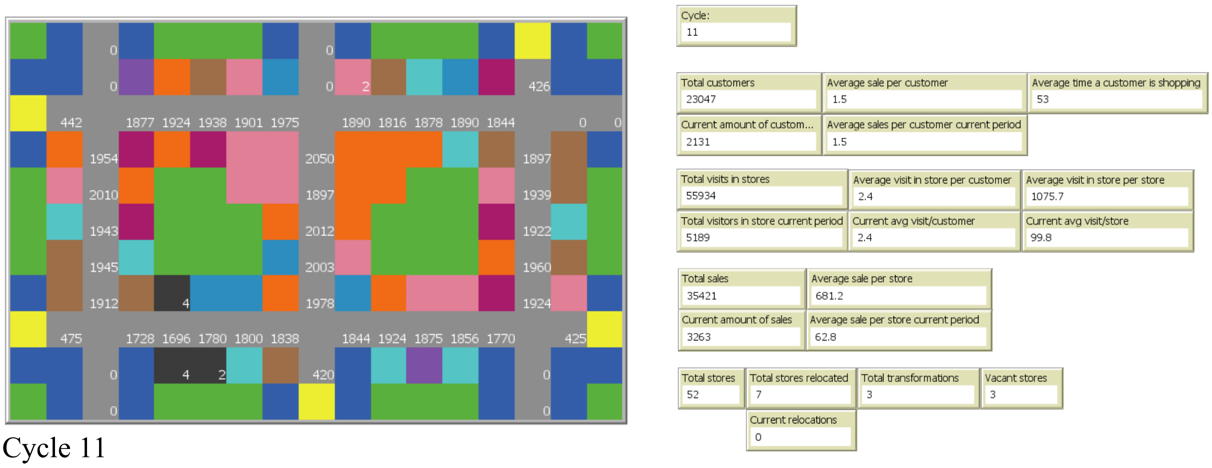
Figure 22: Retail dynamics and metrics across cycles 7 to 9.

Cycle 10 to Cycle 12 (Figure 23): Cycle 10 saw no significant activity. The retailer that relocated during Cycle 9 also failed to achieve profitability, following similar trends as the previous occupants of this store. Similarly in Cycle 11, no significant activity.

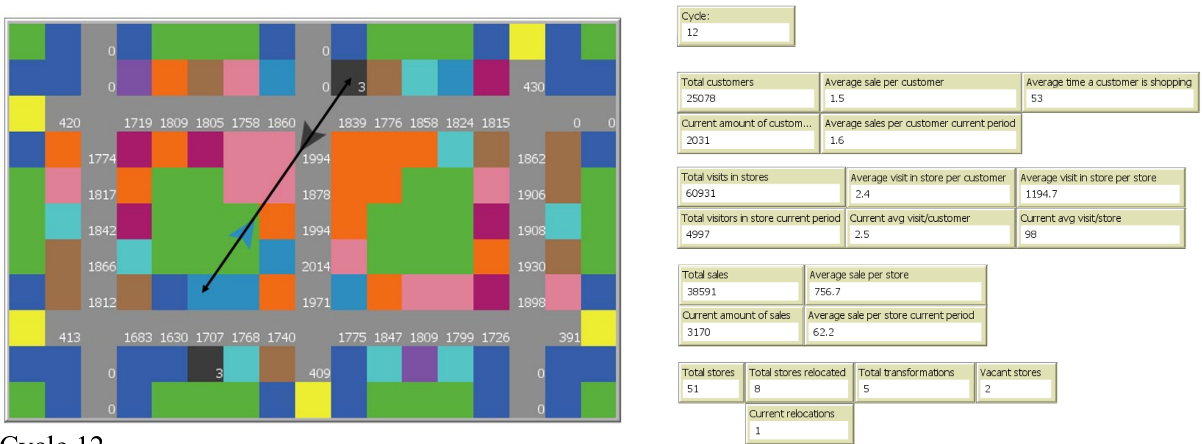
Finally, by the end of Cycle 12, one last retailer with a Daily store function left the southwest street, relocating to a northern location previously occupied by a In/around the house retailer three cycles earlier. Also two stores were transformed into different function in the same street. Meanwhile, the overarching trends influencing foot traffic and retail performance continued to align with patterns observed in earlier cycles.



Cycle 10



Cycle 11



Cycle 12

Figure 23: Retail dynamics and metrics across cycles 10 to 12.

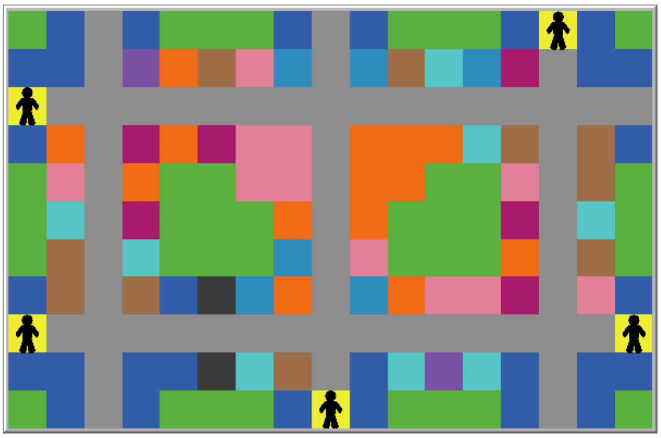


Figure 24: Spatial environment after 12 cycles

Summary of the base scenario
Figure 24 illustrates the final composition of the base scenario, and reveals that the most retail dynamics occurred in the southwestern street, it became clear that this street was struggling halfway of the simulation. Decaying visitor counts led to many retailers moving out of the street. The southeastern street, while not struggling as severely as the previously mentioned street, also attracted significantly less visitors compared to other streets. These two streets are located far away from the anchor stores, also the RFA of most stores in these streets is well below the average of 200, see Appendix A for details. It appears that a combination of anchor store proximity and RFA is an influential factor in customers' behaviour. Proximity to anchor stores also was a leading factor for retailers relocations.

The middle street was the most popular street most of the cycles, this street is as close to the anchor stores as the two northern streets. However, the RFA sizes of the stores in the middle street are the highest of these three. Seeing some evidence of the impact of RFA on customers' behaviour.

The influence of distance on customers' behaviour was not clearly evident in the base scenario, mainly due to the scattered entry points. This makes it impossible to see evidence if stores farther away from entry points are in a disadvantage. The impact of clustering was dubious as well, as retailers did not respond at all to clustering. Customers' behaviour was only seen to be influenced slightly, as in some cycles streets with high number of clusters were attracting more visitors but not on a constant basis.

5.2.2 Scenario variations

In the section different mechanisms and alterations are tested in several scenarios. The scenarios are compared to the base scenario, or are an extension of the previous scenario.

Scenario 1: Adding an entry point south-west

The aim of this scenario is to improve the profitability of underperforming stores observed in the base scenario by adding an entry point near the southwestern street, this was the street most struggling in the base scenario. Resulting from the literature it was concluded that entry point placement and distance have significant impact on customer movement and store success (Borgers and Timmermans, 1986; Brown, 1992).

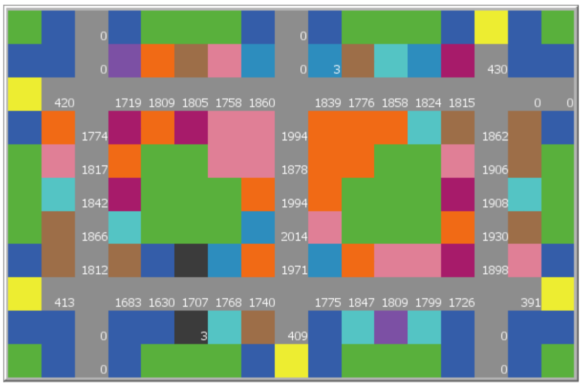


Figure 25a: Base scenario customer distribution

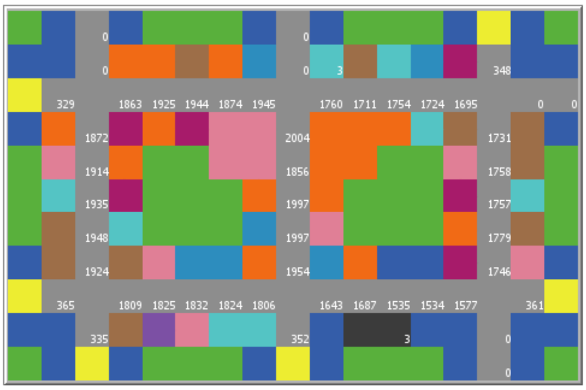


Figure 25b: Scenario 1 customer distribution

Figure 25a and 25b show the customer distribution and spatial environment of both the base and first scenario. It can clearly be seen that in scenario 1 the struggling street shifted from the southwestern street to the street located on the southeast. This results in clear evidence that the finding of the literature about importance of entry points confidently is replicated in the system. However, the impact of distance still looked relatively minor in the scenario.

Scenario 2a: Only entry points to the bottom southwest

Scenario 2a aims to make the impact of distance clear by only placing entry points to the bottom southwest. Research by Borgers and Timmermans (1986) highlighted that entry points act as psychological anchors, shaping customer movement. Brown (1992) added to this that customers rarely explore an entire shopping area, instead favouring stores close to entry points or along convenient routes.

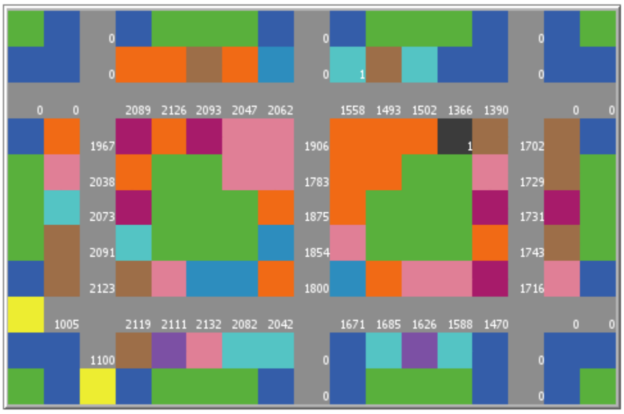


Figure 26: Scenario 2a visitor distribution

The model successfully captured how localized entry points keeps the distribution of foot traffic near the entry points, with stores closer to the entry thriving while more distant stores, especially in the east, experienced reduced foot traffic (see Figure 26). Both northern and southern streets have two transformed stores, with the northern having a store that became vacant recently. The outcome reflects the literature's insights on distance sensitivity and the importance of distributed access points.
However, while foot traffic was indeed concentrated around the entry points, a significant number of customers still travelled to the eastern part of the shopping area. Perhaps this might contradict Brown's (1992) findings that customers rarely explore the entire shopping area. However, it should be noticed that the case study by Brown concerned a bigger shopping centre. The scenario validates the simulation's ability to capture nuanced pedestrian behaviour.

Scenario 2b: Increasing the distance weight

As previously mentioned Borgers and Timmermans (1986) found that distance is one of the main determinants in customers' behaviour. Brown also stated that customers rarely explore entire shopping areas, and prefer shorter distances. In the base scenario the distance customer to store weight was set to 0.04. In this scenario the entry points are again only located at the southwest of the shopping area, but also the distance customer to store weight is increased to 0.4. A comparison is made between the visitor distribution and the metrics of Scenario 2a and Scenario 2b in Figures 27 and 28 below:

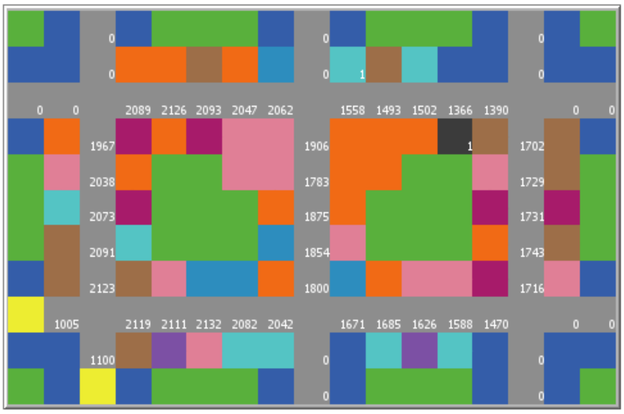


Figure 27a: Scenario 2a visitor distribution

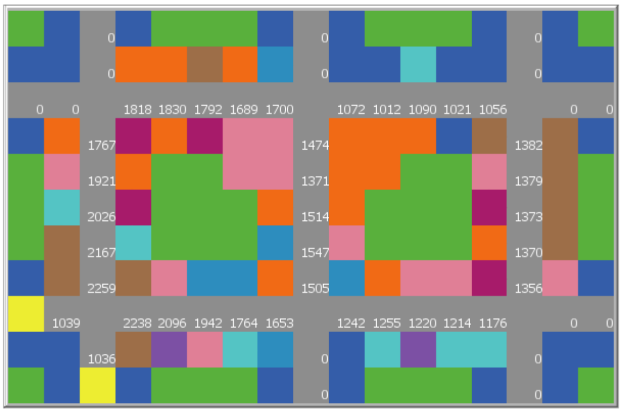


Figure 27b: Scenario 2b visitor distribution

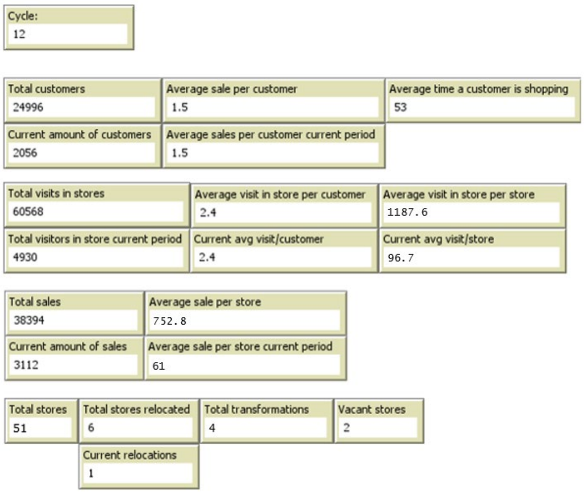


Figure 28a: Scenario 2a metrics

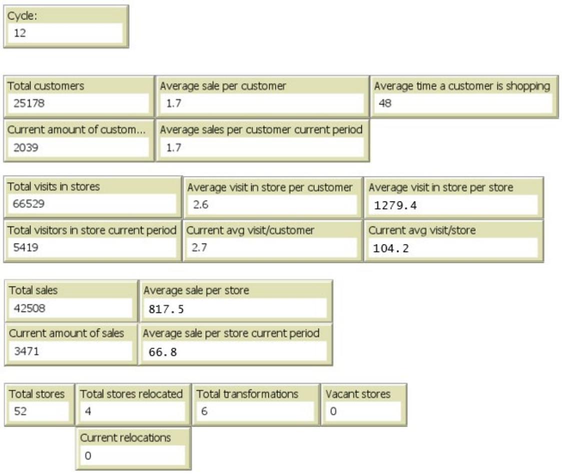


Figure 28b: Scenario 2b metrics

In Figure 27b it can be seen that the visitor distribution quickly diminishes when going further away from the entry points, the difference gradually decreasing with about a 30% decrease in the street located in the northeast. The streets connected to the entry points are actually only visited slightly more at the first street patch, with the amount of visitors even in these streets quickly decreasing. Having even less visitors than Scenario 2a.

Both streets mentioned in Scenario 2a (northeast and southeast streets) were the only streets having experienced shifts during Scenario 2b. However, the street located southeast only had one transformation. While the street located farthest away from the entry points, the northeast street struggled significantly more with five transformations in total.

A side effect of the adjustments in Scenario 2b can be observed in Figures 28a and 28b: average visits and sales increased by about 10% across the area, while the average time spent shopping decreased by about 10%. Also there were less store relocations, but more transformations. The increase in sales can be explained by the fact that customers select more nearby stores to by the products on their shopping lists, and therefore get less tired and thus will be less inclined to leave the shopping centre prematurely. The outcome of this scenario provided emphasized evidence of the replication of distance from customer to store influence, found in the literature.

Scenario 3: Increased RFA-culture weight

This scenario assessed the importance of Retail Floor Area (RFA) by significantly increasing the RFA weight for Culture & Recreation from 0.00059 to 0.0059, to observe how increasing this weight attracts more customers, as highlighted in the literature (Arentze et al., 2005). In this scenario only one cycle was simulated and compared to the base scenario. The comparison is made in terms of sales per Cultural & Recreation store, and the number of visitors on the street.

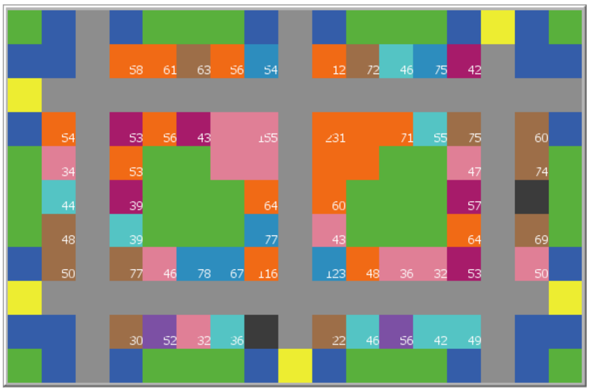


Figure 29a: Base scenario number of sales per store (one cycle)

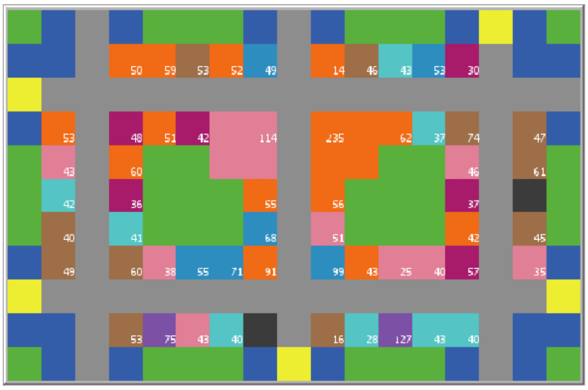


Figure 29b: Scenario 3 number of sales per store (one cycle)

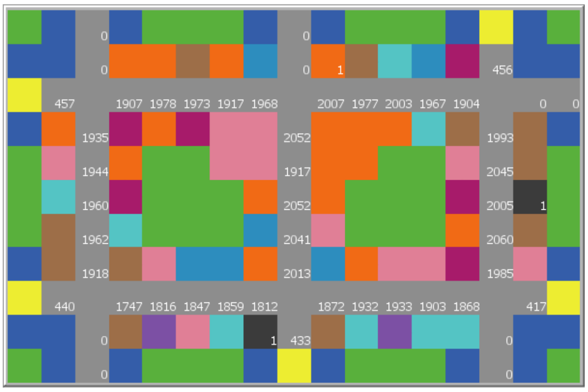


Figure 30a: Base scenario number of visitors (one cycle)

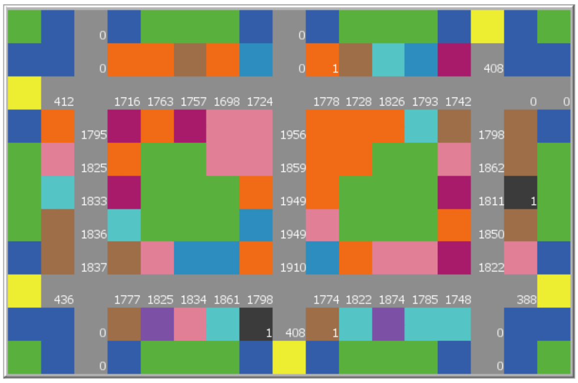


Figure 30b: Scenario 3 visitor distribution (one cycle)

As shown in Figure 29a and 29b, the sales made by the Cultural and recreational (see magenta coloured patches) store on the south-west went from 52 to 75 sales, whereas the store on the south-east has doubled the amount going from 56 to 127. This clearly indicates that RFA attraction is integrated in the system. also implying that – on average – other types of store become relatively less attractive. In figure 30a and 30b the visitors are compared between the scenarios. The number of visitors decreased in all streets; this needs further investigation.

Scenario 4a: Increasing clustering weight

This scenario tested the effect of significantly enhancing the clustering weight in the utility function for customer behaviour from 0.1 to 1.0 to observe the impact of agglomeration of similar retail functions, as the literature review (Nelson, 1958) highlights that agglomeration of similar stores is a factor increasing attractiveness for all stores in this cluster.

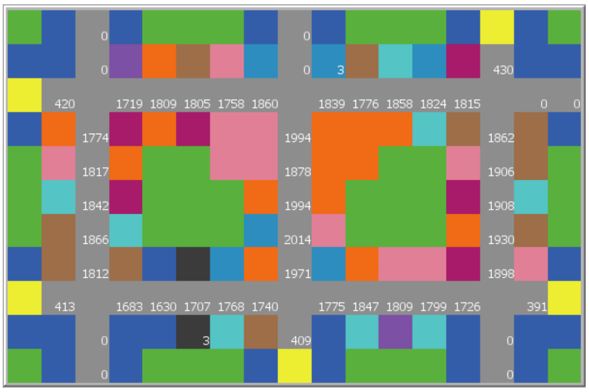


Figure 31a: Base scenario visitor distribution

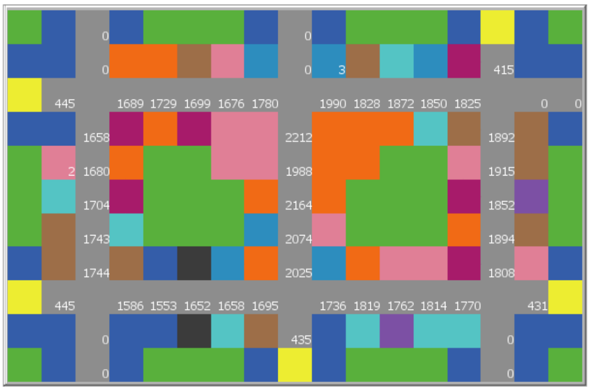


Figure 31b: Scenario 4a visitor distributior

After increasing the clustering weight to 1.0, the expected impact on customer foot traffic and store viability was not clearly observable in this simulation (Figures 31a and 31b). A problem in capturing the effects of clustering is that most of the initial clusters were broken by retailers moving out, and no other significant clusters were formed. The largest cluster is the most eastern street with a total of 4 hospitality stores, and the amount of visitors does not differ compared to the base scenario (also with 4 hospitality stores in this street). Therefore, in order to test the effects of clustering scenario 4b is run.

Scenario 4b: Increasing cluster size

Scenario 4b used a different approach to find if the clustering of stores is indeed an influential factor of customer preference in the system. In this scenario an extreme cluster of a total of 10 hospitality stores was placed in the western street. The clustering weight was reduced from 1.0 to 0.1 again. This scenario was only simulated for 1 cycle, so that relocations over time would not break the cluster.

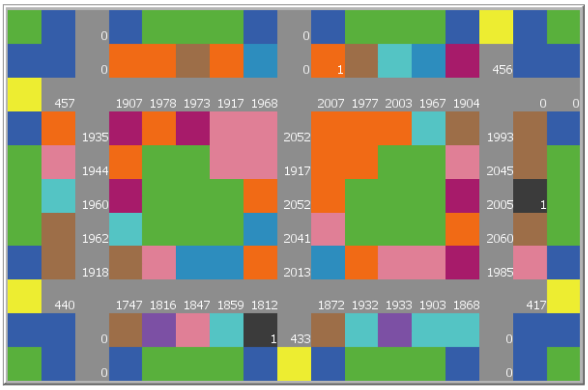


Figure 32a: Base scenario visitor distribution (one cycle)

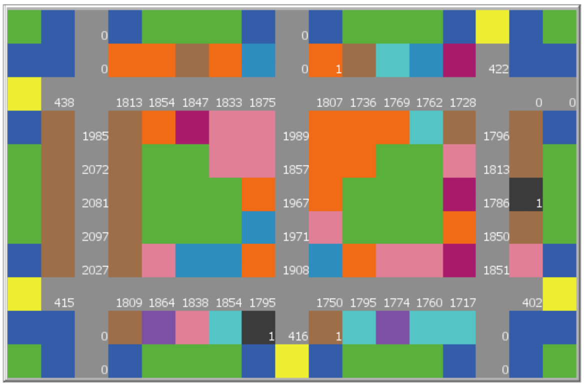


Figure 32b: Scenario 4b visitor distribution (one cycle)

Scenario 4b (Figure 32a and 32b) reveals that the large cluster of hospitality stores did attract the most customers in all of the shopping area. Clustering attractiveness is only integrated in customers' preference if it is on the shopping list of the customer. All customers with hospitality on their shopping list, automatically have an utility score of +0.9 (for each hospitality store in the west street, there are 9 other hospitality stores in the same street) for all of these stores. With the highest utility score normally being ± 2.5, this signals a significant impact, therefore making these stores having high probabilities to be chosen. This outcome implies that an extreme cluster configuration does influence customers' behaviour, replicating the finding of the literature.

Scenario 5: Removing proximity of anchor store influence

Teklenburg et al. (1997) found that anchor store presence influenced store performance of surrounding stores in a positive way. In the base scenario the two southern streets were both struggling the most. The reason could not be pointed out, therefore in this scenario the impact of distance from a store to an anchor store on customers' preference was completely removed (the weight was changed from 0.04 to 0.0).

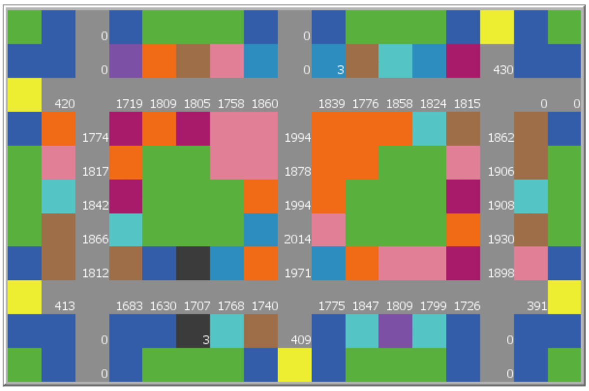


Figure 33a: Base scenario visitor distribution

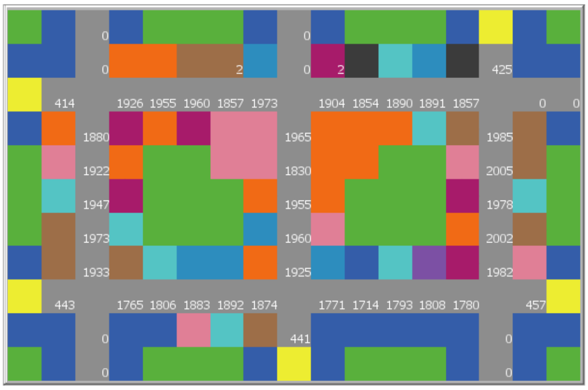


Figure 33b: Scenario 5 visitor distribution

In Figure 33a and 33b the visitor distribution can be seen. The visitor distribution was more evenly distributed over the area, what could indicate streets with other strong factors were more thriving. In the eastern street there is a large cluster of hospitality stores, which indicates on being a strong factor in this scenario. However, the retail dynamics in both the southern streets were not affected, and still were the worst performing streets with all transformations. Therefore, there is no evidence that the results of the base scenario were influenced by anchor store proximity.

Scenario 6: Faster vacancy and transformation rates

Research by Ossokina et al. (2017) revealed that stores will be transformed into another function if a retail function is determined no longer profitable, and that this occurs mostly at the edges of shopping areas. Struckell et al. (2020) found that retailers are constantly evaluating their store performance and will base their decision of closing, relocation of staying upon it. In Scenario 6 these retailers' behaviour are tested by accelerating the pace in which they will go vacant and transform their stores. In the base scenario, the unprofitable stores become vacant after 3 consecutive cycles, after 5 consecutive cycles the store will be transformed. These are now set to 2 and 3 cycles respectively. Other retailers will relocate if 2 out of the following 3 demands are met: does the vacant location have more visitors, offers better clustering, or is it closer to an anchor store. This is now set to only 1 demand to be satisfied.

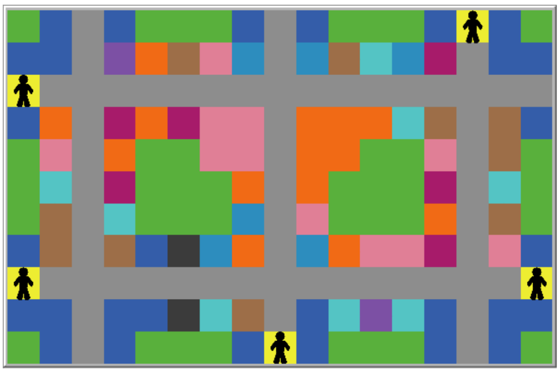


Figure 34a: Base scenario environment

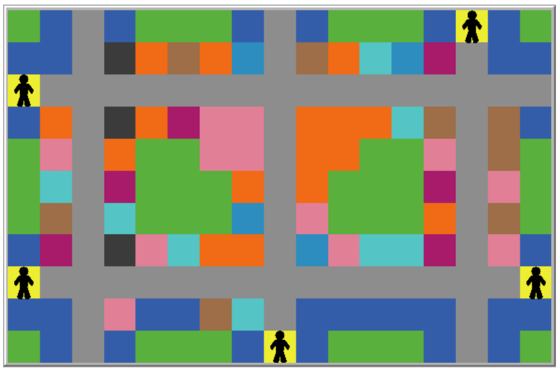


Figure 34b: Scenario 6 environment

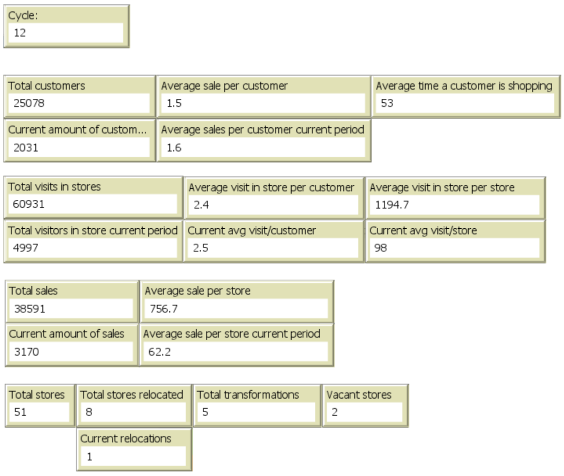


Figure 35a: Base scenario metrics

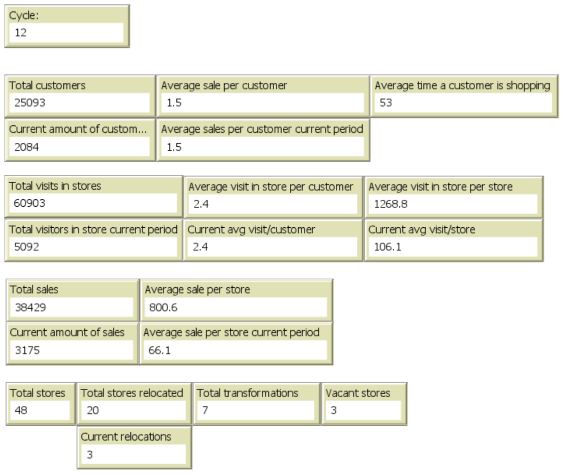


Figure 35b: Scenario 6 metrics

A comparison of figures 34a and 34b reveals that the same southern streets continued to struggle in both scenarios. However, the southeastern street now exhibited slightly more challenges compared to the southwest street. The analysis of figures 35a and 35b highlights significant changes in store relocations between the two scenarios, less significant in transformations. In Scenario 5, the number of store relocations increased dramatically from 8 in the base scenario to 20. The total number of transformations rose from 5 in the base scenario to 7 in the new scenario. With 5 of those being in one street.

These adjustments demonstrate a more dynamic retail environment, with increasing relocation and transformation activities. The retailers were constantly looking to improve their location to get more sales, thus replicating the literature. Also the edges of the shopping area were most prone to transformations.

Scenario 7: 30% increase in customers

This scenario simulates a future where downtown retail areas are more densely populated, with a higher number of residents contributing to increased foot traffic and customer interactions. The goal is to examine how such increased customer flow would influence store profitability, and vacancy rates.

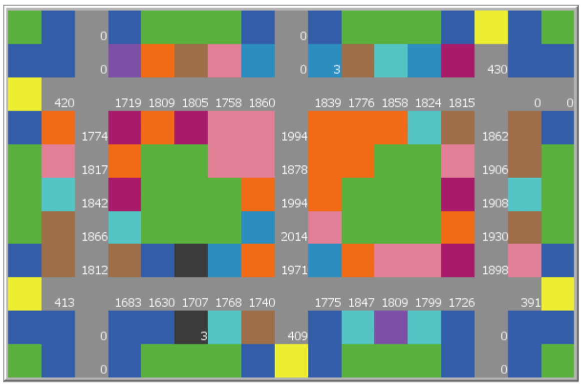


Figure 36a: Base scenario visitor distribution

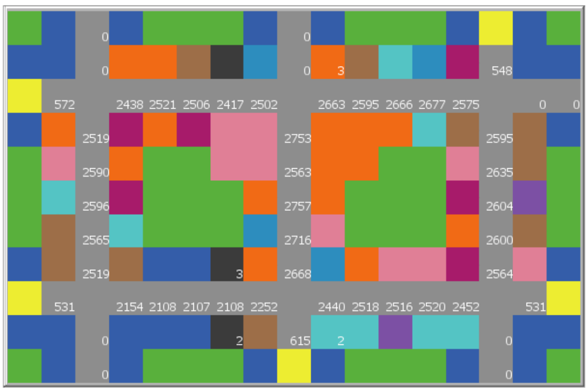


Figure 36b: Scenario 7 visitor distribution

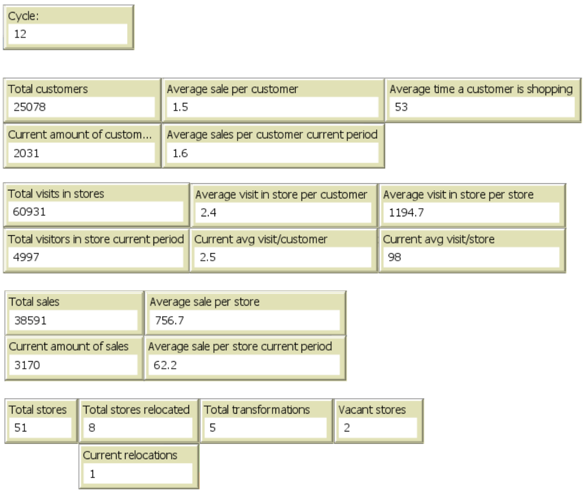


Figure 37a: Base scenario metrics

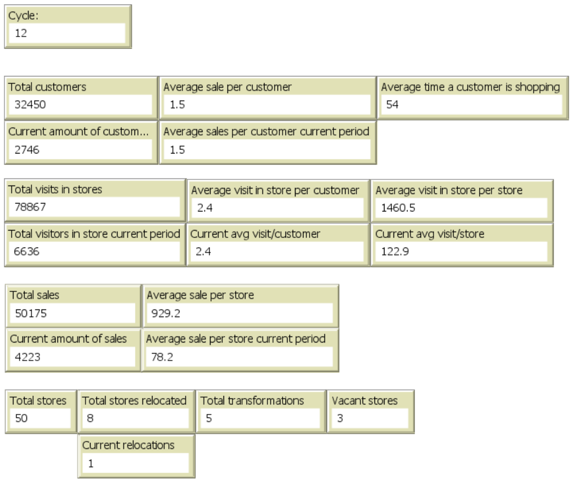


Figure 37b: Scenario 7 metrics

As shown in Figure 36a and 36b, the total sales and average sales per store increased by approximately 28–29%, with the number of visitors per street patch also increasing by 29% (see Figure 31). This reflects a proportional increase of foot traffic across the shopping area. Averages across the metrics, including average sales per customer and average shopping time remained unchanged. As expected, the total metrics such as customer count, store visits, and total sales scaled proportionally, rising by approximately 30%. The retail dynamics also occurred in similar areas with almost identical statistics as seen in Figures 37a and 37b. The system effectively adjusted to the increase in customers, without significant change.

Despite this rise in total metrics, the number of vacant stores did not decrease as anticipated. Although the dynamic rent structure—half based on visitor numbers and half on Retail Floor Area (RFA)—suggested that higher foot traffic could reduce vacancies, this was not reflected in the simulation outcome. This suggests that a 50% share of visitor number on rent is disproportionate.

Scenario 8: Increased unplanned visits/impulse purchases

This scenario assessed the effect of increasing unplanned visits or impulse purchases, as emphasized in the literature as a critical factor in customers' behaviour and retail success (Dijkstra et al., 2013). In the base scenario, the unplanned visit factor was set to 2%; this was increased to 10%.

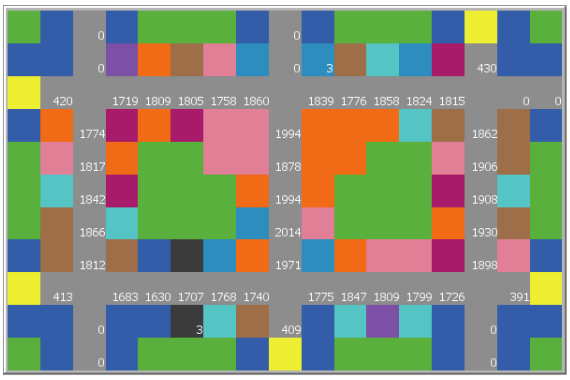


Figure 38a: Base scenario visitor distribution

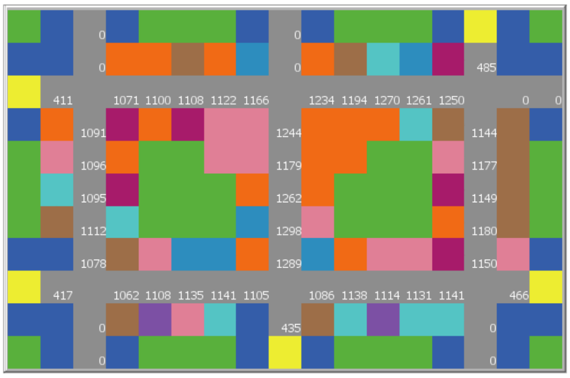


Figure 38b: Scenario 8 visitor distribution

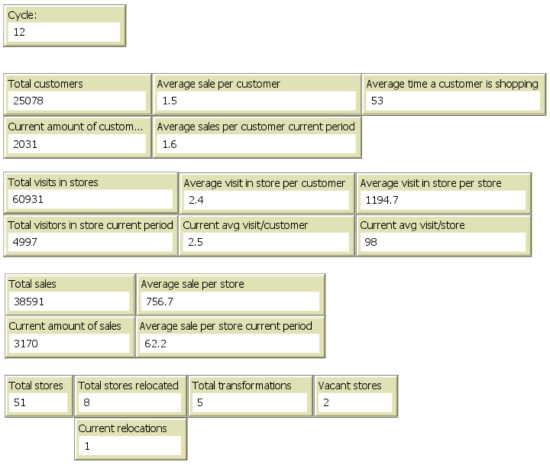


Figure 39a: Base scenario metric

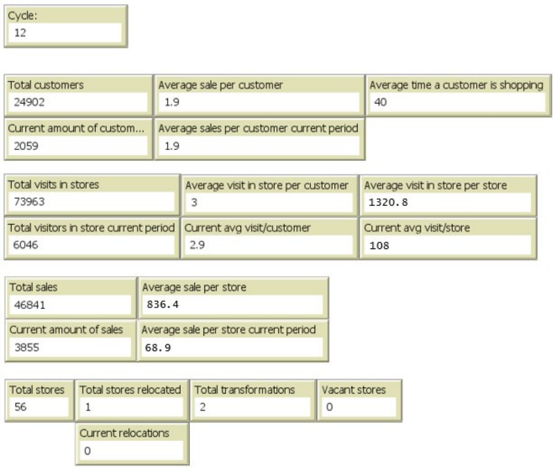


Figure 39b: Scenario 8 metrics

Figures 38a and 38b reveal that overall there is a significant reduction in foot traffic in scenario 8. The reason becomes clear when comparing Figures 39a and 39b, which show a substantial decrease in average time a customer is shopping, going from 53 ticks (minutes) to only 40. Indicating that customers went home much faster. Because of the increased impulse visits, customers could finish their shopping list faster, reducing foot traffic. Total store visits increased from 60,469 to 73,963 (+22%), the sales show similar figures. In scenario 8, only one retailers relocated into an initially vacant store location, no further retailers moved, and the two vacant locations transformed into another function. This depicts the overall retail environment flourished, as indicated by the increased sales and visits. The positive impact of impulsive purchases is replicated in the system.

5.3 Conclusion

In this chapter the different mechanisms were tested that affect customers' and retailers' behaviour by simulating several scenarios. A base scenario is fully documented and explained. Subsequent scenarios are simulated and compared to the base scenario. The outcomes are used to assess if the different mechanisms implemented into the system replicate the findings of the literature review.

From the base scenario, it quickly became evident that stores in streets located at the south were performing the worst. Attracting the least amount of customers overall. Also most retail dynamic activities occurred in this street, with the most amount of retailers relocating out of these streets. With lasting vacancy, transformations resulted. Retailer decisions were all based on the improvement of anchor store proximity and visitor counts, and fell short on the impact of clustering. The factors impacting customers' behaviour were less apparent from the base scenario and were tested in the subsequent scenarios.

Most findings that impact customers' behaviour highlighted in the literature, were successfully replicated in the simulation system. Entry point placement, the distance from customer to store, RFA size, unplanned visits, and an increase of the total number of customers were found to influence customer movement and/or store performance on a consistent base. However, less convincing were the effects of clustering on customers' behaviour as these were only to be found in extreme interventions. Anchor store proximity, even though a leading factor for retailer relocations, could not be determined as great influence in the system.

Overall, the outcomes and comparisons of the scenarios offer insight in the capabilities of the system to replicate established theories and findings. However other areas still require refinement, especially in clustering and anchor store proximity.

6. Conclusion

6.1 Summary of findings

This thesis set out to answer the main research question: **“***How can downtown retail dynamics be simulated to develop a system that can predict the profitability of individual shops and shopping streets?***”** To address this, the question was broken into seven sub-questions, each focusing on a specific facet of downtown retail dynamics. Together, these sub-questions provide a comprehensive answer to the main question.

The simulation system required robust capabilities, including agent-based modelling, spatial layouts, flexibility, user-friendly design, real-time visualization, scalability, and scenario testing. NetLogo was selected as it met these requirements, offering multi-agent and spatial modelling to capture customer movement, retailer decisions, and clustering effects. Its intuitive interface, pre-built models, strong visualization, and its proven use in urban studies validated its suitability.

Customer behaviour was modelled using a utility functions and probabilities were calculated using a Multinomial Logit (MNL) model. This model incorporated factors identified in the literature, such as retail floor area (RFA), clustering, proximity to stores and anchor stores. A Monte Carlo simulation was used for unplanned visits and purchases, every time a customer moved past or went into a store. Placement of entry points was critical for customer distribution and store visibility. These mechanisms reflected established patterns of customer behaviour that were found in the literature review, though clustering and anchor store proximity effects showed mixed results and require refinement.

Retailers’ decisions to either close, relocate or stay were influenced based on store profitability, this meant stores had to make sufficient amount of sales in order to afford their rent. Rent is based on visitor count and RFA size. When a store was assessed unprofitable it led to vacancy, and lasting vacancy resulted the store to transform into another function. Vacant locations meant opportunity for other retailer to relocate in these locations. These potential relocations were done by retailers trying to improve their store location in terms of visitor counts, proximity to anchor stores and clustering with similar retailers. Whereas visitor count and proximity to anchor stores was found of great influence to the decisions of retailers, the clustering factor did not show evidently.

The simulation system allows for the evaluation of policy measures by running simulation runs with adjusted parameters like entry point placement and increasing the amount of customer inflow, and comparing the results from the adjusted scenarios to a base scenario. Real-time outputs provided insights into customer movement, retailer performance, and vacancy patterns. The tool’s performance was assessed through validation against established theories, scenario consistency, and sensitivity testing. Key metrics included the impact of several variables in customer movement, retailer decisions, and retail dynamics.

6.2 Contribution to urban planning and real estate

Smits (2023) identified a gap in the research regarding spatial retail patterns and agglomeration dynamics in Dutch medium to small-sized downtown city centres. She recommended future research to explore the relationship between this gap and the effects of store openings, closures, and clustering. This research was therefore build upon that recommendation, by developing a simulation system that includes both customer’s and retailer’s behaviour and effects of spatial settings.

The simulation system developed so far is an initial step towards a system more accurately predicting retail dynamics, further refinement is necessary. An advanced tool such as the envisioned system could be beneficial for different stakeholders such as urban planners, retailers, municipalities and real estate developers.

The contribution of the system for urban planners would be to assess their plans and urban interventions in downtown retail areas. The system can provide insight if the effects of infrastructural changes on retail dynamics, such as adding new entry points or pedestrian streets. For retailers it would be useful in determining where to relocate and how it will affect them. It could potentially predict store performance regarding location characteristics such as the turnover per m^2 of retail floor area. Municipalities could test policies to aid in the revitalization of downtown retail. In real estate development, the tool can be helpful to determine the value of a store at a certain point in the shopping district.

6.3 Critical discussion

The simulation system is the initial step in an attempt to simulate and predict realistic downtown retail dynamics, including customers' and retailers' behaviour in a spatial setting. Where it does replicate some proven theories, the system still has its limitations in realism and applicability, highlighting the opportunity for refinement.

The first limitation is the simplified representation of customers' behaviour. The customers shop in a simple schematic spatial shopping area and excludes factors like shop window appeal, street furniture, crowding, and whether shoppers prefer lively streets. All these factors – pointed out in research done by Borgers and Timmermans (2015) – are essential to model the customer journey well. Moreover, the population of customers is generalized where all customers being the same. The introduction of demographics in customer generation with various behavioural differences makes the system more complex. Also the customer shopping list is currently not tied into a schedule, together with a lack of smart routing choice this limits the optimalization and realism of customers' behaviour.

Customers' behaviour is also limited due to the simplification of customer distribution at the entry points. The integration of entry point choice with transportation mode choice and subsequent choice of parking place for car or bike, or a public transportation stop by the agents further enhances realism. Lastly, in terms of customers' behaviour, a limitation is the absence of learning over time; currently customers do not have memory.

In the current state of the simulation system it was chosen to construct the utility function in a way that all stores are potential target stores, including stores that do not have items from customers' shopping lists. Further refinement is needed to determine whether this choice is effective or if these stores should be excluded to establish a more defined choice set. Also static parameters restrict model flexibility. The weights assigned to the factors that influence customer preference are all pre-set values instead of estimates based on actual data, and therefore do not generate accurate predictions. Additionally, the economics in the model exclude dynamic factors, such as fluctuating rent and the use of adaptive leasing strategies that are vital for simulating real-world competitive dynamics.

The absence of temporal trends further limits the system as well. Excluding the influence of e-commerce growth or societal shifts means that the resulting data only is a static snapshot in time, not capturing retail evolution over time. Validation is the last area of refinement, as the lack of GIS-based data or observed datasets limits the possibility to actually validate outcomes to a real-world scenario.

6.4 Recommendations for future research

The limitations mentioned in Section 6.3, such as improving the complexity of customers' behaviour, static parameters, lack of dynamic economic factors, absence of external temporal trends and lack of validation via GIS-driven data highlight gaps, can form a foundation for future work in order to improve realism, adaptability and applicability of the simulation.

Beyond these improvements, future studies should consider adding new aspects to the simulation. Introducing several customer types, such as experience-based or discount-driven shoppers, would paint a more realistic picture of customers' preferences. Also the number of customer could adapt over time as response to environment changes, such as e-commerce growth or societal shifts, creating dynamics in inflow of customers.

Finally, the application of machine learning could enhance the predictive power and real-time adaptability, rendering the simulation effective in analysing and forecasting retail and urbanization patterns.

References

Arentze Theo A., Borgers Aloys W.J., and Timmermans Harry J.P. (1993). “A Model of Multipurpose Shopping Trip Behavior,” *Papers in Regional Science*, 72(3), 239–56.

Arentze, T. A., Oppewal, H., & Timmermans, H. J. P. (2005). A multipurpose shopping trip model to assess retail agglomeration effects. *Journal of Marketing Research,* 42(1), 109–115.

Arnold, M.J., and Reynolds, K.E. (2012). Approach and avoidance motivation: investigating hedonic consumption in a retail setting. *Journal of Retailing*, 88(3), 399-411.

Babin, B.J., Darden, W.R. and Griffin, M. (1994). Work and/or fun: measuring hedonic and utilitarian shopping value. *Journal of Customer Research*, 20, 644–656.

Berry, B. J. L., & Garrison, W. L. (1958a). A note on central place theory and the range of a good. *Economic Geography,* 34(4), 304.

Berry, B. J. L., & Garrison, W. L. (1958b). Recent developments of central place theory. *Papers and Proceedings of the Regional Science Association, 4*, 107.

Borgers, A., & Timmermans, H. J. P. (1986). City centre entry points, store location patterns and pedestrian route choice behaviour: A microlevel simulation model. *Socio-Economic Planning Sciences, 20*(1), 25-31.

Borgers, A and Timmermans, H. (2005). Modelling pedestrian behaviour in downtown shopping areas. Proceedings of CUPUM 05, Computers in Urban Planning and Urban Management at Centre for Advanced Spatial Analysis, University College London.

Borgers A., Kemperman, A. and Timmermans, H. (2006). Entry point choice of downtown shopping area visitors. Proceedings of the RARCS Conference, Budapest.

Borgers, A. and Vosters, C. (2011). Assessing preferences for mega shopping centres: A conjoint measurement approach. *Journal of Retailing and Customer Services*, 18, 322-332.

Borgers, A., & Timmermans, H. (2015). Modeling pedestrians' shopping behavior in downtown areas. In J. Ferreira, Jr., & R. Goodspeed (editors), *CUPUM 2015 - 14th International Conference on Computers in Urban Planning and Urban Management* Artikel 202 CUPUM.

Bouwinvest. (2019). *Dutch retail sector heads multichannel on the road to a new normal*. Bouwinvest. Retrieved December 6, 2024, from https://www.bouwinvest.nl/media/4411/bouwinvest-retail-paper-dutch-retail-sector-heads-multichannel-on-the-road-to-a-new-normal.pdf

Brown, S. (1987). Institutionally-driven retail cycles. *Geografiska Annaler. Series B. Human Geography, 69*(2), 167-178.

Brown, S. (1992). Tenant mix, tenant placement and shopper behaviour in a planned shopping centre. *The Service Industry Journal*, 12, 384-403.

Brown, S. (1993). Retail location theory: Evolution and evaluation. *The International Review of Retail, Distribution and Customer Research, 3*(2), 185-229.

Burt, S., & Sparks, L. (2003). E-commerce and the retail process: A review. *Journal of Retailing and Customer Services, 10*(5), 275–286.
Christaller, W. (1933). *Die zentralen Orte in Süddeutschland*. Jena: Gustav Fischer.
Cilliers, E. J., Timmermans, W., Van den Goorbergh, F., & Slijkhuis, J. S. A. (2021). The impact of COVID-19 on public space: An evaluation of European cities. *Planning Practice & Research, 36*(4), 400-421.
Dallinga, R., Ploegmakers, I., Loof, B. de, & Martinus, T. (2009). Jones Lang LaSalle Retail Market Special 2009. Jones Lang LaSalle.
Damian, D. S., Curto, J. D., & Pinto, J. C. (2010). The impact of anchor stores on the performance of shopping centres: The case of Sonae Sierra. *International Journal of Retail & Distribution Management, 39*(6), 456–475.
Dawson, J. (1980). *Retail geography (RLE Retailing and Distribution)*: Routledge.
Dawson, J. A. (1983). *Shopping centre development.* London, England: Longman.
Dawson, J. A. (2008). *Retail trends in Western Europe: Structural changes and policy implications*. *European Retail Research*, 22(1), 11–32.
Dijkstra, J., Timmermans, H. J. P., & de Vries, B. (2009). Modeling impulse and non-impulse store choice processes in a multi-agent simulation of pedestrian activity in shopping environments. In H. J. P. Timmermans (Ed.), *Pedestrian behavior: Models, data collection and applications* (pp. 63–87). Emerald Group Publishing Ltd.
Dijkstra, J., & Jessurun, J. (2013). Modeling planned and unplanned store stops for the scenario-based simulation of pedestrian activity in city centers. In *Proceedings of the Fifth International Conference on Advances in System Simulation (SIMUL 2013)* (pp. 107–112). IARIA.
Dolega, L., Reynolds, J., Singleton, A., & Pavlis, M. (2021). Beyond retail: New ways of classifying UK shopping and consumption spaces. *Environment & Planning B: Urban Analytics and City Science, 1*, 132–150.
Evans, J. R. (2011). Retailing in perspective: The past is a prologue to the future. *The International Review of Retail, Distribution and Customer Research, 21*(1), 1–31.
Evers, D., Slob, G., Content, J., Van Dongen, F. (2020). *Veerkracht op de proef gesteld: Een verkenning van de impact van corona op binnensteden.* PBL Netherlands Environmental Assessment Agency. Retrieved on December 7th 2024 from: https://www.pbl.nl/sites/default/files/downloads/pbl-2020-veerkracht-op-de-proef-gesteld-4288_0.pdf
Fici, A., Bilucaglia, M., Casiraghi, C., Rossi, C., Chiarelli, S., Columbano, M., Micheletto, V., Zito, M., & Russo, V. (2024). From e-commerce to the metaverse: A neuroscientific analysis of digital customer behavior. *Behavioral Sciences, 14*(7).
Garner, B. J. (1966). *The internal structure of retail nucleations.* Evanston, IL: Northwestern University Studies in Geography.

Gaur, S., & Singh, R. (2023). A comprehensive review on land use/land cover (LULC) change modeling for urban development: Current status and future prospects. *Sustainability, 15*(2), Article 903.

GIS Agents. (2023). *Urban growth model in NetLogo*. Retrieved October 26, 2024, from http://www.gisagents.org

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Journal of Retailing, 93*(1), 1–6.

Grimmeau, J.-P., & Wayens, B. (2020). Assessing the evolution of retail vacancy in Brussels using spatial and statistical analyses. *Tijdschrift voor economische en sociale geografie, 111*(2), 199–216.

Haar, F. t., & Quix, F. (2020). *Retail postcorona impactanalyse.* Q&A Consultancy bv. Retrieved February 17, 2024, from https://retailland.nl/app/uploads/2020/07/Retailagenda_Retail-postcorona-impactanalyse_juli2020_DEF.pdf

Haig, R. M. (1927). *Regional survey of New York and its environs.* New York, NY: New York City Planning Commission.

Hardin, W. G. III, & Wolverton, M. L. (2000). Micro-market determinants of neighborhood centre rental rate. *Journal of Real Estate Research, 20*(3), 299–322.

Haklay, M., O'Sullivan, D., Thurstain-Goodwin, M., & Schelhorn, T. (2001). So go downtown: Simulating pedestrian movement in town centres. *Environment and Planning B: Planning and Design, 28*(3), 343–359.

Hallsworth, A. G., & Coca-Stefaniak, J. A. (2018). National high street retail and town centre policy at crossroads in England and Wales. *Cities, 79*, 134–140.

Hanson, S. (1980). Spatial diversification and multipurpose travel: Implications for choice theory. *Geographical Analysis, 12*, 245–257.

Helm, S., Kim, S. H., & Van Riper, S. (2020). Navigating the retail apocalypse: A framework of customer evaluations of the new retail landscape. *Journal of Retailing and Customer Services, 54*.

Heppenstall, A., Crooks, A., See, L., & Batty, M. (Eds.). (2016). *Agent-based models of geographical systems.* Springer.

Hirschman, E.C. (1981). Retail Research and Theory in B.N. Enis and K.J. Roering (eds.), *Review of Marketing*, Chicago: AMA, pp. 120-133.

Holbrook, M. B., & Hirschman, E. C. (1982). The experiential aspects of consumption: Customer fantasies, feelings and fun. *Journal of Customer Research, 9*(2), 132–140.

Hotelling, H. (1929). Stability in competition. *Economic Journal, 39*(153), 41–57.

Huizinga, F. H., & Ossokina, I. V. (2014). Leegstand: een opgave voor beleid? *Real Estate Research Quarterly*, *13*(1), 18-24.

Ibrahim, M., & Ng, C. (2002). Determinants of entertaining shopping experiences and their link to customer behavior: Case studies of shopping centres in Singapore. *Journal of Leisure Property, 2*(4), 338–356.

ING Economic and Financial Analysis. (2023). Growth and challenges for Dutch hospitality industry. ING. Retrieved October 22, 2024, from https://think.ing.com/articles/a-challenging-year-ahead-for-dutch-hospitality/

Isarsoft. (2023). Top 10 KPIs for every retail business. Retrieved October 25, 2024, from https://www.isarsoft.com

Kaltcheva, V. D., & Weitz, B. A. (2006). When should a retailer create an exciting store environment? *Journal of Marketing*, 70(1), 107–118.

Kent, T., & Omar, O. (2003). *Retailing.* New York, NY: Palgrave Macmillan.

Konishi, H., & Sandfort, M. T. (2003). Anchor stores. *Journal of Urban Economics, 53*, 413–435.

Koster, H. R. A., Van Ommeren, J., Tang, C. K., & Bras, N. (2022). COVID-19 restriction policies and shopping streets. *Plos One, 17*(7), e0267160.

Lesger, C., & Delaney, K. (2011). *Patterns of retail location and urban form in Amsterdam in the mid-eighteenth century. Urban History.* Retrieved February 17, 2024, from https://www.jstor.org/stable/44614561?seq=1#metadata_info_tab_contents

Ligmann-Zielinska, A., & Jankowski, P. (2014). Spatially-explicit integrated uncertainty and sensitivity analysis of criteria weights in multicriteria land suitability evaluation. *Environmental Modelling & Software, 57*, 235–247.

Lösch, A. (1940). *Die räumliche Ordnung der Wirtschaft.* Jena: Gustav Fischer.

Messinger, P. R., & Narasimhan, C. (1997). A model of retail formats based on customers' economizing on shopping time. *Marketing Science, 16*(1), 1–23.

Nelson, R. L. (1958). *The selection of retail location.* New York, NY: F. W. Dodge.

O'Kelly, M. (1981). A model of demand for retail facilities incorporating multistop, multipurpose trips. *Geographical Analysis, 13*(2), 134–148.

Oppewal, H., & Timmermans, H. (1997). Retailer self-perceived store image and competitive position. *International Review of Retail, Distribution and Customer Research, 7*(1), 41–59.

Oppewal, H., & Holyoake, B. (2004). Bundling and retail agglomeration effects on shopping behavior. *Journal of Retailing and Customer Services, 11*(1), 61–74.

Ossokina, L., Sviták, J., Teulings, C., & Zwaneveld, P. (2016). *De vastgoedmarkt reageert marktconform. Den Haag: Centraal Planbureau.* Retrieved February 17, 2024, from https://research.tue.nl/en/publications/winkelleegstandna-de-crisis-de-vastgoedmarkt-reageert-marktconfo

Ossokina, I. V., Svitak, J., & Teulings, C. (2017). Leegstand en transformatie van winkelvastgoed. *Real Estate Research Quarterly, 16*, 12–20.

Pashigian, B. P. and Gould, E.D. (1998), Internalizing externalities: the pricing of space in shopping malls. *Journal of Law and Economics*, 41, 115-142.

Passaro, P., Salomone, S., & Petruzzellis, L. (2016). Retail concentration: The shopping streets. *European Scientific Journal, 12*(16), 122.

Province North-Brabant. (2021). *Feiten en cijfers Brabantse retail.* Retrieved February 17, 2024, from https://publicaties.brabant.nl/feiten-en-cijfers-brabantse-retail-2021/cover-feiten-en-cijfers-brabantse-retail-2021/

Rao, A. S., & Georgeff, M. P. (1995). *BDI Agents: From Theory to Practice*. Proceedings of the First International Conference on Multiagent Systems (ICMAS)

Reilly, W. J. (1931). *The law of retail gravitation.* New York, NY: Knickerbocker Press.

RetailSonar. (2020). *Impact coronacrisis op klantgedrag & winkelprestaties.* Retrieved on February 17, 2024 from https://www.retailinsiders.nl/docs/3b9151b1-d9cb-4ebb-b18c-444430c3ed7c.pdf

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. *Journal of Retailing, 88*(2), 308-322.

Ruiter, T. (2004) Warenhuizen in problemen, nieuwe trekkers dienen zich aan. *Real Estate Magazine*, 36, 16- 19.

Smirnova, V., & Lukianchuk, S. (2023). From potential to employment: Revolutionizing career guidance in Russia. Savonia University of Applied Sciences.

Smits, I. H. M. (2023). Retail-related developments in medium-sized Dutch inner-city shopping areas at the beginning of the 21st century. Master’s thesis Eindhoven University of Technology, Eindhoven.

Statistics Netherlands. (2023). *Minder winkels in 2023*. Retrieved on February 17, 2024 from https://www.cbs.nl/nl-nl/nieuws/2023/19/minder-winkels-in-2023

Strabo & JLL. (2016). Retail rental dynamics: An analysis of store rents and vacancies in urban shopping areas (2009–2015). Strabo Real Estate Consultancy and Jones Lang LaSalle.tang

Struckell, E. M., Ojha, D., & Manikas, A. S. (2020). Retail store churn and performance: The moderating role of sales amplitude and unpredictability. *International Journal of Production Economics, 222*, 107489.

Tangpong, C., Islam, M., & Lertpittayapoom, N. (2009). The emergence of business-to-customer e-commerce. *Journal of Leadership & Organizational Studies, 16*(2), 131-140.

Teklenburg, J.A. F., A.W. J Borgers, P.J.H.J. van der Waerden, & H.J.P. Timmermans. (1997). The interdependence of urban layout, shop location and pedestrian flows. Paper presented at the 28th annual conference of the Environmental Design Research Association, May 7-11, Montreal, Canada.

Teller, C., Reutterer, T., & Schnedlitz, P. (2008). Hedonic and utilitarian shopper types in evolved and created retail agglomerations. *The International Review of Retail, Distribution and Customer Research, 18*(3), 283-309.

Van Leeuwen, M. (2018). *E-commerce statistics for individuals. Statistics Netherlands (CBS)*. Retrieved November 17, 2024, from https://www.cbs.nl/en-gb/news/2018/e-commerce-statistics-for-individuals

Veesion. (2023). R*etail KPIs: 10 essential indicators for assessing your store's performance.* Retrieved on 25th of October 2024 from https://www.veesion.io

Weltevreden, J.W., & Rietbergen, T.V. (2007). E-shopping versus city centre shopping: The role of perceived city centre attractiveness. *Tijdschrift voor economische en sociale geografie, 98*(1), 68-85.

Whyatt, G. (2008). Which factory outlet centre? The UK customer's selection criteria. *Journal of Retailing and Customer Services*, 15(4), 315-323.

Yeates, M., Charles, A. and Jones, K. (2001). Anchors and externalities. *Canadian Journal of Regional Science*, 24(3), 465-484.

You, T. S., Crosby, N., Lizieri, C. and McCann, P. (2001). The management of positive inter-store externalities in shopping centres: some empirical evidence. Europeans Real Estate Society Conference, Helsinki, 1-22.

Zhang, D., Zhu, P., & Ye, Y. (2016). The effects of E-commerce on the demand for commercial real estate. *Cities, 51*, 106-120.

Appendices

Appendix A: Store information

Table 2: Store information

ID	x	y	RFA	Initial Store Function
1	-5	4	200	Fashion & Luxury
2	-4	4	210	Fashion & Luxury
3	-3	4	170	Hospitality
4	-2	4	220	Fashion & Luxury
5	-1	4	120	Daily
6	1	4	250	Fashion & Luxury
7	2	4	140	Hospitality
8	3	4	230	Speciality
9	4	4	130	Daily
10	5	4	150	Leisure
11	-7	2	85	Fashion & Luxury
12	-5	2	130	Leisure
13	-4	2	55	Fashion & Luxury
14	-3	2	160	Leisure
15*	-1	2	1000	In/Around House
16**	1	2	1400	Fashion & Luxury
17	3	2	240	Fashion & Luxury
18	4	2	140	Specialty
19	5	2	190	Hospitality
20	7	2	180	Hospitality
21	-7	1	150	In/Around House
22	-5	1	320	Fashion & Luxury
23	5	1	130	In/Around House
24	7	1	160	Hospitality
25	-7	0	150	Specialty
26	-5	0	180	Leisure
27	-1	0	380	Fashion & Luxury
28	1	0	350	Fashion & Luxury
29	5	0	155	Leisure
30	7	0	250	Hospitality
31	-7	-1	190	Hospitality
32	-5	-1	160	Specialty

33	-1	-1	360	Daily
34	1	-1	370	In/Around House
35	5	-1	300	Fashion & Luxury
36	7	-1	200	Hospitality
37	-7	-2	210	Hospitality
38	-5	-2	190	Hospitality
39	-4	-2	180	In/Around House
40	-3	-2	170	Daily
41	-2	-2	180	Daily
42	-1	-2	340	Fashion & Luxury
43	1	-2	340	Daily
44	2	-2	290	Fashion & Luxury
45	3	-2	160	In/Around House
46	4	-2	140	In/Around House
47	5	-2	150	Leisure
48	7	-2	190	In/Around House
49	-5	-4	180	Hospitality
50	-4	-4	190	Culture & Recreation
51	-3	-4	200	In/Around House
52	-2	-4	160	Specialty
53	-1	-4	210	Fashion & Luxury
54	1	-4	170	Hospitality
55	2	-4	180	Specialty
56	3	-4	300	Culture & Recreation
57	4	-4	210	Specialty
58	5	-4	170	Specialty

** Cluster of patches: -2 2, -1 2, -2 1, -1 1*
*** Cluster of patches: 1 2, 2 2, 1 1, 2 1*

Appendix B: Multinomial Logit (MNL) Model

Multinomial Logit (MNL) is a widely used statistical model to predict the likelihood that an individual will select one choice out of a set of discrete choices. It relies on the idea that agents choose the alternative with the highest utility.

Utility Function

Each alternative i is associated with a utility U_i, which is composed of two parts:

$$U_i = V_i + \epsilon_i$$

- V_i: The deterministic component, which is calculated from observable attributes (e.g., price, distance, quality) and parameters that quantify their influence.
- ϵ_i: The random component, accounting for unobserved factors or randomness in the decision-making process.

Probability of Choosing an Alternative

The probability of choosing alternative i is derived from the utility function and is given by the logit formula:

$$P_i = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)}$$

Where J is the total number of alternatives.

This formula ensures that the probabilities are positive and sum to 1 across all alternatives.

Appendix C: Cumulative distribution

A cumulative distribution describes how probabilities accumulate over multiple events. It is derived by summarising probabilities in a stepwise fashion from a probability distribution.

Steps to Create a Cumulative Distribution

1. **Define the Probabilities**: Begin with a set of probabilities $p_1, p_2, \ldots, p_n$ that correspond to the likelihood of individual outcomes. These probabilities should sum to 1:

$$\sum_{i=1}^{n} p_i = 1$$

2. **Calculate the Cumulative Probabilities**: Compute the cumulative probability for each outcome i by summing all probabilities up to that point:

$$C_i = \sum_{i=1}^{n} p_i$$

This produces a cumulative distribution $C=[C_1, C_2, \ldots, C_n]$, where:

- $C_1 = p_1,$
- $C_2 = p_1 + p_2,$
- $C_n = 1.$

Example

Suppose you have three outcomes with the following probabilities:

$$p_1 = 0.4,\ p_2 = 0.35,\ p_3 = 0.25$$

Cumulative probabilities are calculated as:

$$C_1 = p_1 = 0.4$$
$$C_1 = p_1 + p_2 = 0.4 + 0.35 = 0.75$$
$$C_3 = p_1 + p_2 + p_3 = 0.4 + 0.35 + 0.25 = 1.0$$

The cumulative distribution is:

$$C = [0.4, 0.75\ ,1.0]$$

Application

Cumulative distributions are often used in simulations or sampling processes, such as in Monte Carlo simulation in this research.

Appendix D: Monte Carlo simulation

Monte Carlo simulation works by using random sampling to model uncertainty and make predictions. For example, in this context, a random float between 0 and 1 is generated. This float is then compared against a set of cumulative probabilities assigned to different outcomes (e.g., stores). The float determines which segment of the cumulative probabilities it falls into, effectively selecting the corresponding outcome. This process is repeated many times to simulate a variety of potential scenarios and capture the range of possible outcomes. This is the essence of Monte Carlo simulation.

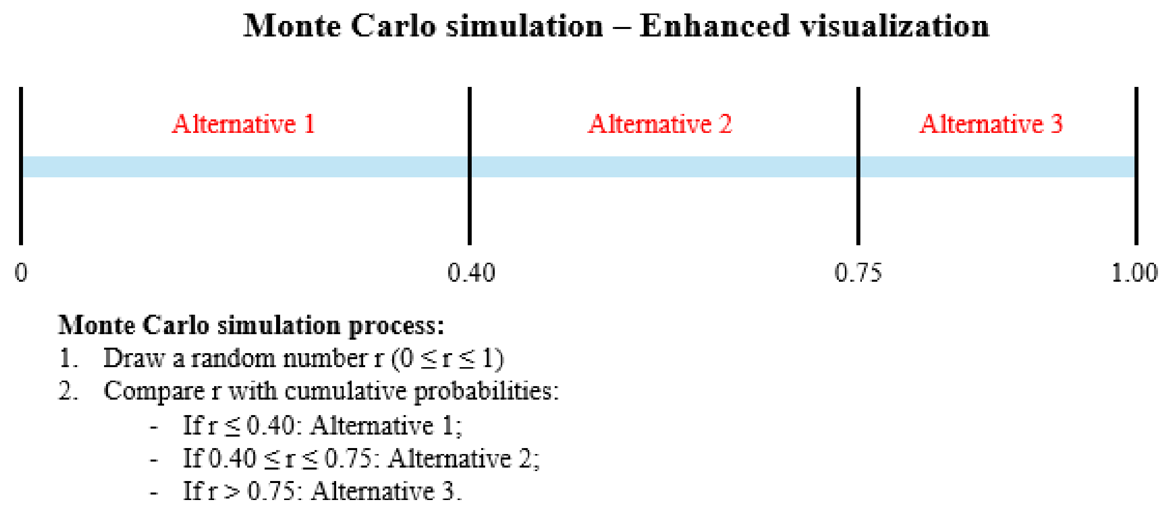


Figure 40: Monte Carlo explanatory visualization

Appendix E: phases in the simulation system

Phase 1: Initialization (Ticks = 1)
Once the simulation starts, the environment is reset so that no remaining data will affect the results. Customers are introduced, and all places, like stores or streets, are stripped of prior states. This offers a fresh start to the simulation cycle.

Phase 2: Customer Movement and Shopping (Ticks = 2 to end of shopping period)
The customers start moving around in the retail area, going from store to store. The customers select target stores and moves through the environment to get there. On the way, customers might stop at unplanned stores. They go to a store and try to buy something of their list. Customers with empty lists go home.

Phase 3: Store Performance Evaluation (Ticks = end of shopping period + 1 to end of shopping period + 25)
Stores keep track of visitor numbers and sales statistics during the simulation to figure out how profitable they are. The stores that fall below the required rent are categorized as unprofitable. The ongoing performance problems could result in closures and vacant stores. Sometimes vacant stores are transformed into other functions.

Phase 4: Relocation of stores (Ticks = end of shopping period + 26 to end of shopping period + 27)
All stores could decide to move to better places. Relocations are decided according to the visitor count, the proximity to an anchor store and the clustering of similar stores. Once a suitable location is found, retailers get ready for move-in.

Phase 5: Relocation movement (Ticks = end of shopping period + 28 to end of shopping period + 45)
The relocating stores move towards their new location.

Phase 6: End-of-cycle reset (Ticks = end of shopping period + 46)
The environment is updated at the end of each simulation cycle. The visitor and sales data are reset, the clustering and other factors also are recalculated.

Appendix F: Fixed parameters in the simulation system

This appendix explains the fixed values and settings used in the system code. These parameters shape how customers and retailers behave, and how the system operates overall.

1. Behavioural adjustments

Over time, customers are more likely to leave the shopping area. Each step adds 1% to their chance of going home early**.** After each store visit an additional 5% is introduced.

When customers fail to buy something, their chances of succeeding increase with each attempt. The following table shows how their chances improve, it goes beyond the table display:

Table 3: explanatory table of increase mechanisms

Attempt	Initial success rate	Increase after failure	New success rate
1st	Base Rate	+5%	Base Rate + 5%
2nd	Base Rate + 5%	+5%	Base Rate + 10%
3rd	Base Rate + 10%	+5%	Base Rate + 15%

2. Customer spawning

- Timings: New customers are introduced at three shifts per spawn-timing, reflecting early morning, noon and afternoon visits.
- Number of Customers: In each shift, between 50-100% of the maximum possible customers will move into the area.

3. Simulation cycle timing

The length of each evaluation period is based on 10 spawn times for customers. One cycle represents a month, so one spawn time represents 3 days.

4. Customer movement

Customers move step by step during each time interval. They only take one step forward per tick.