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Agent-based Modeling in E-commerce

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Abstract

In the rapidly evolving field of e-commerce, conventional research methods struggle to keep pace with the dynamic landscape characterized by exponential growth and changing user behaviors. To address this challenge, agent-based modeling and simulation offer a promising research paradigm. This paper explores the potential of agent-based modeling and simulation in capturing the intricate dynamics of the e-commerce environment and advancing our understanding of this complex domain.

We provide an overview of agent-based modeling and simulation applications in various e-commerce domains and identify three compelling avenues for future research. Firstly, exploring the emergence of network structures helps understand communication and information-sharing patterns among actors, revealing their impact on e-commerce dynamics. Secondly, considering individual differences in personality and culture unveils how these factors influence behaviors, preferences, and decision-making processes in e-commerce. Lastly, analyzing longitudinal dynamics and asynchronous timelines captures evolving patterns and long-term effects seen in e-commerce phenomena. Agent-based modeling allows researchers to track the evolution of these dynamics over time.

To showcase the power of agent-based modeling and simulation in e-commerce, the chapter presents a case study that focuses on the longitudinal dynamics of multi-stakeholder recommendation systems. It highlights the versatility and effectiveness of agent-based modeling in capturing heterogeneous consumer preferences, diverse objectives of recommendation providers and users of recommendation services, and the longitudinal dynamics of a set of recommendation strategies.
Keywords: Customer behavior, trust, loyalty, service quality, recommender systems, social commerce, multistakeholder recommendation

1 Introduction

In recent decades, the growth of e-commerce has been phenomenal, with no signs of this trend slowing down. According to a recent analysis conducted by the United Nations Conference on Trade and Development, the utilization of electronic commerce has experienced rapid and sustained expansion. In 2020, while only 24% of firms received online orders, approximately 40% of them placed online orders (United Nations Conference on Trade and Development 2022). Furthermore, the private sector witnessed a surge in online shoppers, reaching a staggering 1.5 billion individuals in 2019, followed by a subsequent 5.2 percentage point increase in 2020 (United Nations Conference on Trade and Development 2020b). The economic value of e-commerce has soared in recent years, reaching 26.7 trillion USD in 2019 (United Nations Conference on Trade and Development 2020a).

The concept of e-commerce has undergone significant evolution over the years and continues to evolve at present. As a result, numerous definitions have emerged, leading to a widely accepted understanding that a singular definition does not exist. However, according to the International Organization for Standardization (ISO) standard ISO/IEC 15944-7:2009, e-commerce is defined as a ”business transaction, involving the making of commitments, in a defined collaboration space, among persons using their IT systems, according to Open-edi standards” (Kunesova and Micik 2015). Furthermore, as noted by Goyal, Sergi, and Esposito (2019), e-commerce transactions can be broadly categorized into different types based on the parties involved, namely: business-to-business (B2B), business-to-consumer (B2C), consumer-to-business (C2B), and consumer-to-consumer (C2C).

E-commerce research faces a multitude of challenges due to the dynamic and rapidly evolving nature of the environment, as well as the presence of diverse actors with heterogeneous interests. These actors include sellers, middlemen, customers, and various other stakeholders, depending on the specific context of e-commerce. Interactions take place not only between different groups of stakeholders but also within each group, and they might not only have immediate effects but often also unfold long-term effects. Particularly noteworthy is the interaction between customers, which gives rise to word-of-mouth communication and opinion dynamics. These interactions can lead to dynamic and adaptive behaviors exhibited by all involved actors. Furthermore, the network in which these actors interact can be emergent and dynamic, further influencing the overall emergent behavioral dynamics.

Gaining insights into the dynamics that arise from interactions among multiple players in dynamic environments using traditional research methods, such as surveys or experiments, is challenging due to the complexity of the overall situation.[1] However, agent-based modeling and simulation offer a well-suited approach to address such complexities, mak-

1. A systematic comparison of the advantages and disadvantages of agent-based modeling and simulation over other research methods is provided in Wall and Leitner (2021).

ing them particularly valuable for e-commerce research. This methodology enables the capture of dynamic interactions among diverse actors, dynamic interaction structures and social networks, as well as the dynamic and adaptive behavior of individuals in response to shifting objectives or environmental disruptions, which are of significant interest in the context of e-commerce.

This chapter aims to shed light on the untapped potential of agent-based modeling and simulation as a research method in the realm of e-commerce research and practice. To accomplish this, in Sec. 2, we begin by providing an illustrative overview of the applications of agent-based modeling and simulation in the field of e-commerce, highlighting promising avenues for future research. Subsequently, in Sec. 3, we present a compelling case study that exemplifies the unique potential of agent-based modeling and simulation in e-commerce research and practice. Specifically, we delve into an innovative application of this research method in the domain of recommender systems. Finally, in Sec. 4, we conclude the chapter.

2 Applications of agent-based modeling in e-commerce and emerging research questions

2.1 Overview of ABM-based research in e-commerce

This section presents an illustrative overview of the research strands in e-commerce that rely on agent-based modeling and simulation as the primary research method. It should be emphasized that the scope of this overview is not to provide a comprehensive literature review, but rather to highlight the prevalent research themes in agent-based modeling-based e-commerce research. For readers interested in a more comprehensive review of the e-commerce research literature, we recommend consulting works such as Goyal, Sergi, and Esposito (2019), Attar et al. (2022), Fang and Fang (2022), and Bawack et al. (2022). Our illustrative overview is structured into five sections that cover the following topics: *(i)* customer behavior, *(ii)* trust, loyalty, and service quality, *(iii)* recommender systems, *(iv)* social commerce and social perception, and *(v)* e-commerce and operations management

2.1.1 Customer behavior

The theme of customer behavior has emerged as a significant area of interest in e-commerce research in general. In recent literature reviews, Attar et al. (2022) and Goyal, Sergi, and Esposito (2019) identified that more than 20% of the reviewed research articles focused on customer behavior-related issues. Additionally, Fang and Fang (2022) noted that trust, information, and service quality, as well as C2C consumer behavior, have been prominent topics in e-commerce research since 2006. Next, we give an overview of relevant work in the domains of purchasing, payment, and reviewing behavior that rely on agent-based modeling and simulation as their primary research method.

Purchasing behavior In his research, Deng (2019) investigates the effects of online promotion strategies on consumer behavior and propose a corresponding agent-based model. The model considers that external factors, such as online promotion strategies, interact with a user's characteristics and thereby alter the course of their decisions (Ailawadi et al. 2014). Deng (2019) shows that female users and younger consumers tend to react more strongly to promotion strategies than male users. Furthermore, the results indicate that consumers with a comparatively lower income are more likely to be influenced by online promotions compared to high-income consumers.

Ganzha et al. (2005) and Bădică, Ganzha, and Paprzycki (2007) develop a skeleton of an agent-based model that aims to capture consumer and seller behavior on e-commerce marketplaces. They argue that their model can be further developed to study issues such as the effects of pricing strategies, negotiation protocols, and negotiation strategies. In doing so, Ganzha et al. (2005) and Bădică, Ganzha, and Paprzycki (2007) aim to provide a tool that has an impact not only in academia but also beyond it. Their proposed framework has been used in various applications. For example, Qasim et al. (2020) employ their framework and are concerned with performatives, i.e., with statements or commands that are used in computer-mediated communication systems, such as chatbots, to achieve a specific goal, such as requesting information or giving a recommendation. Qasim et al. (2020) specifically propose performatives to model e-commerce negotiation protocol applications.

In a conceptual paper, Šperka and Slaninová (2012) present an agent-based model for e-commerce systems. The model effectively captures the dynamic modes of interaction between buyers and sellers in such systems. Specifically, the proposed model serves as a decision support system for sellers in e-commerce markets and enables the simulation of customer behavior in response to various design options within the e-commerce system. Ultimately, the model's goal is to enhance the efficiency and reliability of predicting the success of different configurations of e-commerce systems prior to implementation in practice. Similarly, Zhang (2017) proposes an agent-based model that captures the interrelationship between purchasing behavior and e-commerce website quality. The proposed model might also serve as a tool for generating insights into consumer behavior.

In their research, Chen et al. (2008) argue that the consumer-to-business (C2B) model is underrepresented in e-commerce research, and therefore issues such as how to efficiently organize communications between consumers, how to synthesize individual needs into a group consensus, and how to efficiently organize negotiations between consumers and a seller (i.e., the business) in this setting are under-researched. To address this gap, they propose an agent-based model of buyer collective purchasing, which is a model for situations in which a group of customers has flexible requirements regarding the characteristics of a product and individual customers are willing to compromise with the other group members to get the best benefit for the group. Based on their model, Chen et al. (2008) demonstrate how to design the processes of synthesizing individual preferences into a group consensus, communicating within the group of buyers, and collective negotiation with a seller using an example case. Shojaiemehr and Kuchaki Rafsanjani (2013) also address the issue of collective purchasing behavior, proposing an agent-based C2B model where consumers autonomously decide to form a group that brokers a merchant acting as a middleman between buyers and sellers. The merchant's role involves synthesizing the buyers' preferences and requirements, negotiating on behalf of the buyer group, and ultimately closing deals. Using their proposed model, the authors show a clear relationship between the similarity of buyers in the buyer group and their satisfaction. They also highlight an inherent trade-off between satisfaction and the time required for the process of collective purchasing.

Payment behavior Hummel, Kern, and Döhler (2011) address a critical aspect of e-commerce system design, namely the optimal configuration of payment methods in online stores. The authors argue that choosing the right payment methods is a multifaceted problem due to the potential impact on both sales and transaction-based costs. Specifically, while some payment methods may attract new customers and result in increased sales, the addition of new payment methods may also lead to existing customers switching their payment method, thereby increasing payment costs. To address this challenge, Hummel, Kern, and Döhler (2011) propose an agent-based model that simulates customer payment behavior and which is validated with real-world data. The proposed model might thus provide decision support for managers who are tasked with designing effective e-commerce systems.

Reviewing behavior Jiang et al. (2020) focus on the dynamics of posting reviews on online review systems. They argue that reviews have a significant effect on sales and that there are a number of factors that affect reviewing and posting behavior (Forman, Ghose, and Wiesenfeld 2008; Chen et al. 2019). To capture the related dynamics, they propose an agent-based model that simulates online posting behavior. Their analysis focuses on how clicking positions and issues of webpage design affect the users' posting behaviors. They find that clicking positions significantly affect the contributions of individual users, and the number of reviews that are shown on one page moderates the clicking positions. For example, their analysis suggests that users who click on both the first and last page of available reviews, as well as users who only click on the first page of reviews, are more likely to provide a greater number of reviews than users who click on other positions within the review pages.

2.1.2 Trust, loyalty, and service quality

This section provides an overview of research within the closely related stream of consumer behavior that is focused on how trust and loyalty emerge in e-commerce contexts and their relationship to service quality. In their paper, Choi and Nazareth (2014) focus on the issue of trust between partners in e-commerce. They argue that existing research largely focuses on establishing initial trust between e-commerce partners (Gefen, Karahanna, and Straub 2003; Suh and Han 2003), while the issue of ongoing trust and maintenance of existing trust is less extensively researched. To fill this gap, Choi and Nazareth (2014) propose an agent-based model that explicitly addresses the issue of ongoing trust in e-commerce relationships. The particular driver for trust in their model are considerations around information security, which covers issues of authentication, non-repudiation, privacy, confidentiality, and data integrity control (Ray, Ow, and Kim 2011). In general, Choi and Nazareth (2014) show that if trust is once broken, it can be restored. Moderate trust reconciliation strategies are usually sufficient except for the most severe security offenses. However, they also show that re-building trust is a slow process. Interestingly, they also show that low reconciliation efforts do not help in re-building trust and bringing back customers, irrespective of the severity of the security incidents.

In their research, Huang, Cheng, Chie, et al. (2022) are also concerned with trust in e-commerce markets, specifically the effects of dishonesty regarding product or service quality at the sellers' side. They argue that e-commerce systems take a special role in the relationship between customers and sellers, serving as a middleman that establishes information transparency and legal provision in uncertain markets. However, they note that the effects of dishonest sellers are largely under-researched. To address this gap, Huang, Cheng, Chie, et al. (2022) propose an agent-based model to study the effects of dishonesty on e-commerce markets. The results of their study indicate that the emerging dynamics lead to reduced expected quality, falling trading volumes, and, consequently, falling prices for goods in the market. However, they find that in situations where consumers are highly connected, the effect of dishonesty is weaker as information sharing between customers happens more frequently.

Terán, Leger, and López (2022) address the specific challenge of Chinese cross-border e-commerce, where the seller's behavior is uncertain and the quality of products in B2C e-commerce platforms is often variable and uncontrolled. To capture these unique aspects, the authors propose an agent-based model that incorporates word-of-mouth dynamics between buyers. By utilizing their model, Terán, Leger, and López (2022) are able to successfully replicate the real-world order of B2C e-commerce marketplaces in terms of the number of buyers who have made at least one purchase on each respective marketplace. Their findings suggest that reputation and trust in the provider as well as provider size are the primary drivers of this order, followed by the quality of the e-commerce webpage and product and service quality.

2.1.3 Recommender systems

The literature on recommender systems has leveraged ABM techniques to investigate various research questions (Adomavicius et al. 2021). One such study by Adomavicius et al. (2013) examines the impact of product consumption strategies on the temporal dynamics of recommender system performance. The authors develop an ABM that enables an in-depth analysis of the emerging longitudinal dynamics. The results of their investigation reveal that consumption strategies can significantly affect the impact of recommendation quality. Specifically, when customers heavily rely on recommendations, the quality of the recommendations can deteriorate over time as they become increasingly inaccurate and homogeneous. A related study by Zhang et al. (2020) investigates this "performance paradox" phenomenon in more depth. The authors explore the effects of various user populations and consumption strategies, as well as the type of recommendations (personalized vs. unpersonalized). Interestingly, they find that the relevance of recommendations can be sustained over time if users rely on both personalized and unpersonalized recommendations when making their consumption decisions.

The study conducted by Zhou, Zhang, and Adomavicius (2021) focuses on the issue of preference bias in recommender systems. The authors define preference bias as a situation where a consumer's post-consumption preference ratings are influenced by the predictions made by the recommender system. They argue that preference bias can adversely impact the performance of recommender systems since the feedback ratings are utilized as training data for future predictions. The authors show that preference biases can significantly and non-linearly decrease prediction accuracy, relevance for consumers, and diversity over time. Furthermore, they demonstrate that intentionally biased recommendations can exacerbate the negative impact of preference biases on system performance.

The recent study by Ghanem, Leitner, and Jannach (2022) investigates the longitudinal effects of recommendation strategies that consider both consumer preferences and provider profit. To accomplish this, the authors develop an agent-based model that incorporates real-world data and a simplified model of word-of-mouth dynamics. Through the quantification of the effect of different recommendation strategies on service provider performance and trust, the study provides evidence that hybrid strategies—which combine personalized recommendations with those based on provider profit—yield the highest cumulative profit over a long-term horizon. This work represents one of the first examples of multi-stakeholder recommendation systems that utilize agent-based modeling and simulation, and its innovative approach is discussed in detail in Section 3.

2.1.4 Social commerce and social perception

The emergence of social commerce has been observed as an area of growing interest in the literature since 2016, where peer influence, such as through social networks, significantly impacts customer behavior (Hu, Chen, and Davison 2019). Jiang et al. (2014) focus on the evolutionary process of knowledge sharing between users in the context of e-commerce. They argue that users within a social commerce environment can influence the buying behavior of other users by sharing information through mechanisms such as word-of-mouth, recommendation, and the transfer of knowledge and experience (see also Li, Hsiao, and Lee 2013). Specifically, the authors adopt a game-theoretic approach to information sharing and develop an agent-based model to study the impact of network structures and information noise on cooperative behavior. Their findings reveal four key implications for organizations operating in social commerce. First, managerial e-commerce strategies must be customized to the structure of the virtual community. Second, the initial motives of users with respect to information sharing are crucial for e-commerce success, as they can trigger chain-like effects. Therefore, understanding users' motives is essential. Third, the emerging social dynamics and learning of knowledge can be guided with facts. Lastly, providing interaction channels for users can facilitate information sharing and remove communication obstacles, thereby allowing organizations to make use of the emerging dynamics.

In their research, Jiang, Liu, and Wang (2015) concentrate on the relationship between consumers and companies in the context of e-commerce. They focus on situations with collaborative e-commerce platforms and argue that the decisions of vendors and consumers are dynamic and highly interwoven. For example, providers might adapt their pricing policy to consider changes of other e-commerce vendors on the same platform, and consumers might adapt their decisions of buying a specific product or waiting until price changes happen, accordingly. To address this co-evolutionary process, Jiang, Liu, and Wang (2015) propose an agent-based model. They posit that their proposed model can serve as a decision support tool for e-commerce vendors, particularly in areas such as service provision and customer behavior management.

Similarly, Jiang et al. (2018) focus on information exchange between consumers and e-retailers. They argue that online information exchange between retailers and consumers is gaining importance, with the majority of organizations regarding social media as vital for their business and many consumers' purchase decisions being driven by social factors. To capture the dynamics emerging from information exchange between consumers and retailers and to explore the effects of word-of-mouth, network structures, selling strategies, and price adjustments on the retailers' profits, they propose an agent-based model. The results of Jiang et al. (2018) indicate that there is a strong effect of social network structure on the retailers' profits, and they conclude that situation-specific management measures are warranted at the micro-level. Regarding selling strategies, they find that cross-selling or bundling products may not always be an efficient strategy, which is in contrast to previous findings. Finally, they provide evidence for positive effects of dynamic pricing, whereby non-fixed interval price adjustment modes are preferred because e-commerce usually reduces price rigidity. In a similar vein, Čavoški and Marković (2015, 2017) focus on B2C e-commerce models. They propose an agent-based model to evaluate and improve existing selling strategies, with a particular focus on dynamics stemming from word-of-mouth, consumers' search behaviors, and online advertisements. They argue that the primary focus of their model is decision support for organizations in the B2C segment, which can help improve market segmentation, improve business profitability, and test business strategies.

2.1.5 E-commerce and operations management

This section provides an overview of recent topics within the research field located at the interface between ABM-based research in e-commerce and supply-chain management. In their conceptual paper, Ganzha et al. (2008) argue that there are specific differences in how logistics and restocking decisions are made when sellers operate on e-commerce marketplaces. These differences are particularly found in mechanisms such as product demand prediction, offer selection criteria, interactions with wholesalers, price negotiations, and time management. The authors highlight the need for particular attention to the logistics of e-commerce sellers. To address this challenge, Ganzha et al. (2008) introduce an innovative agent-based model that effectively captures the corresponding logistics, such as handling reservations and warehouse management, forecasting, and handling individual orders.

The work of Zhang and Bhattacharyya (2010) delves into the supply chain operations of sellers who conduct business on e-marketplaces. Specifically, their study centers on inventory control and order fulfillment. The authors present an agent-based supply network model, which enables them to highlight two key distinctions between conventional sellers and those who participate in e-marketplaces. The first finding of note is that sellers who operate on e-marketplaces tend to maintain higher levels of inventory. The second significant difference is that these sellers backlog fewer orders than their counterparts in more traditional supply chains.

The studies conducted by Alves et al. (2019) and Alves et al. (2022) shed light on the impact of the growing prevalence of e-commerce on urban logistics. The authors contend that the majority of e-commerce orders require the presence of buyers at the time of delivery, resulting in a significant number of failed delivery attempts. To address this issue, the authors present a framework that relies on agent-based modeling and simulation to evaluate e-commerce urban freight. The model enables the authors to demonstrate the efficiency of delivery lockers as a last-mile solution for e-commerce deliveries. Specifically, the authors' findings indicate that the implementation of delivery lockers significantly reduces costs, distances traveled, and delivery time.

In a recent study, Ma and Yang (2023) focus on the phenomenon of manufacturer channel encroachment. The authors propose an agent-based model that characterizes scenarios in which manufacturers use official websites, apps, and other digital platforms to establish new sales channels for direct sales to consumers. This practice, known as channel encroachment (Xia and Niu 2020), can potentially harm e-commerce platforms by diverting their customers. The model introduced by Ma and Yang (2023) accounts for variations in product quality across channels. The study reveals that consumers' quality preferences and their preferences for specific sales channels play a vital role in determining the benefits that e-commerce platforms reap. Furthermore, the authors demonstrate that the maintenance costs of direct sales channels tend to be high, which often discourages manufacturers from engaging in channel encroachment.

2.2 Emerging research questions

Agent-based modeling and simulation is a relatively new research methodology in the field of e-commerce. While some pioneering work has already employed ABM, as discussed in Sec. 2.1, the full potential of this approach for e-commerce research has yet to be realized. This section highlights some emerging research questions that should be addressed through ABM-based research in the future.

Emergence of network structure in e-commerce Current ABM-based e-commerce research appears to under-represent the issue of emergent network structures. E-commerce features a multitude of networks, such as those between consumers sharing experiences with e-commerce platforms, between providers sharing information, and along the supply chain to organize product flows. However, in most cases, these networks are exogenously given, and as a result, the research findings are often highly dependent on these network structures. This line of future reserach could, for example, build on the work presented in Jiang et al. (2014) who argue that e-commerce strategies should be tailored to the structure of the virtual community and social dynamics can be guided by facts. A promising avenue for future research could be to endogenize the network structure by parameterizing agents with empirically founded decision rules and allowing for bottom-up emergence of networks. These emergent networks can play a crucial role in all five predominant research themes identified in Sec. 2.1. For example, given emergent networks, opinion dynamics among customers could influence trust and, consequently, customer behavior. Furthermore, understanding the dynamics of network emergence in e-commerce contexts can help to better manage e-commerce supply chains.

Differences in personality and culture of users One of the distinctive features of ABM-based research approaches is the incorporation of heterogeneous actors into the simulation models (Adomavicius et al. 2021). This allows for the modeling of the characteristics of actors who engage in e-commerce contexts. Existing work has already started to analyze the effects of differences in personal characteristics on e-commerce success. For example, Deng (2019) present findings on differences in buying behavior caused by the users' age. Future work could extend this line of research. For example, first, future research could develop ABMs that feature cultural differences in actors to test the robustness of existing e-commerce theories to variations in national culture. This promising line of research not only contributes to the practice of e-commerce but also advances theory building.

Second, ABM allows for the modeling of behavioral norms that emerge from interactions between actors (Khodzhimatov, Leitner, and Wall 2021, 2022). In an e-commerce context, such norms could emerge from interactions between customers and/or sellers, affecting, for example, what is socially accepted buying or payment behavior, or how frequently and truthfully public feedback is given via reviews. This issue is only partly reflected in existing work. For example, Chen et al. (2008) and Shojaiemehr and Kuchaki Rafsanjani (2013) address issues of collective purchasing behaviors. We believe that extending this line of research and further exploring emergent characteristics of social systems with behavioral consequences in an e-commerce context is a potentially fruitful line for future research.

Third, ABM allows for the integration of non-rational actors into the simulation model (Leitner and Wall 2015; Wall and Leitner 2021) This approach could advance the modeling of customer behavior and bring ABM-based research even closer to the real world, thereby significantly increasing the value of ABM-based e-commerce research for corporate practice.

Finally, as discussed in Sec. 2.1.1, payment is a crucial aspect of every e-commerce transaction, and there is a risk of non-payment. ABM-based research could incorporate non-payment risk as a feature of the simulation models to better understand the drivers of non-payment on e-commerce transactions and explore potential solutions.

Longitudinal dynamics and asynchronous time axes Previous e-commerce research often focuses on analyzing e-commerce systems at a single point in time, but agent-based modeling and simulation offers a unique feature of allowing for the analysis of these systems over time, including the emergence of properties, as discussed above. Longitudinal analysis of the effects of e-commerce design elements, such as recommendation algorithms or webpage design, is one example of how ABM can provide insights into the dynamics of e-commerce systems. Pioneering work in this line of research is, for example, provided in Ghanem, Leitner, and Jannach (2022) and Adomavicius et al. (2013). Another potential research direction that is enabled by this feature of ABMs is that of asynchronous timelines. For instance, if researchers model a comprehensive e-commerce environment, users of e-commerce platforms and providers of services and/or products can enter and leave the system at different times, leading to different states of information, phases of the lifecycle, and experience with the modeled e-commerce environment. Incorporating asynchronous timelines into ABM-based research can thus provide a better understanding of the co-evolution of e-commerce systems over time and how actors adapt to changes in the e-commerce environment.

3 Case-study: Analyzing the effects of online recommendations using agent-based modeling and simulation

While Sec. 2 offered a broader overview of the applications of agent-based modeling and simulation in e-commerce research and pratice, this section delves deeper into the specific realm of recommender systems. Here, we explore the innovative work of Ghanem, Leitner, and Jannach (2022), who utilize agent-based modeling and simulation to investigate the longitudinal dynamics of recommendation strategies. Their research goes beyond the common practice of solely considering customers' perspectives and instead captures the interplay of recommendation algorithms that also incorporate the objectives of the recommendation providers. Additionally, the study examines the impact of information sharing between customers and the long-term behavioral consequences resulting from the implemented recommendation algorithms.

3.1 Background and motivation

Automated recommendations, e.g., in the form *"Customers who bought ... also bought ... "*, have become a common feature of modern e-commerce sites. *Amazon.com*, one of the most important players in this area, was one of the first large e-commerce organizations which relied on recommender systems at scale (Linden, Smith, and York 2003). While many of Amazon's recommendations may primarily aim to increase *cross-sales* on the site, there are various other ways in which automated recommender systems can create value for an organization. Besides increased sales, these systems can serve organizations in more indirect ways as well, e.g., by increasing customer engagement, loyalty and retention, see Jannach and Jugovac (2019) for a survey.

Importantly, however, recommender systems are commonly designed to create value (also) for the consumers. Recommendations in e-commerce are not just functioning as ads. Instead, they should help consumers find or discover relevant items on catalogs, which often include tens of thousands of products. Since the first academic papers on recommender systems from the mid-1990s, the literature has largely focused on this consumer (or: end-user) perspective. Thus, in computer science, the predominant goal for many decades now was to design increasingly more complex and accurate machine-learning algorithms to predict—in a personalized way—which items consumers would like and probably purchase.

Only in the most recent years, the research community paid more attention to the fact that in many e-commerce settings the potentially competing goals of different stakeholders must be taken into account when designing a recommendation algorithm. On a hotel booking site, for example, an algorithm might not only try to find a hotel that is a good match for the interests of the consumer, it may also consider profitability aspects for the booking site (e.g., in the form of sales commissions) and at the same time try to make sure that each offering of the property providers (e.g., a hotel chain) receives a minimum level of exposure to potential buyers. A number of examples of *multistakeholder* recommendation problems are described in Abdollahpouri et al. (2020) and Abdollahpouri and Burke (2022).

A special case of multistakeholder application problems in e-commerce are scenarios where the recommender system should be "price and profit aware". In such a scenario, mainly two stakeholders are considered: the customer and the recommendation service provider. Moreover, the goal of the provider is to incorporate business considerations in a rather direct way, e.g., through revenue or profit. A number of algorithmic approaches to address this problem setting were proposed in the literature, see Jannach and Adomavicius (2017). Some technical proposals are for example based on re-ranking accuracy-optimized lists, other use optimization techniques, some follow an analytic approach. The commonality of all approaches however lies in their goal of balancing consumer value and provider profitability.

A shortcoming of many of these existing works is that they adopt a "one-shot" evaluation approach, i.e., they assess the consumer value and provider profitability at one certain point in time. In reality, however, a longitudinal perspective must be taken: If a provider focuses too much on profitability, the value of the recommendations for consumers can become low, which over time may lead to a loss of trust towards the provider, thereby affecting customer retention. In the next sections, we will therefore describe an agent-based simulation model from Ghanem, Leitner, and Jannach (2022), which can be used to model the dynamics of applying price and profit aware recommendation strategies over time.

We emphasize that the work presented in Ghanem, Leitner, and Jannach (2022) is not the first to rely on agent-based or other simulation approaches to study longitudinal aspects of recommender systems. Notable works in the information systems and computer science literature include Zhang et al. (2020), Zhou, Zhang, and Adomavicius (2021), Jannach et al. (2015), Ferraro, Jannach, and Serra (2020) (see also Adomavicius et al. 2021). These works however mostly focus on algorithm-related aspects, e.g., if algorithms lead to higher or lower recommendation diversity of time due to reinforcement effects, and not on business-related research questions. Another line of simulation-based research can be found in the area of reinforcement learning, e.g., Rohde et al. (2018). Here, however, the simulation models are not agent-based, and the focus of the simulations is typically limited to the expected consumer value.

3.2 Model description

We recall that the goal in Ghanem, Leitner, and Jannach (2022) is to study longitudinal effects of adopting different profit-aware recommendation strategies on *(i)* the consumers' trust in the service provider, and *(ii)* the resulting impact on the provider's profit. A simplified, yet general e-commerce marketplace environment is modeled, which involves two types of agents. First, we assume that there is one (e-commerce) *provider*, who uses a recommender system to make automated item suggestions to users. The provider can choose between different recommendation strategies, where each of these strategies takes profitability considerations into account to a different extent. Second, there are *consumers* who receive these personalized recommendations. Depending on their assessment of the received recommendations, the trust of consumers towards the provider—and thus their propensity to make a further purchase in the future—may change over time. Given the strong potential influence of online reviews and worth-of-mouth recommendations on a provider's reputation and consumer choices[2], the proposed simulation model supports an indirect information exchange between consumers about their experiences with a provider through *social media*.

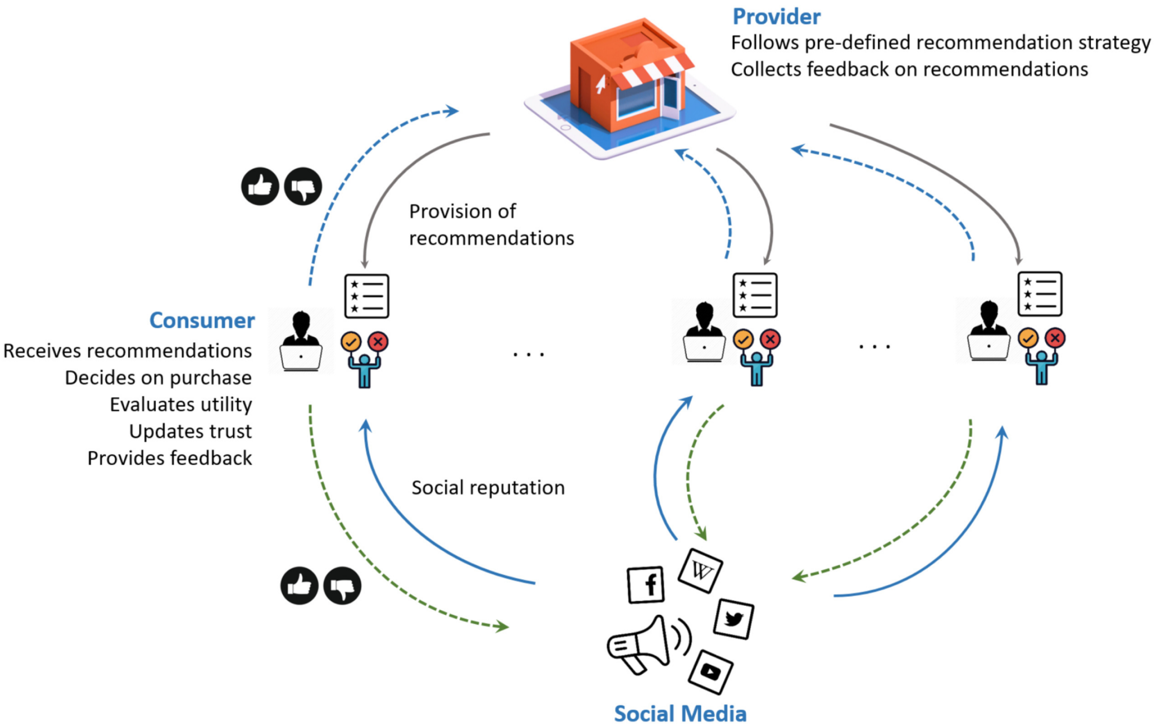

Figure 1: High-level overview of the simulation model (Ghanem, Leitner, and Jannach 2022).
Source: https://doi.org/10.1016/j.elerap.2022.101195 under the CC BY license.

A high-level overview of the actors and communication links in the model is provided in Figure 1. The specifics of the model can be summarized as follows.

2. See Gavilan, Avello, and Martinez-Navarro (2018) for a study in the tourism domain.

3.2.1 Provider

The e-commerce business (i.e., the *provider*) has a static set of items in the catalog, and each of this item has a certain profit value attached. As an application example, let us assume the provider is a movie streaming service with a *pay-per-view* business model. The provider uses a recommender system to make personalized recommendations to consumers, e.g., when they visit the website of the streaming service. To accomplish the personalization task, the provider collects feedback by consumers on the items they have consumed in the common form of star ratings ranging from 1 to 5. To study the effects of different recommendation strategies on consumer trust and profitability, we consider four levels of including profit considerations in the recommendation process.

- *Consumer-centric*: In this configuration, profit considerations are not considered at all, i.e., the recommendations are purely ranked based on their assumed relevance for the consumer.

- *Consumer-biased*: Here, the recommendations are predominantly ranked (with a weight factor of 90%) according to consumer relevance.

- *Balanced*: In this setting, profitability and consumer relevance are assumed to be equally important.

- *Profit-centric*: This extreme and non-personalized strategy always recommends the most profitable items to the consumers.

In addition to these strategies, the provider can choose a non-personalized *popularity-based* strategy, which consists of recommending the most popular items in the catalog to everyone. Showing consumers "what's popular" is a common feature of many e-commerce sites, and usually a safe choice when little is known about individual consumer preferences.

After consumers have received the recommendations, they might pick some of them and from time to time may give feedback to the provider about their experience with the item in the form of a star rating. This feedback is then incorporated into the provider's recommendation model and considered in the next round of recommendations. A main underlying assumption of the model is that focusing too much on profitability—and thus not taking consumer interests into account to a sufficient extent—may lead to a lower quality experience at the consumer's side.

3.2.2 Consumers

Consumers receive recommendations from the provider and from time to time they "accept" one of the recommendations. After experiencing the chosen item, i.e., after watching the movie in our application example, consumers make an assessment of the quality of the recommendation. This assessment, i.e., if they actually liked the quality of the recommended movie or not, is relevant in the further process in two ways.

- *Trust development and future consumption probability:* We assume that the consumers' trust towards a provider is formed through repeated experiences with the service. For each consumer, we therefore model a trust level, which is updated each time the consumer accepts one of the recommendations. The trust slightly increases whenever the chosen item matches the consumer's quality expectations, and it decreases if this is not the case. The resulting trust level in turn is modeled to influence a consumer's future consumption probability, which means how often a consumer will accept one of the recommended items. If trust becomes lower over time, the probability of picking one of the recommendations decreases as well, and vice versa. Ultimately, when providers focus too much on profit—and thus frequently include non-relevant items in the recommendations—the consumer's trust and consumption probability may decrease over time, which in turn may negatively impact the profitability figures of the provider.

- *Communication of the quality assessment:* Consumers have to opportunity to share their experience with the recommended items in two ways. First, as mentioned above, they can give feedback to the provider in the form of a star rating. Second, from time to time they may share their experience on social media using a common binary (thumbs-up/thumbs-down) feedback scale. In the simulation model, this social media feedback by the consumers is aggregated and shared with the consumers. In addition to their own experiences, consumers may then consider the public reputation of the provider in their trust assessment.

The specifics and the mathematical formulation of the behavior of the agents are described in detail in Ghanem, Leitner, and Jannach (2022). We note that the model has various stochastic elements and relies on a number of corresponding probability functions to ensure that the simulation are realistic.

3.2.3 Implementation details

To initialize the simulation model, Ghanem, Leitner, and Jannach (2022) used a publicly available dataset from the MovieLens[3] movie recommendation service. The dataset includes rating profiles (on a 1-5 scale) by 610 users for about 9,700 movies. The provider uses a state-of-the-art learning model based on matrix factorization[4] to generate *personalized* recommendations based on the given user profiles. Depending on the chosen strategy,

3. The MovieLens-100k dataset was used from https://grouplens.org/datasets/movielens/.
4. The implementation is based on the SURPRISE library (Hug 2020).

profit considerations are incorporated in the ranking process as described above. A set of top-N recommendations, N=10 in the simulation, are presented to each consumer in each simulation time step. The machine learning model is periodically retrained—as done in practical use cases—to consider feedback from the consumers during the simulation. Since the MovieLens datasets have no profit information attached, Ghanem, Leitner, and Jannach (2022) randomly assigned profitability values for each item from a normal distribution. During one simulation run, we assume that the provider selects one of the described strategies and sticks to it throughout the run. To compare the effects of the different strategies, the simulation is executed independently using each of the described strategies.

Given the particular dataset, the simulation model consists of 610 independently acting agents, who receive personalized recommendations based on their past preferences and who maintain their individual trust level towards the single provider in the simulation. The agents furthermore communicate their feedback to the provider and to social media as described above. In this context, a central problem in the simulation is to model to what extent a consumer is satisfied with a specific chosen recommendations. In the particular implementation and use case described here, the rating predictions generated by the machine learning model are assumed to reflect the true relevance of an item reasonably well, an assumption which seems appropriate given the widespread use of these types of models in practice. In case the provider focuses strongly on profit, we may often expect that items are recommended which are of somewhat limited relevance for the consumer. The consumers' satisfaction is then determined by the discrepancy between the true relevance of a recommended and chosen item and their quality *expectations*, which are determined by their past experiences, and thus ratings. The mathematical formulation of this process is detailed in Ghanem, Leitner, and Jannach (2022).

The entire simulation model is implemented in the Python programming language. Code and data are shared online to ensure reproducibility.[5]

3.3 Simulation outcomes and observations

Ghanem, Leitner, and Jannach (2022) ran a variety of simulations with different settings, and they report a selection of main insights here. Each simulation run consists of 1,000 time steps. To obtain more reliable results, each simulation run is repeated multiple times; the corresponding confidence intervals are shown in the figures.

Figure 2 shows the outcomes of the simulations for the simpler case where reputation-building through social media is *not* considered. Specifically, the figures show how three key indicators in our simulation change over time:

1. the *average consumption probability* across all agents, which is depending on the trust level of the individual agents;

5. https://github.com/nadaa/rec-strategies-abm/

2. the *profit* that the provider makes *in each time step*, which depends on the consumption probability of the agents and the average profitability of the recommended items;
3. the *cumulative profit* so far of the provider at each time step.

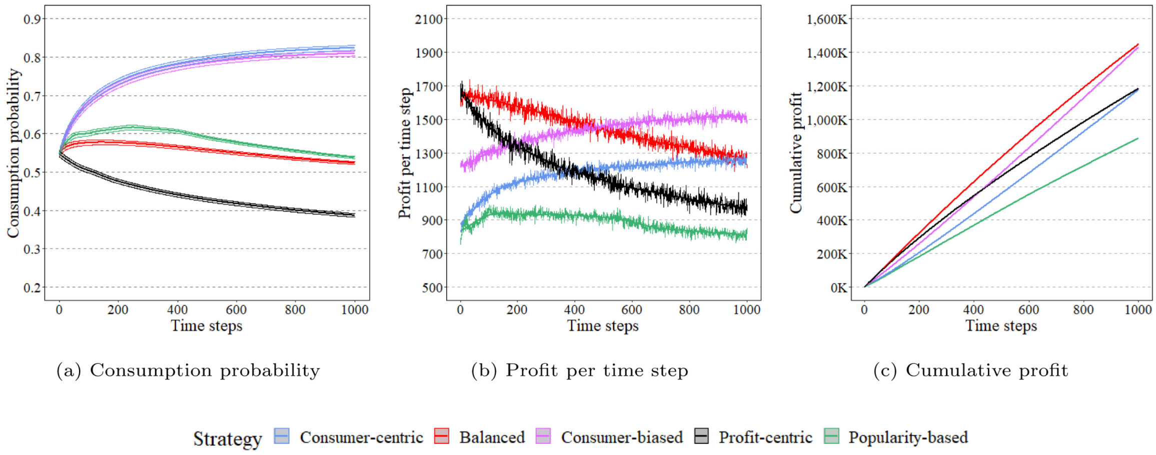

Figure 2: Effects without considering social media (mean with ±95 % CIs) (Ghanem, Leitner, and Jannach 2022).
Source: https://doi.org/10.1016/j.elerap.2022.101195 under the CC BY license.

At the beginning of the simulation the *consumption probability* (and provider trust) is identical for all agents. When the recommendations are focusing solely or exclusively on the value for consumers—i.e., for the *consumer-centric* and *consumer-biased* strategies—the consumption probabilities begin to increase quite sharply in the beginning and then flatten out at a high level. The *balanced* strategy, in contrast, does not help to increase trust further in the provider and is even performing slightly worse than the strategy of recommending popular items in a non-personalized way. This indicates that the balanced strategy at least from time to time recommends items that are not a good match for the given consumer preferences. Furthermore, as the consumption probability remains quite stable, this observation confirms that popularity-based methods can be a comparably safe choice and at least not too harmful in terms of the consumers' trust. The *profit-centric* strategy as expected leads to a marked decrease in terms of consumption probabilities over time. Ghanem, Leitner, and Jannach (2022) iterate that this strategy mainly serves as a baseline and lower bound in terms of consumer satisfaction, as it does not take the consumer preferences into account at all.

Looking at the *profit per time step*, the *balanced* and *profit-centric* strategies lead to the highest values at the beginning—as trust is still relatively high—but soon start to drop as the consumption probabilities begin to drop. The drop of the *balanced* strategy is slower, because its recommendations always consider consumer relevance and satisfaction to a certain extent. The profits per time step in contrast consistently grow over time for the *consumer-centric* and the *consumer-biased* recommendation strategy, as consumers pick a recommended more frequently due to their increasing trust towards the provider. Regarding the *popularity-based* method, it can be observed that it is much lower than the *balanced* approach. While these two strategies are comparable in terms of consumption probabilities, the balanced method is biased towards items with higher profit to a certain extent.

Finally, considering the *cumulative profit* of the compared strategies, please notice that after 1,000 time steps the *balanced* method and the *consumer-biased* methods turn out to be the most favorable options. However, looking at the development over time it can easily be seen that the *balanced* method profits from still reasonably high consumption probabilities from the beginning of the simulation, and that it will be outperformed by the *consumer-biased* method in the future. The lowest cumulative profit is recorded for the *popularity-based* method, which does not consider personalization or profits at all. The pure *consumer-centric* strategy is in the middle and leads to a cumulative profit that is comparable to the *profit-based* strategy. The trajectories of the curves however clearly indicate that the consumer-centric strategy will outperform the pure profit-oriented strategy in the future.

Overall, these results indicate that considering both factors, i.e., both consumer satisfaction and profit considerations, is favorable from an organizational perspective. The choice of the strategy in our specific setting depends on the considered time horizon. More profit-oriented strategies profit from relatively high consumer trust in the beginning, but soon start to perform worse in terms of monetary value. Moreover, as trust can drop significantly when the focus on profitability is high, the danger exists that consumers will quite the service at some stage, an aspect which is not included in the model. Moreover, it may be difficult to re-establish trust after many negative experiences.

Figure 3 finally shows the effects when social media is considered. A parameter Δ is used in the simulation that determines the strength of the social influence, with smaller values of Δ meaning less influence. In Figure 3 (a), Δ is set to zero, which means no social influence, the figure is thus identical to Figure 2 (a). With increasing values of Δ, it can however be observed in Figures 3 (b) to (c) that social media influence can amplify the developments of trust in both directions, both positively and negatively. In both directions, the slope of the curves become steeper in the initial phases when Δ is increased. Overall, these results confirm the importance of considering social media and word-of-mouth effects for trust-building in e-commerce.

While the simulations lead to important insights and allow to study longitudinal effects of various strategies, we have to be aware that simulations of this type can have a number of limitations. It is therefore of utmost importance to make all assumptions explicit that are made when modeling the agents' behavior and to provide clear justifications for various parameters and thresholds which influence the outcomes of the simulation.

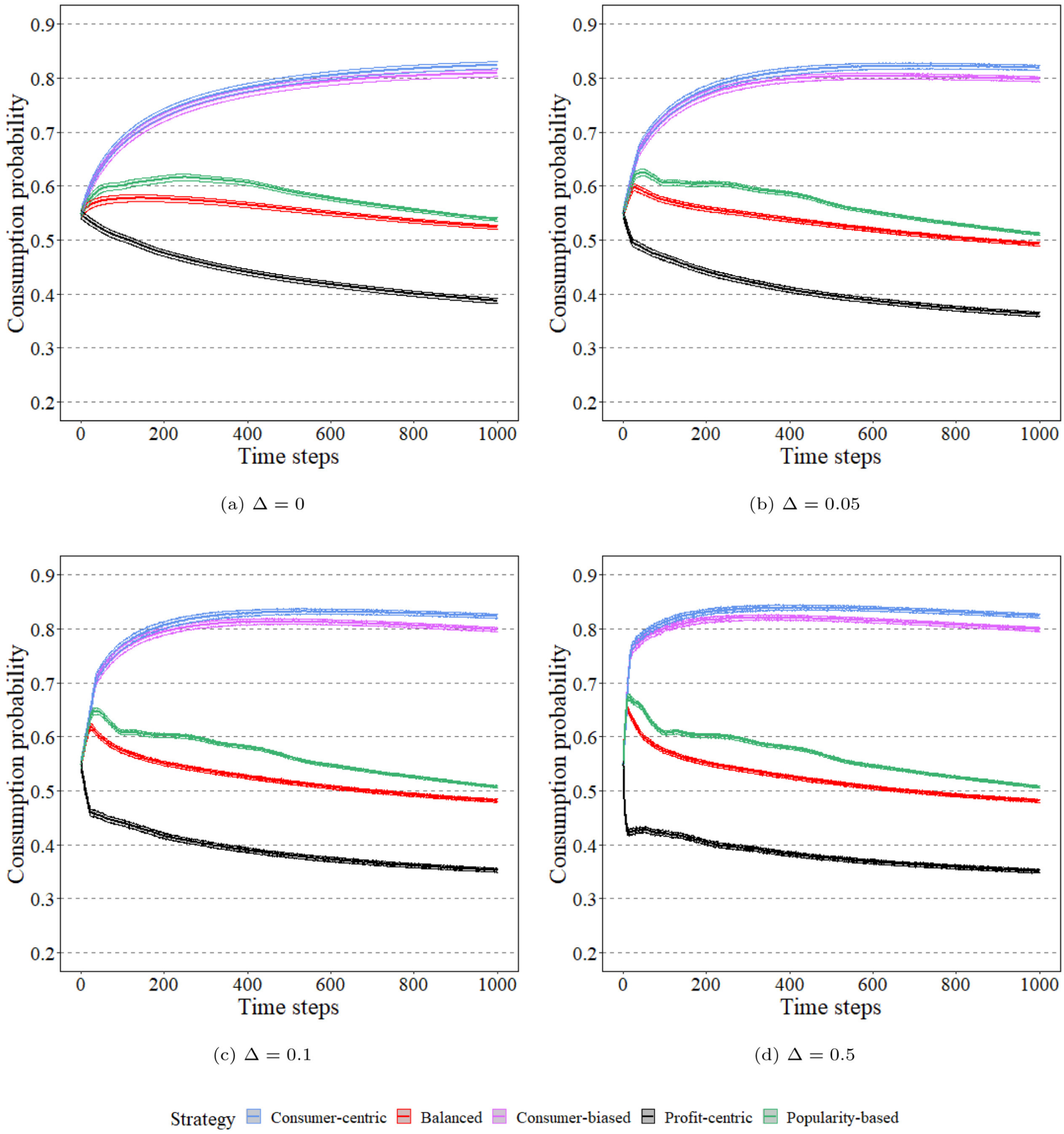

Figure 3: Effects on consumers' consumption probabilities with different levels of reliance on social media (Ghanem, Leitner, and Jannach 2022).
Source: https://doi.org/10.1016/j.elerap.2022.101195 under the CC BY license.

Overall, we also see the described simulation model mainly as a first step, and various extensions are possible. For example, simulations with more than one provider and consumers who can switch providers would be a natural next step to consider. In addition, it would be interesting to study effects when the catalog can be updated over time and when new consumers enter the simulation while others leave. Finally, experiments in other application domains and with real-world profitability data seem important in the future.

4 Conclusion

This chapter discussed the potential of agent-based modeling and simulation as a valuable methodology for e-commerce research and practice. Specifically, Sec. 2 provided a comprehensive overview of the applications of agent-based modeling and simulation in various contexts, including research on *(i)* consumer behavior, *(ii)* trust, loyalty, and service quality, *(iii)* recommender systems, *(iv)* social commerce and social perception, and *(v)* e-commerce and operations management. Building upon this overview, three promising avenues for future research were identified: Firstly, it was argued that in order to capture the full complexity of real-world e-commerce dynamics, agent-based modeling and simulation enables the examination of the emergence of network structures used for communication between customers and the diverse actors involved in e-commerce transactions. Secondly, it was proposed that analyzing the influence of individual actors' personality traits and cultural backgrounds could provide valuable insights into understanding the behavioral patterns exhibited in e-commerce. Lastly, it was emphasized that e-commerce policy decisions, such as marketing campaigns, recommendation algorithms, and website design, often exhibit longitudinal dynamics. In this regard, agent-based modeling and simulation emerged as an effective method for generating insights into the evolution and consequences of these dynamic processes.

In Sec. 3, we presented a remarkable illustration of agent-based modeling and simulation applied to research on recommender systems. This exemplary case study effectively harnesses the potential of agent-based modeling and simulation, as highlighted earlier in this chapter. Notably, the case study incorporates several essential aspects, and thereby it demonstrates the power and versatility of agent-based modeling and simulation in the context of recommender systems research: *(i)* It takes into account the heterogeneity among actors, acknowledging that consumers possess individual preferences and have the capacity to autonomously adapt their preferences over time. *(ii)* The case study considers the divergent objectives of both customers and the recommendation providers, recognizing that their motivations may differ. *(iii)* Furthermore, the study goes beyond a mere short-term perspective and delves into the longitudinal dynamics that arise from various stylized recommendation strategies, providing insights into the evolution of recommendation dynamics over time.

In conclusion, it is important to highlight that the application of agent-based modeling and simulation in e-commerce research and practice continues to evolve. To facilitate this progress, it is important to prioritize interdisciplinary collaboration, leveraging perspectives from various scientific disciplines to gain comprehensive insights into the intricate dynamics of e-commerce. This collaborative effort should involve researchers from diverse fields, including business and management, information systems and informatics, psychology, and beyond. By fostering these interdisciplinary partnerships, we can effectively harness collective expertise and insights, preparing the way for enhanced understanding and utilization of agent-based modeling and simulation in e-commerce research and practice.

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