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ORIGINAL PAPER

An agent-based simulation of customer multi-channel choice behavior

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Abstract Experimenting with multi-channel operations in reality is both costly and risky, because it can severely affect a firm's revenues, profitability, customer churn, and other customer metrics. In this paper, we introduce an agent-based simulation approach as a means for exploring and analyzing the impact of (combinations of) multi-channel activities on customer channel choices before having implemented them in practice. The simulation takes into account the heterogeneity of customers, social dynamics in their behavior, and the various phases of the purchasing process. To this end, customers are represented by agents whose phase-specific channel perceptions determine their channel choices. These perceptions may be altered by communication with other agents, first-hand experience of the channel, and/or marketing activities. The approach is illustrated through a sample application for which data from an international multi-channel retailer as well as from an empirical study among Austrian customers have been used.

Keywords Agent-based simulation · Marketing · Multi-channel choice

1 Introduction

With the prevalence of the Internet, most firms have supplemented their traditional channels (i.e., shops, catalogs, etc.) with a web channel as an efficient and effective

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means to reach customers (Geyskens et al. 2002). Today, the web channel is considered an integrative part of companies' multi-channel strategies (Grewal et al. 2004) and, more often than not, further channels (e.g., mobile channels) have been established as well. As a consequence, many customers prefer to use more than one channel across the different phases of the purchasing process. These multi-channel customers can be described as "combining various channels and approaches, searching online to buy offline, searching offline to buy online—and everything in between" (Wind and Mahajan 2002, p. 65) and companies strive to attract them because they constitute a particularly valuable market segment (Kumar and Venkatesan 2005; Thomas and Sullivan 2005; Neslin et al. 2006; Ansari et al. 2008). Multi-channel operations accordingly play a major role in firms' attempts to gain and retain customers. However, corresponding measures may have critical consequences with effects on a firm's revenues, profitability, customer churn, and other customer metrics which is why firms cannot simply test alternative scenarios in reality.

We therefore have developed an agent-based simulation of customer multi-channel choice behavior that allows for (1) virtually experimenting with different settings for which empirical data is not available since firms have not actually implemented these scenarios (yet) as well as (2) better analyzing the social dynamics in multi-channel customer behavior. While the first issue is "just" of high practical concern, the latter also is of interest for researchers in this field.

Our approach is, to the best of our knowledge, the first instance of implementing an agent-based simulation for this purpose. The underlying mathematical model in particular is unique in that it (1) pays attention to all phases of the purchasing process relevant for channel choice, (2) considers customers with their individual characteristics and attitudes toward channels, and (3) incorporates social interaction and its influence on individual channel choice behavior. The simulation is integrated in a decision support tool that makes it possible to simulate the impact of various marketing activities such as channel design activities, promotional activities, and integration activities on customer channel choice. Its applicability is demonstrated by means of a sample application with data from an international multi-channel retailer.

The remainder of this paper is structured as follows: Firstly, we provide background information on multi-channel choice behavior and outline shortcomings in traditional approaches that have motivated our work (Sect. 2). Then, we introduce a novel agent-based simulation model (Sect. 3), briefly describe its software implementation in a simulation tool (Sect. 4), and discuss exemplary results from four sets of simulation runs (Sect. 5). The paper concludes with a summary as well as with suggestions for further research (Sect. 6).

2 Background

As multi-channel management has risen in importance, customer channel choice behavior has increasingly been identified as a relevant topic for research (Devlin and Yeung 2003; Keen et al. 2004; Coelho and Easingwood 2005; Rangaswamy and Bruggen 2002; Neslin et al. 2006; Verhoef et al. 2007). Most studies, however, have focused on the design and management of channels rather than on customer channel choice behavior and factors determining channel choice and, thus, *neglect the impact of customer attitudes toward channels* (cf. Berman and Thelen 2004; Kumar and Venkatesan 2005; Wang et al. 2006; Albesa 2007).

Although the customers' decision-making processes can be strongly influenced by social interactions, marketing models usually do not directly address the social dynamics among customers. To this end, agent-based simulations come into play, because they are particularly well suited for representing these *interactions between customers* (Macy and Willer 2002; Garcia 2005; Bakken 2007). A general discussion of simulation approaches and how they can contribute to theory development is provided by Borshchev and Filippov (2004) and Davis et al. (2007). Notably the modern agent-based simulation approach has received considerable attention in the research of social behavior. In such a simulation, relevant stakeholders (e.g., customers) are represented as independent "agents" with individual (i.e., heterogenous) needs and preferences. These agents show individual behavior, learn from other agents and/or through first-hand experiences and they correspondingly adapt their (channel choice) behavior over time. While the agents act on the basis of their limited (local) information at the micro-level (e.g., in a purchasing event), the resulting emergent behavior of the system (i.e., the market) can also be observed and analyzed at the macro-level. Applying an agent-based simulation approach thus allows for capturing complex structures and dynamics even without a priori knowledge about the exact "functionality" of the overall system.

Most previous research also does not account for the fact that customers pass through *different phases across the purchasing process*, although strengths and weaknesses of channels typically vary in these phases. In the context of multi-channel management, companies have to take into account differing customer needs and behavior in various situations during the purchasing process (Nicholson et al. 2002; Soopramanien and Robertson 2007). Studies so far have mostly focused on the search and purchase phases (e.g., Verhoef et al. 2007), but have neglected the delivery and after-sales phases (Konuş et al. 2008).

Only some studies analyze the impact of *communication activities* (e.g., catalog or e-mail marketing) on channel selection (e.g., Thomas and Sullivan 2005; Ansari et al. 2008). To our knowledge, no previous study has taken into consideration the impact of channel design activities and integration activities on multi-channel customer behavior.

The simulation tool introduced in this paper enables a managerial decision-maker to analyze and compare the *impact of marketing activities on individual customer channel choice* and resulting emergent behavior patterns and, thus, provides support in planning and evaluating marketing strategies before making costly investments in integration activities such as introducing store pickup. Simulating the impact of marketing activities on customer channel choice behavior can also be a useful supplement to the traditional analysis of data from, for instance, a loyalty program that captures information on the preferences, characteristics, and purchasing behavior of individual customers (Hansotia and Rukstales 2002; Ganesh 2004; Kumar et al. 2006).

3 The agent-based model

3.1 Framework

In our model framework (see Fig. 1 for an overview), customers are represented by N agents who are embedded in a social network in which communication between them takes place. Their perceptions of channels are influenced by these communication events as well as by personal experiences and/or marketing activities to which they are exposed to.

Customer agents may either enter a purchasing process, talk to other customer agents, or stay inactive. When in a purchasing process they may pass through four *phases* referring to (1) search, (2) transaction, (3) delivery, and (4) (optional) return. In each phase an agent decides for one of the available *channels* based on individual preferences and the performance of the channels with respect to *attributes* such as channel convenience, security, cost avoidance, accessibility, and (service) quality. Note that in our sample application the customers' decisions are limited to the brick-and-mortar store and the web channel; however, it is straightforward to add further channels for other applications. After having chosen a particular channel in the search phase,

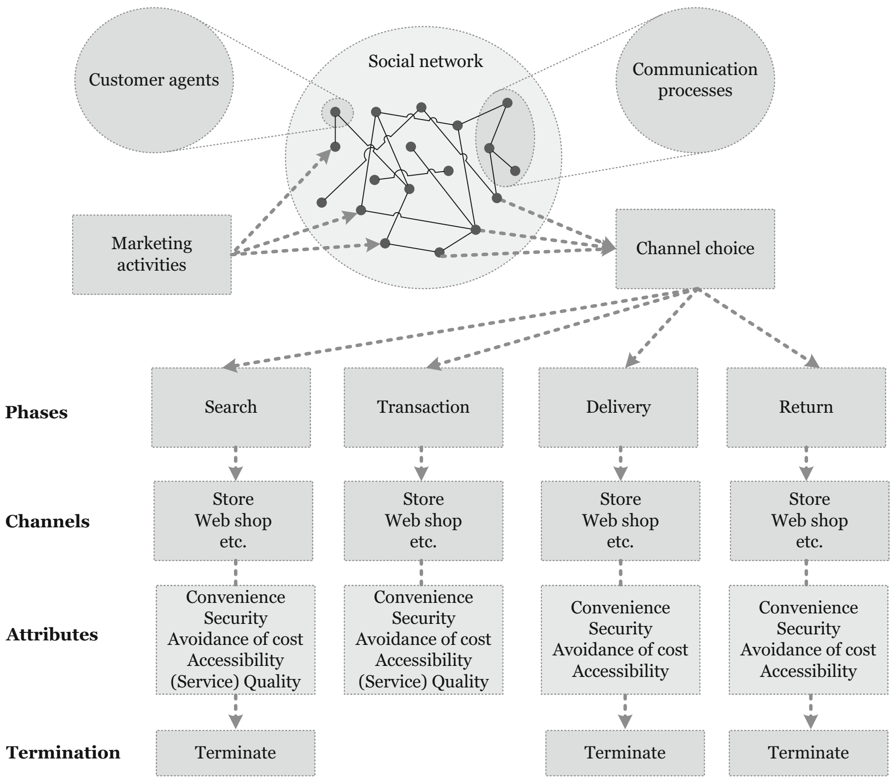

Fig. 1 Model framework

the customer agent might immediately *terminate the purchasing process*. Reasons for termination could be, for example, that she did not find the proper product, or that she had a disappointing experience when using the channel (e.g., because of low-quality service). After having purchased a product (i.e., paid and received the product), the customer agent can terminate the purchasing process also after the delivery phase if she is satisfied with the product. While technically feasible, it is obvious that customer agents would not terminate after the transaction phase, because it can be assumed that they want products they have paid for to be delivered. If a customer agent is not satisfied with the product, however, she may return the product; naturally, this phase always marks the end of the purchasing process.

In each phase of the purchasing process, a customer agent gains first-hand experience about the chosen channel. Moreover, an agent can communicate with peers in the social network and learn from their notions, or the agent is exposed to information provided through a marketing measure. All these events may have an influence on the agent's multi-channel behavior in future.

On a general note, it should be pointed out that the model's features described in the following are grounded in literature, but not all of them necessarily play a major role in each application. In such cases, some features can be disabled.

3.2 Customer agents

In our model, customers follow an individual behavior pattern that determines the probabilities of entering the purchasing process, communicating about channel experiences, or staying inactive. Over the course of a simulated business year, these probabilities may vary in order to reflect sales peaks (e.g., the Christmas season). Customer agents i may or may not be aware of the existence of channel k in phase p which is indicated by binary variables b_{ipkt}. If they are not aware of a channel in time t (i.e., $b_{ipkt} = 0$) this may change later on, but not vice versa (i.e., forgetting about a channel is not implemented). Agents also carry phase-specific and multi-dimensional information on the perceived channel (attitude) values a_{ipkht} with index h referring to a particular channel attribute (e.g., convenience, security, or cost avoidance). The attitudes may be influenced by exposure to a company's marketing campaigns (cf. Sect. 3.3), communication with others in the social network (cf. Sect. 3.4), and/or first-hand experiences with a channel (cf. Sect. 3.5). The perceived channel values can also be understood as a customer's expectation of a channel value (Oliver 1980), which will play a role in modeling disappointment as a result of first-hand channel experience.

Furthermore, each agent is equipped with phase- and attribute-specific individual preference weights $w_{iph} \in [0, 1]$ that indicate the importance that a customer i attaches to attribute h in phase p. Note that preferences may vary considerably among customers (following, e.g., Burke 2002; Laukkanen 2007).

3.3 Marketing activities

The marketing activities implemented in the simulation tool so far can be roughly divided into three groups, namely, channel design activities, promotional activities, and integration activities. Decision-makers, who strive for additional information on the effectiveness of potential campaigns, can freely combine them in a simulation scenario, in which the chosen activities will be carried out in the scheduled time periods.

Channel design activities allow for changing attribute performance values for a specific channel. For instance, a retailer could train sales personnel in customer service in order to increase in-store service quality in the search phase. Such channel design activities affect a customer agent's perceived channel value once she uses a certain channel which leads to an adjustment of her perceived channel value as a result of personal first-hand experience.

Promotional activities trigger the distribution of information on phase-specific channel attribute performance. An example could be a TV commercial on a web shop's convenience. These activities may vary with respect to the message communicated through the activity (i.e., which attribute is addressed), the stochastic variable determining the number of agents that are actually reached, and/or the timing of the promotional activities. Concerning the latter, they may be active in a given time period, in a given number of succeeding periods starting with a designated time period, or in several waves, for which the beginning and the length of each wave can be defined separately. Irrespective of their design, promotional activities can either create general awareness for the existence of a channel (i.e., affect variables b_{ipkt}) or increase a customer agent's perceived channel values a_{ipkht}.

Integration activities help to create an integrated multi-channel environment that enables customer agents to switch between channels across the phases of the purchasing process independently from their preceding channel choice (e.g., a customer can buy a product online and then pick it up in the store). Currently, such channel switching opportunities are still rather limited in most firms (Wakolbinger and Stummer 2013).

3.4 Interpersonal communication

In setting up the customers' social network, we have opted for the well-established small-world network structure (Watts and Strogatz 1998). It provides small diameters, i.e., the average path length between two nodes is low, and shows high clustering. Accordingly, the resulting social network contains several hubs, i.e., some agents have a high number of connections. A similar network has already been used by Delre et al. (2007) and many others and it is considered a good representation of reality (Barabási and Bonabeau 1999); for a recent overview on various interaction topologies cf. Kiesling et al. (2012). We also have performed a (limited) sensitivity analysis for network parameters p (probability) and D (neighboring nodes) and it turned out that results remain fairly robust.

Within the network, edges between customers are non-directional, since communication typically takes place bi-directionally. Each edge has a weight v_{ijt} representing the strength of the relationship between two agents i and j. It is assumed that edges between customer agents have the same weight for both directions, i.e., customer agent i talks to customer agent j with the same probability as vice versa. Communication events are triggered by agents according to their communication behavior pattern. When they *decide to communicate*, potential partners are selected by drawing a random number. If it is lower or equal than the weight v_{ijt} of an edge to an interconnected other agent, the communication event takes place. Note that edge weights increase with every communication event by a factor ζ in order to reflect the dynamics of social relationships (Burgess and Huston 1979). On the other hand, if agents have not talked to each other for a long time, an edge decay factor φ reduces the probability that these agents will communicate with each other in future.

After having identified a communication partner, agents *choose a communication topic*, i.e., the attribute-specific performance for a particular channel such as the service quality in the company's brick-and-mortar store when returning a product. Since people normally prefer to talk about extreme experiences, agents primarily learn from others' extreme perceived channel values. Taking into consideration this behavior, the lowest and the highest perceived attribute-specific and phase-specific channel values of the two agents are selected as topics for the conversation.

Communication between agents *affects their perceived channel values*, since information from the communication partner j is added to the information pool of agent i and vice versa. The information traded represents the mean value over all (weighted) pieces of information an agent has recorded earlier. Thus, information received from the peers affects information that is passed on to (other) peers later on. When adding new information to an agent's information pool, the new information is weighted higher than previous information, i.e., it is multiplied by a factor $(1 + \vartheta)^t$, which reflects memory decay over time.

For the time being, we have not considered trustworthiness of communication partners. Furthermore, it has not been accounted for effects that relate to the amount and diverseness of information received so far, although it is reasonable that additional information being consistent with prior information will reduce a customers uncertainty in choosing the "best" channel (cf., e.g., Graf and Six 2014). Such additional information may also increase the agent's assurance concerning the properness of her information pool which may positively affect her confidence when talking to other customer agents and, thus, may relate to higher credibility of this information. Corresponding extensions of the model will be interesting topics for further research.

The impact of promotional activities on a customer's perceived channel value is modeled analogously to the update process in interpersonal communication. Information received by means of an advertising event, however, will in general be weighted lower than information received in the course of interpersonal communication because of the different effectiveness of personal and impersonal communication (Rogers 2003). Still there is a link between marketing activities and interpersonal communication since low-weighted marketing activities also alter attitudes toward channels and thus may trigger high-weighted interpersonal communication.

3.5 Channel choice and first-hand experience

Channel choice constitutes the most prominent decision event in this simulation. For this purpose, a customer agent i determines the utility u_{ipkt} of the (available) channels alternatives with respect to (1) the perceived performance a_{ipkht} of channel k's various attributes h in purchasing phase p and simulation period t and (2) the agent's preferences w_{iph} for these attributes. In the absence of any indication requiring a different form, we have opted for a classical additive utility function. An alternative would have been, for example, to use some heuristic procedure that takes into consideration just the two (or three) attributes having assigned the highest weights and to dismiss all other attributes (following, e.g., Gigerenzer and Gaissmaier 2011). A sensitivity analysis has shown, however, that deviations in overall results are limited (although we have noticed a number of diverging decisions on the individual agent level). This has encouraged us to stick with the traditional form

$$u_{ipkt} = b_{ipkt} \cdot y_{plkt} \cdot \left(\sum_h a_{ipkht} \cdot w_{iph} \right) + \epsilon_{ipt} \quad (1)$$

for which the binary variable b_{ipkt} describes channel awareness and binary parameter y_{plkt} indicates the opportunity to switch between two channels across the phases of the purchasing process with l being the channel that was chosen in the preceding phase $p-1$ and k referring to the channel under consideration (for $p = 1$ the following rule applies: $y_{plkt} = 1$ if at time t channel k is available in the search phase and $y_{plkt} = 0$ otherwise). Remember that channel switching may not be allowed in all phases of the purchasing process. The stochastic error term ϵ_{ipt}, finally, represents further factors that may play some role, but have not been explicitly considered.

Obviously, a customer agent chooses the channel with the highest utility value and enters this channel with her expectations concerning the channel attributes. In doing so, the agent makes a first-hand experience, i.e., gets a subjective impression of the actual ('true') channel performance values $a^{\star}_{pkht}$, which results in an update of the agent's perceived channel values in an analogous way to the information update for communication or promotional events but with a considerably higher weight. First-hand experience thus not only has a major influence on an individual agent's notion of specific channels and her future multi-channel choice behavior, it will also spread in the social network through word-of-mouth communication. If a customer's experience is disappointing (i.e., $a_{ipkht} \ll a^{\star}_{pkht}$ for attributes with high preference weights w_{iph}), she might also decide to terminate the purchasing process. For the latter, we have introduced an individual frustration tolerance level (following ideas by Strebel et al. 2004).

4 Implementation issues

The simulation tool has been coded in the object-oriented programming language Java. It consists of three modules. The *scenario generator* allows for setting global parameters (e.g., network parameters), agent parameterization (e.g., with respect to the agents' individual purchasing behavior), initialization of performance values for the channels, and specification of marketing activities (e.g., with respect to channel design, promotions, and/or integration) in a given scenario. The *simulation module* forms the core of the tool and performs the simulation. The *analyzer module*, finally, provides measures for evaluating and interpreting the simulation output (e.g., number of channel switchers or number of terminating customers). It consists of a MySQL database and an application to generate graphs from the data.

The above processes are supported by several libraries. Most prominently MASON,[1] a multi-agent simulation toolkit, has been used for implementing the simulation model. Furthermore, routines from the Colt[2] project, an open source library for high performance scientific and technical computing, are used during the simulation runs, and the JUNG[3] framework has been used for implementing the social network.

5 Sample application

The agent-based simulation introduced in the preceding sections has been applied as part of an industry-funded research contract for an international multi-channel retailer from the luxury goods market. The company representatives approved of the results and have been satisfied with overall project outcomes. Nevertheless, we are not allowed to name the company, because it has enacted very strict general rules concerning information to the public.

In the following, Sect. 5.1 gives an overview on general parameters set for the sample application and Sects. 5.2–5.5 provide corresponding results for four scenarios with various marketing activities. Such measures may increase/decrease the performance (i.e., attributes) of one of the channels, apply activities promoting a particular channel, or implement a specific integration activity that enables customers to switch between channels.

It should be noted that the agent-based simulation tool described in the preceding sections has been developed as a rather generic approach in the course of a basic research project and, in particular, has not been tailored to the specific application case at hand. Some of the model's features therefore do not make much of a difference for the simulation outcome in this case, but may play a more distinct role in other cases.

5.1 Parameterization

Parameters for the sample application came from three different sources, namely, (1) an empirical study among customers, (2) parameter sets used in previous agent-based simulations, and (3) sales data and other case-specific information from the company for which the simulation has been performed. Whenever data on specific parameters were missing and could not be gathered directly, we asked our industry partner for reasonable assumptions and also performed sensitivity analyses for these parameters to check whether corresponding variances in simulation results remain within acceptable boundaries.

1 http://cs.gmu.edu/~eclab/projects/mason/.

2 http://dst.lbl.gov/ACSSoftware/colt/.

3 http://jung.sourceforge.net/.

The most important data source for parameterizing customer behavior patterns was an empirical study among 300 customers on the Austrian market. The study was carried out by a professional market research institute that runs an online-access panel with a large pool of respondents. In order to gain a representative sample for our case study, the common quota sampling procedure was used. Quotes were imposed on gender, following our industry partner's distribution of their customers' gender, as well as on geographical position, for which quotes were built in relation to the number of inhabitants of each federal state of Austria. All respondents had to be familiar with the company and at least one of its distribution channels. Therefore we have excluded all prospective participants who had not purchased products of the company within the past 12 months. As incentive for participation subjects received credit points from the market research company for fully completing the questionnaire. These points can either be converted into a shopping voucher or donated to a non-profit organization.

The questionnaire had five parts. Part A contained demographic questions that were primarily used for quota sampling. Part B consisted of several conditional questions on whether a respondent is aware of the brick-and-mortar store and/or the web channel in the different phases of the purchasing process. Responses were used for the initial settings for the awareness variables b_{ipkt}. Part C inquired how often a respondent has actually used these channels for information search, product purchase, and product return. From these data, parameters for entering the purchasing processes and the termination rates were estimated. It turned out, for instance, that customers start a purchasing process by entering the search process approximately four times per year, but in about one out of three cases do not continue to the transaction phase (more often so when using the web shop). Obviously, this is an average number and customers are heterogeneous in their behavior which is why customer agents in our model are heterogenous as well. Next, respondents indicated how often they had purchased products during peak periods and they provided information on how often they had talked to others about their shopping experiences. This data was used to fine-tune the shopping behavior and for parameterizing edge weights v_{ijt} in the social network. In Part D of the questionnaire, customers provided information concerning the importance they attach to each channel attribute for the specific phase (e.g., "How important is the store's/web channel's service quality when you search for products?"). This data was used for the initialization of preference weights w_{iph}. Part E, finally, served to derive values for the customers' initial perceived channel values a_{ipkht}. If respondents stated that they have already used the channel in a specific phase they were asked to provide their actual evaluation ("How do you evaluate the convenience offered by the brick-and-mortar store when searching for products?"). Otherwise, we sought to capture their current perception of a channel's value ("How do you perceive the convenience offered by the brick-and-mortar store when searching for products?").

The above empirical data served as a means to initialize characteristics for the customer agents with respect to their individual purchasing patterns, their communication frequency, their initial perceived channel values, and a few less prominent parameters. Each of the respondents from our empirical study constituted an agent prototype. As the simulation in our sample application has been executed with 10,000 agents, prototypes were cloned with an appropriate multiplicity.

For the parameterization of the small-world network we also took into account settings from previous agent-based simulations on innovation diffusion on the Austrian market (cf. Kiesling et al. 2009; Günther et al. 2011). Correspondingly, the network was constructed with parameters $D = 4$ and $p = 0.2$, and the edge weight increase and decay factors were set to $\zeta = 0.1$ and $\varphi = 0.9$. Furthermore, we set the information decay parameter to $\vartheta = 0.01$. The error terms ϵ_{ipt} representing additional factors for the agents' channel switching decision were set to 0.10 for the search phase, 0.05 for the transaction phase, and 0.07 for both the delivery and the return phase, and kept constant over time. Sensitivity analyses for these parameters showed that results are sufficiently robust for this application case.

Our industry partner disclosed information on current multi-channel settings, assessments with respect to the actual channel attributes $a^{\star}_{pkht}$ (see Table 1), the sales distribution in the course of a calendar year, and various statistics concerning characteristics of its customers. Management also supported this work by helping us with calibrating parameters for the baseline scenario (representing the firm's status quo) and providing us with expert feedback with respect to results gained from other scenarios.

Apparently, the brick-and-mortar store shows a slightly better performance for channel service quality and security in the search phase while the web channel performs better in convenience and has a slight advantage with respect to cost avoidance. For the transaction phase, the brick-and-mortar store is characterized by higher performance values for quality and security, whereas the web channel has advantages in convenience and cost avoidance. In the delivery phase, the web channel shows a higher performance than the brick-and-mortar store for the attribute convenience, but cost avoidance is better for the brick-and-mortar store. The store also excels in the attribute security. For the return phase, the performance values are equal to those of the delivery phase. Note that 'quality' as a separate channel attribute is not taken into account in the latter

Table 1 Rounded (initial) channel attribute performance values $a^{\star}_{pkht}$

Phases	Attributes	Store ($k = 1$)	Web ($k = 2$)
Search ($p = 1$)	Convenience ($h = 1$)	0.6	0.8
	Security ($h = 2$)	0.9	0.8
	Cost avoidance ($h = 3$)	0.8	0.9
	Quality ($h = 4$)	0.8	0.7
Transaction ($p = 2$)	Convenience ($h = 1$)	0.6	0.7
	Security ($h = 2$)	0.9	0.7
	Cost avoidance ($h = 3$)	0.7	0.8
	Quality ($h = 4$)	0.8	0.7
Delivery ($p = 3$)	Convenience ($h = 1$)	0.5	0.7
	Security ($h = 2$)	0.9	0.5
	Cost avoidance ($h = 3$)	0.9	0.7
Return ($p = 4$)	Convenience ($h = 1$)	0.5	0.7
	Security ($h = 2$)	0.9	0.5
	Cost avoidance ($h = 3$)	0.9	0.7

two phases since it primarily refers to service (i.e., assistance) which does not play a role for delivery and return.

The simulation horizon was $T = 156$ periods, with each period representing 1 week. Thus, the simulation covers 3 years which corresponds with the planning horizon of our industry partner and, from a technical point of view, also reasonably limits the runtime for the simulation. Peak seasons were set for Valentine's Day (3 weeks), Mother's Day (3 weeks), and Christmas (5 weeks).

Each scenario was repeated 100 times, and results were averaged over all repetitions. Simulation runs for the industry project were performed on a dedicated simulation server with a Dual Core Xeon 3 GHz processor and lasted several hours to complete a scenario. Since runtime has not been an issue, this was acceptable. On a server with a more modern processor completion time will be less than one hour.

5.2 Baseline scenario without marketing activities

In the baseline scenario, no marketing activities are performed. Also, it is only possible to switch channels between the search and the transaction phase, i.e., parameters y_{plkt} are set to 1 only for $p = \{1, 2\}$ and, of course, if $l = k$, which occurs when the purchasing process is continued in the same channel.

Channel choices in the search phase and the transaction phase of the baseline scenario are visualized in Fig. 2. Note that the fluctuations at the beginning of the simulation run are due to the simulation's stabilization phase. They can be attributed to discrepancies between the initial channel perceptions measured in the empirical study and the actual channel performance values specified by our industry partners. Consequently, customer agents need to adjust their perceived channel values to correspond to their first-hand channel experiences. Once the perceived values have approximated the actual performance values, the curves become considerably smoother. For practical applications, attention should therefore always be paid to the trend indicated by the channels' usage over time.

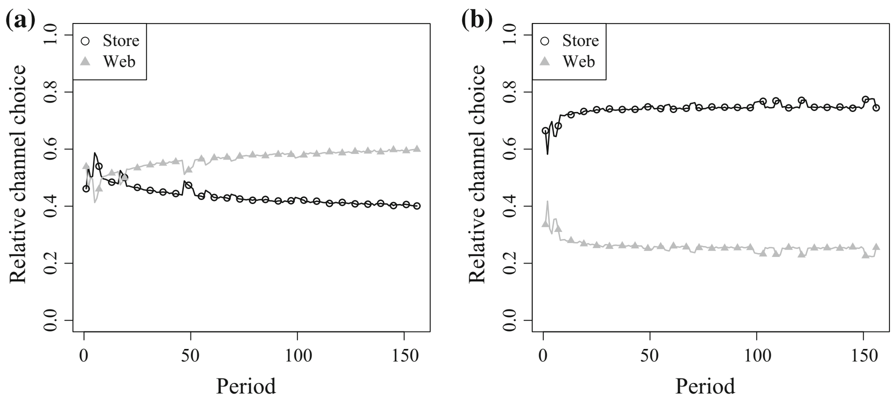

Fig. 2 Channel choice for the first two phases in the baseline scenario. **a** Search phase in baseline scenario. **b** Transaction phase in baseline scenario

Obviously, the web channel plays a dominant role in the *search phase* (see Fig. 2a). At the beginning of the search phase, about the same number of agents decide for the brick-and-mortar channel and for the web channel, respectively. Customers who choose the web channel then experience it first-hand and (some) realize its advantages, which leads to a higher share of (their) web channel usage for product search over time. The growing share of the web channel is also reinforced by personal communication.

In the *transaction phase*, on the other hand, the store is clearly preferred and stabilizes at a level of about 75 % (see Fig. 2b). No termination of the purchasing process occurs at the transition from the transaction to the delivery phase since customers naturally take their products with them or want to have them delivered.

As channel switching has not been allowed for the *delivery phase*, channel choice behavior pattern remains the same as in the preceding phase. This also holds for the *return phase* that anyway does not play a significant role in our application case, because only few customers actually return their products.

With respect to channel switching of agents, nearly all multi-channel agents have switched from the web shop in the search phase to the brick-and-mortar store in the transaction phase. This trend could have been expected from everyday experience since it is more likely in a traditional setting with no channel-integration activities applied that users who search in the web switch to the store for actually purchasing than the other way round. Such a search-purchase behavior is also in line with findings of Verhoef et al. (2007).

For the calibration of the baseline scenario we have been able to use real company data. This, however, has limited us to just the two channels that have existed in this company, while the simulation model would have allowed for further channels as well.

5.3 Scenarios with channel design activities

In the baseline scenario the brick-and-mortar store was performing slightly better in channel quality and security, but did not offer as much convenience as the web shop for the search phase. In the following, the impact of modifying attribute-specific performance values on channel choice is illustrated by applying channel design activities that increase the performance of the brick-and-mortar store's channel service quality in the search phase from 0.8 to $a^{\star}_{1,1,4,t} = 1.0$ (with indices $p = 1$ referring to the search phase, $k = 1$ referring to the store channel, and $h = 4$ referring to the fourth attribute 'quality'). An example of such a channel design activity could be a workshop for sales personnel in customer service and friendliness. The channel design activity can be scheduled for any point in time during the simulation which will be demonstrated by means of three alternative scenarios. In the first scenario the channel design activity is active from the beginning of the simulation run (i.e., $a^{\star}_{1,1,4,t\geq 1} = 1.0$), whereas in the second scenario it starts in the middle ($a^{\star}_{1,1,4,t\geq 78} = 1.0$). The third scenario comes with an increase of channel quality at the beginning coupled with a decrease in channel quality to the original performance level of 0.8 in the middle (i.e., $a^{\star}_{1,1,4,t<78} = 1.0$ and $a^{\star}_{1,1,4,t\geq 78} = 0.8$). A reason for such a decrease could be a reduction of sales personnel due to budget restrictions. Figure 3 provides an overview over simulation

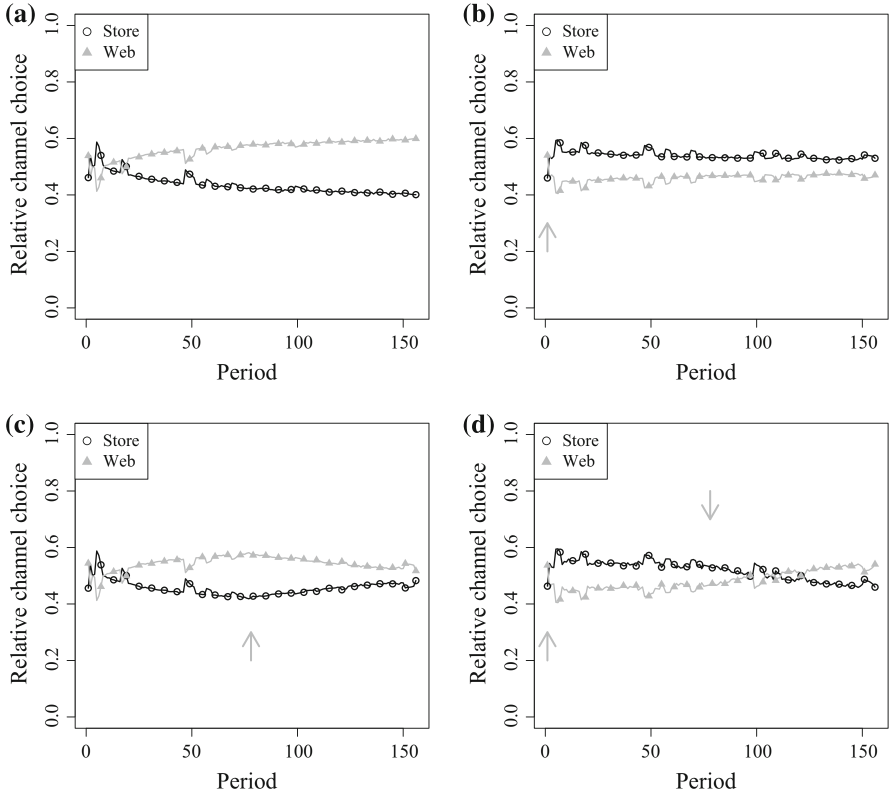

Fig. 3 Channel choice for the search phase after channel design activities have increased the store's quality for this phase. **a** Baseline. **b** Increase of store's quality at $t = 1$. **c** Increase of store's quality at $t = 78$. **d** Increase of store's quality at $t = 1$ and decrease at $t = 78$

results; arrows mark the points in time in which the channel design activities have become active.

Recall that in the search phase of the baseline scenario customers learn from others about the advantages of the web shop which results in a rise in perceived channel value and, accordingly, in the usage share (see Fig. 3a that is just a copy of Fig. 2a). When increasing the store's quality performance from 0.8 to 1.0 at $t = 1$, the usage share of the store increases and becomes even higher than for the web channel (see Fig. 3b). However, a slow convergence of channel usage can be observed over the simulation run. This effect might be caused by agents talking with others who have a high perceived value of the web channel, thus countervailing the effect of the marketing activity favoring the store.

Alternatively, an increase of the store's quality just at time $t = 78$ still counteracts the increase of web shop usage and leads to a convergence of the channel usage shares over time (see Fig. 3c). Noteworthy is also that the effect does not occur right at the time when the marketing activity becomes active but about ten periods later, because information on the store's enhanced performance needs some time to reach customers who had a low initial perceived channel value of the store or who in the past have lowered their perceived channel value due to negative first-hand experiences in it.

In the third sub-scenario, being depicted in Fig. 3d, a reversal of channel usage shares takes place after decreasing the channel value for the second half of the simulation run. Once again there is a delay of this effect as the activity's impact becomes particularly noticeable in peak periods in which more customers enter the purchasing process.

5.4 Scenario with an integration activity

In the baseline setting, in which no integration activity has been applied, about 25 % of agents have preferred the web channel in the transaction phase (see Fig. 4a). Since it has not been possible to switch channels between the transaction and the succeeding delivery phase in this initial scenario, these customer agents also had to collect purchased products through the web channel (i.e., products have been sent to them by mail). The scenario at hand investigates effects of implementing an integration activity.

Firstly, agents who have purchased the product online are enabled to pick up these products in the stores if they wish. Technically, this is achieved by setting binary parameter $y_{3,2,1,t\geq 1} = 1$ (with $p = 3$ referring to the delivery phase, $l = 2$ referring to the web channel in the preceding purchasing phase, $k = 1$ referring to the store being eligible in this situation as well). Simulation results indicate that the share of the brick-and-mortar store in the transaction phase then increases from the initial 75 % to about 90 % (see Fig. 4b) with remarkable high numbers of channel switchers using the store pickup during peak periods.

Alternatively, we also simulated the effects of a home delivery service for customer agents who purchase their products in the store (i.e., setting $y_{3,1,2,t\geq 1} = 1$). This integration activity turns out to not attract many customers as long as it is not coupled with further measures. Some agents tried the service at the beginning of the simulation run, but most of them did not use it again, presumably so, because of the higher delivery costs. The relative channel choice accordingly does not deviate significantly from the scenario without this integration activity.

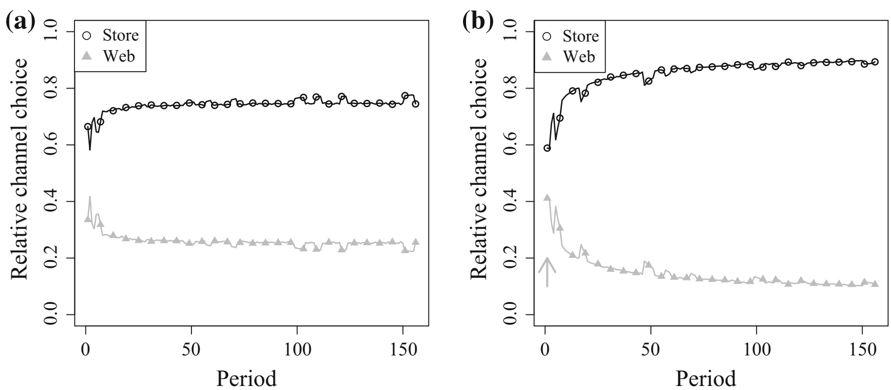

Fig. 4 Channel choice for the transaction phase after establishing a store pickup service. **a** Baseline. **b** Integration measure at $t = 1$

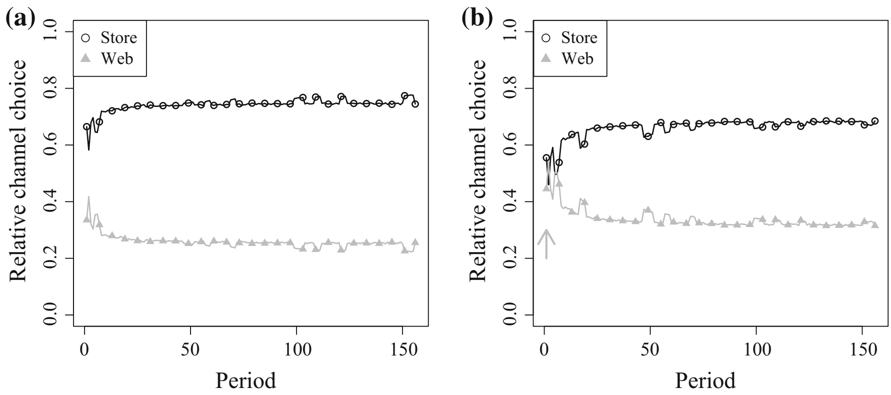

Fig. 5 Channel choice after establishing home delivery service coupled with an increase in the web shop's cost avoidance for the delivery phase and with promotional activities. **a** Baseline. **b** Combined activities at $t = 1$

5.5 Scenario with combined activities

In the final scenario, the above-mentioned (and quite unsuccessful) home delivery service that allows for sending bulky or expensive products purchased in the store to a home or office address is coupled with a channel design activity that increases the web channel's cost avoidance for delivery from 0.7 to 0.9 (i.e., $a^{\star}_{3,2,3,t\geq 1} = 0.9$). Moreover, a promotional activity is launched throughout the first 30 periods of the simulation horizon that reaches 50 % of the customer agents, of whom 20 % actively pay attention. While the store still remains the preferred channel for delivery, the combined activities have increased the share of web channel usage for the delivery phase from about 25 % in the baseline scenario (see Fig. 5a) to about 32 % (see Fig. 5b).

6 Conclusion

Analyzing customer channel choice behavior is a necessity for managing an integrated multi-channel retail environment. The agent-based simulation model introduced in this paper addresses this issue. Its structure and dynamics have been designed with respect to findings from previous studies and/or are based on data from an empirical study as well as on input from the management of an international multi-channel retailer. From a modeling perspective, our approach extends the current state-of-the-art in three ways: it takes into account different phases of the purchasing process, it models customers as individuals with particular channel perceptions, and it lets customers interact with each other in a social network. The mathematical model has been implemented in a software tool that is capable of simulating the impact of a mix of marketing activities on multi-channel choice behavior across the different phases of the purchasing process. Applying the simulation tool thus can support managerial decision-makers in learning about social dynamics in multi-channel customer behavior. It also provides them with means for inexpensively simulating the outcome of applying various types of marketing activities, stand-alone or in combinations, which—by enriching it with internal data on the costs of these activities—allows for a thorough cost-benefit analysis before large investments have to be actually made.

The model still could be extended in several ways. For instance, it does not cover *spill-over effects between phases* (cf. Verhoef et al. 2007). These effects may be particulary relevant for the transition between the return phase and the search phase (i.e., the beginning of a new purchasing process), since, for example, customers might not enter another search process if they were disappointed by long delivery times. Furthermore, disappointment could also lead customers to use channels of close competitors. This behavior is not taken into account for the application case at hand, because customers are assumed to be rather loyal, but it could play an important role in other applications. Next, when generalizing the model for a variety of applications we need to consider *additional factors* that moderate the purchasing process (e.g., product category or customer expertise; cf. Alba and Hutchinson 1987; Balasubramanian et al. 2005) and/or the communication process (e.g., trustworthiness or events that trigger additional communication). Then, a *spatial model* could be incorporated that explicitly takes into consideration geographical positions of customers and shops based on geographical information system (GIS) data. Spatial factors can also be considered when initializing the underlying social network by locating customers according to their actual place of residence. Access to brick-and-mortar stores can thus be calculated based on the Euclidean distance between the customer's and the shop's geographical position. This also would allow for testing the impact of geographically-targeted marketing activities on customer behavior (e.g., Günther et al. 2011). From a decision theoretical point of view, finally, it also would be worthwhile to more closely address research questions concerning the identification of the appropriate set of channel-selection criteria (for a discussion cf. Keeney 2013) and/or alternative methods for utility elicitation as well as for measuring risk attitudes toward the use of specific channels (cf., e.g., Löhndorf et al. 2014).

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