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Consumer Product Search and Purchasing Behavior in Social Shopping Communities — A Clickstream Analysis

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Preface of the Authors

The advent of Web 2.0 is rapidly moving the online landscape into a consumer-driven era. Social shopping communities (SSC) emerge as a new business model, evolving from a linkage of social networking and online shopping. Apart from search features in shopbots, e.g., category and price, SSC additionally offer user-generated features. These include ratings, recommendation lists, styles (i.e., assortments arranged by users), tags, and user profiles. Purchases can be made by following a link to an online shop ('click-out'). SSC are experiencing very high growth-rates in the number of members and visitors, e.g., *Polyvore* attracts more than six million unique visitors per month. Thus, this business model has received considerable venture capital in recent years, e.g., *ThisNext* with nearly $9 million.

Social networking + online shopping = social shopping

SSC: an emerging business model

Against this background, it is of increasing business significance to monitor and observe what consumers do in the context of SSC and to analyze how their behavior can be predicted and influenced. This is the first study analyzing consumer purchasing behavior in SSC based on clickstream data. We analyze nearly 3 million visiting sessions from a leading SSC focussing on the product categories fashion, living, and lifestyle. For each session, the pages viewed and the viewing duration of the pages are recorded. Our data spans six months from May 1, 2009 to October 31, 2009.

The study fills in a research gap

Database: 3 million sessions

We found that the trait 'log-in' (i.e., the visitor is logged-in within a given session) exerts a strong positive effect on the likelihood of a click-out. This key finding implies that logged-in visitors may be more profitable than ordinary visitors. The view time has also a strong positive effect, while the average view time per page has a negative effect. The more direct-search mechanisms and, interestingly, the more lists and styles are used, the less likely the visitor is to make a click-out. Increasing transaction costs and information overload could be potential reasons. Hence, the commonly held view that visitors of social shopping channels rely heavily on every kind of user-generated features when conducting a click-out, is not supported. However, the more tags are used and the higher the overall rating for products as well as shops, the higher the likelihood of a click-out.

Empirical results show importance of community and indicate rational considerations of consumers

Hagen, January 2011

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Overview of the research results

I.   *Social media have become an important source of information and communication for consumers. Social media such as (micro-)blogs, forums, sharing platforms, and particularly social networking communities provide consumers with many methods of creating and sharing user-generated content. In the area of e-commerce, this results in a linkage of online shopping and social networking, initiating a new form of e-commerce: social shopping (Chapter 1.).*

II.   *The business model of SSC is emerging. SSC connect consumers and provide various forms of user-generated recommendations, so as to initiate or simplify purchase decisions. The business model has several advantages over traditional e-commerce business models, e.g., online shops. SSC profit from their decentral orientation, interactivity, and trustworthiness of user-generated content (Chapter 2.).*

III.   *Clickstream research in marketing is still in its infancy. Studies in the research stream of online consumer behavior with clickstream data can be divided into three categories: (1) website usage and navigation, (2) advertising on the internet, and (3) online shopping and e-commerce. Our study affects all categories (Chapter 3.).*

IV.   *Our empirical results show that user behavior is consistent with rational considerations involving time constraints and cost-benefit trade-offs. The more direct-search features that are used within a session, the lower the probability of a click-out. Moreover, consumer focus on functional aspects and goal-directedness is also confirmed by our result that a high average view time per page correlates negative with a click-out.*

     Furthermore, this study enhances the research field of user-generated content and purchase conversion. The logit regression analysis indicates a strong impact of user-generated social-shopping features on purchase conversion – both negative and positive. While ratings and tags have a positive impact, lists and styles have a negative effect on the likelihood of a click-out. Consumer reactance, information overload, and high transaction costs could be potential explanations. In general, the monetization of UGC is a challenge for website operators. As our results show, it seems to be the same for operators of SSC. Nevertheless, lists and styles could be regarded as an important website design element that stimulate browsing and inspiration, as well as enhancing trust. Hence, lists and styles could lead to positive long-term effects on the click-out rate (Section 5.1.).

V.   *There are several implications for an operator. First of all, enhancing community-building is crucial. Paying attention to members' behavior and developing tools to increase their loyalty may be a prudent tactic.*

With regard to the cost-benefit perspective, an operator should provide effective search tools to visitors. Due to the fact that ratings and tags positively correlate with a click-out, an operator should animate visitors to rate and tag products, as well as shops. Lists and styles are novel features that are used to enhance the 'stickiness' of a site, stimulate browsing, and enhancing inspiration. To avoid reactance and information overload, as well as to stimulate the usage of social-shopping features, an operator should explain the concept of a SSC, particularly novel features.

Moreover, we found that a frequent usage of the home page exerts a strong negative impact on a click-out. Providing relevant information, search tools, and support on the home page could lead to more orientation and stimulate the visitor to continue searching. Furthermore, we found that a high average view time per product detail site correlates positively with a click-out. This indicates that consumers intensively check all the information given there. Therefore, an operator should provide detailed transactional information on product detail sites (Section 5.2.).

VI.   *Online retailers as well as manufacturers with their own online shop should be aware of the emergence of new shopping channels in Web 2.0. They must integrate this development into their marketing strategy. SSC could be one important component. Online retailers and manufacturers should animate consumers to rate and tag their shops and products. Lists and styles are an innovative marketing tool, too. Stimulating consumers to create lists and styles with specific manufacturers' products could lead to a high degree of awareness. For example, some apparel brands are already experimenting in SSC, e.g., by conducting a contest. Such a contest could also be used as a forecasting-tool. Moreover, online retailers could license the SSC technology for use on their own websites.*

Last but not least, we found that the direct-search filter mechanism for price correlates positively with a click-out. Thus, shop managers should take this into account and develop appropriately specific pricing strategies (Section 5.3.).

VII.   *Despite our original findings, some research questions remain open. It would be useful to investigate the behavior of registered users in greater detail. Furthermore, the integration of demographic profiles and revenue, the investigation of further product groups, the integration of actions in participating online shops and social networks, and applying further data mining methodologies could enhance the research in the fast emerging area of social shopping channels (Chapter 6.).*

1. Web 2.0 and User-generated Content as Origin of Social Shopping

Parallel to the increasing importance of the internet as a shopping channel,[1] the advent of Web 2.0 is rapidly moving the online landscape into a consumer-driven era.[2] Web 2.0 provides consumers with many methods of creating and sharing user-generated content (UGC).[3] Social media such as (micro-)blogs, chat rooms, message boards, social networking communities have become an important source of information and communication and continue to grow rapidly.[4] In particular, consumers increasingly exchange information in their personal social network communities, such as *facebook*.[5]

Web 2.0 leads to consumer-driven era

In the area of e-commerce, this results in a linkage of online shopping and social networking, initiating a new form of e-commerce, that of social shopping.[6] According to STEPHEN AND TOUBIA 2010, social shopping connects customers.[7] Therefore, various different user-generated product recommendations are provided in SSC, so as to initiate or simplify purchase decisions. SSC are experiencing very high growth-rates in the number of registered members and visitors. For example, USA-based *Polyvore* attracts more than six millions unique visitors per month.[8] Thus, this business model has received considerable venture capital in recent years,[9] e.g., *ThisNext* with nearly $9 million.[10]

Social shopping as a linkage of online shopping and social networking

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[1] Cf. e.g. HOLZWARTH/JANISZEWSKI/NEUMANN 2006; SU 2009.

[2] Cf. e.g. BUCKLIN/SISMEIRO 2009; DHAR/CHANG 2007; STEPHEN/TOUBIA 2010.

[3] Cf. e.g. GHOSE/IPEIROTIS 2009; O'REILLY/BATTELLE 2009.

[4] Cf. e.g. BUCKLIN/SISMEIRO 2009; NIELSEN MEDIA RESEARCH 2009.

[5] Cf. e.g. O'REILLY/BATTELLE 2009; OWYANG 2009; TRUSOV/BUCKLIN/PAUWELS 2009.

[6] Cf. e.g. DENNIS/MERRILEES/JAYAWARDHENA/WRIGHT 2009; TEDESCHI 2006.

[7] Cf. STEPHEN/TOUBIA 2010.

[8] Cf. MILLER 2010.

[9] Cf. e.g. TEDESCHI 2006.

[10] Cf. RAO 2010. Further popular SSC are, e.g., *Kaboodle* and *Stylehive*. In Germany, *edelight* and *smatch* are leading SSC. For recent developments and strategies of SSC see, for example, EXCITING COMMERCE 2010.

User-generated features in SSC

Apart from conventional direct-search features in search engines and shopbots, such as product category and price, social-shopping channels additionally offer several user-generated social-shopping features. These include user-provided product ratings, recommendation lists, styles (i.e., assortments arranged by users, who invite other users to browse their assortments), tags, and user profiles. For example, registered users can publish recommendation lists with their favorite products, gift ideas, desires, recommendations, and product ratings. In addition, product information can be merged and linked to comments and tags, price comparisons can be made, as well as purchases, by following a link to a participating online shop. The latter activity is referred to as a 'click-out'. These means of interpersonal information transmission through UGC represent an important component of SSC and can be regarded as a form of electronic word-of-mouth[11] (eWOM). Especially personal collages, called 'styles' or 'sets', are a popular mechanism. For example, the members of *Polyvore* have created more than twenty million sets and create more than 30,000 sets daily.[12] Thus, some popular brands are using styles to create a contest to increase brand awareness, e.g., *Nike* ("Create a set that showcases how sport is part of your life").[13] Both styles and recommendation lists can be embedded on blogs and easily shared in social networks. Thus, these functionalities enhance the reach in social media. In general, a decentralised orientation could be one of the most important success factors in e-commerce in the future.[14]

Enhancing awareness through 'styles'

Aim and originality of the study

Against this background, it is of increasing business significance to monitor and observe what consumers do in the context of SSC and to analyze how their behavior can be predicted and influenced. To the best of our knowledge, no prior study has analyzed the purchasing behavior in SSC with aid of clickstream data, especially the impact of social-shopping features in the form of lists, styles, and tags. Hence, our study entails the following, original research question:

What features and consumer traits are most significant for predicting consumer purchasing behavior within social shopping communities?

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[11]   Cf. e.g. PARK/LEE/HAN 2007.

[12]   Cf. POLYVORE 2010a.

[13]   Cf. POLYVORE 2010b.

[14]   Cf. e.g. PETERS/ALBERS/ASSELMANN/SCHÄFERS 2009; HOLSING/SCHÄFERS 2010.

Our research makes several contributions that are useful for researchers and practitioners, e.g., it provides researchers with new insights into consumer use of SSC and provides operators, online-retailers, and manufacturers with guide-lines on the design, management, and use of SSC. The remainder of this paper is structured as follows. In Section 2, the business model of SSC is introduced. The theoretical background and hypotheses are introduced in section 3. An overview of the data as well as key findings is presented in Section 4, and implications in Section 5. Finally, the limitations of our study and further research questions are discussed in Section 6.

Contributions of the study and research outline

2. Business Model 'Social Shopping Community' under Consideration

In general, business models are at heart stories that explain how an enterprise works. Business models describe, as a system, how the pieces of the system fit together.[15] Moreover, it can be defined as the methods and techniques employed by a firm to generate revenue and sustain its position in the value chain.[16] The term "business model" is perhaps one of the most discussed and least understood aspect of the web.[17] The term was most frequently but not only used in relationship with the Internet from the 1990s onwards.[18]

Developments in online user behavior have created many new business opportunities for electronic commerce.[19] There are an increasing number of e-commerce business models as more businesses choose the path of electronic commerce.[20] Generally, business models are essential because they could help in understanding the basics of specific businesses. The high level of uncertainty that prevails in the e-commerce business world is

Many new business opportunities for e-commerce

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[15]   Cf. e.g. MAGRETTA 2002.

[16]   Cf. e.g. JALOZIE/WEN/HUANG 2006.

[17]   Cf. e.g. RAPPA 2010.

[18]   Cf. e.g. OSTERWALDER/PIGNEUR/TUCCI 2005.

[19]   Cf. e.g. RAPPA 2010.

[20]   Cf. e.g. AMIT/ZOTT 2001. Recent developments in e-commerce are, e.g., facebook-commerce, grouponing, live shopping, shopping clubs, etc. Some of these developments are described in HOLSING/SCHÄFERS 2010.

another reason why companies involved in e-commerce should have a sound and stable business model in place.[21] There are many different definitions, but generally e-commerce business models include the value stream, the revenue stream and the logistical stream.[22] We are not interested in describing the innovative business model of SSC in detail. Therefore, we simply describe the SSC under consideration, e.g., how value is provided to the user and revenue is generated. We let a detailed discussion of each stream of the business model for future work.

Site under consideration focuses on fashion, living, and lifestyle

The site considered in this study (name undisclosed at the request of the operator) connects conventional direct-searching for products with several user-generated social-shopping features. The site focuses on the product categories of fashion, living, and lifestyle.

Figure 1 provides a general overview of the searching possibilities and user activities on a SSC.
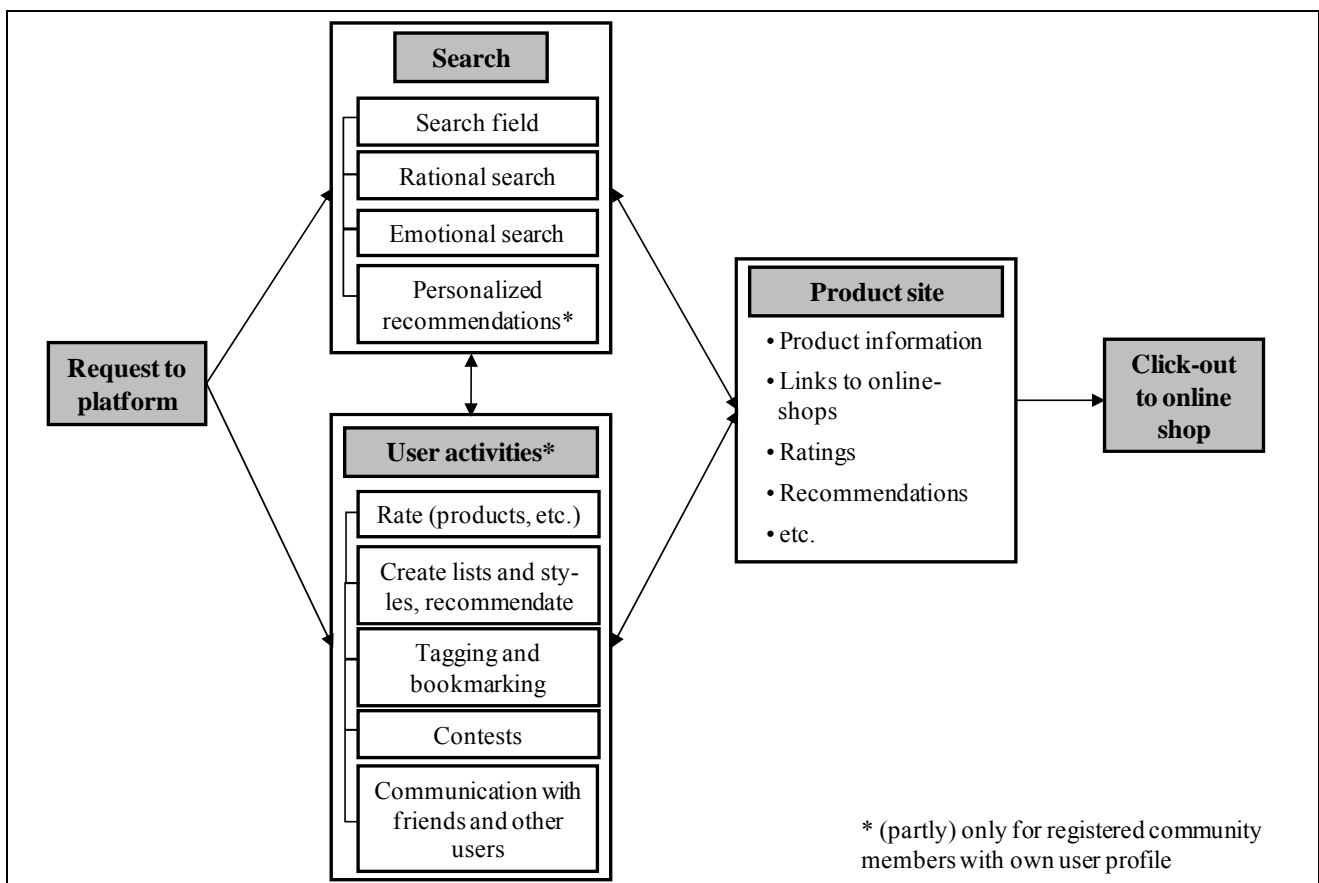

Figure 1: Possibilities of Searching and User Activities on SSC

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[21]   Cf. e.g. JALOZIE/WEN/HUANG 2006.

[22]   Cf. e.g. MAHADEVAN 2000.

There are several conventional direct-search features available to the visitor (see box "Search" in figure 1). One common feature is the search field in which the visitor can enter search key words, e.g., "black dress". Furthermore, the visitor can search by means of several direct-search filter criteria ("rational search"; see figure 1), such as product (sub-) category, gender, brand, price, and shop. Accordingly, the search results can be narrowed down considerably.

Direct-search features

There are many social-shopping features that a visitor can integrate into his search process ("emotional search"; see box "Search" in figure 1). For example, the visitor can look at recommendation lists. A recommendation list is created by a registered user, and contains various different products listed by the user. There are many reasons why a user may wish to create such list. The creator can use such lists as a wish list for his birthday, Christmas, or marriage presents and share this with friends (potential gift-givers). The wish lists at Amazon are a good example. Alternatively, such lists could be used to collect products that are simply of general interest or as recommendation for friends and other visitors.

Several social-shopping features

A so-called 'style' is a very new type of UGC that registered users create via a 'style-editor' (see also box "Activities" in figure 1). A style is an assortment arranged by registered users, who invite other users to browse their selection. A style contains several products all of which relate to a particular theme. Comparing this feature with the offline shopping world, a shop window is an appropriate parallel. A shop window displays products with a specific theme. For instance, at a fashion store, a mannequin is dressed in clothes with a particular style, perhaps boots, a dress, jacket, and accessories that match in terms of colors and the surrounding draperies. A style at our investigated SSC is comparable. Prior studies have shown that specific functionalities and interactive applications in online shopping environments could emulate consumer experiences with the bricks-and-mortar shopping.[23] In addition to the products a user can integrate, it is possible to insert pictures and colors as a background or to write comments. Styles and lists also appear in a users' profile and as tips for other visitors during their search process. Thus, styles can be regarded as user-generated

Creating own styles via 'style-editor'

Parallels of styles and shop windows in bricks-and-mortar

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[23]   C.f. e.g. MACAULAY/KEELING/MCGOLDRICK/DAFOULAS/KALAITZAKIS/KEELING 2007; MANDEL/JOHNSON 2002.

product recommendations that enhance e-interactivity.[24]

<div style="margin-left: auto; text-align: right;">Tagging</div>

Tagging is another type of UGC.[25] In SSC, user-generated tags are assigned to products, brands, shops etc. Visitors can use tags within the search process, by clicking on a tag and searching through the resulting products.

Social networking

The site also offers social networking features, such as user profiles in which a user can publish personal information, e.g., photos and a self-description. Furthermore, a user can show his favorite brands and shops and label these with a tag. Other users can leave a message in a guestbook within the profile site. User profiles are a familiar and popular feature, but a profile site is not directly relevant to a search.

Ratings for products and shops

Ratings are another familiar and important feature. On this site, registered users can rate a product on a 5-star scale. Furthermore, ratings for shops are also shown to visitors.

Detailed information on product detail sites

On a product-detail site, the user obtains detailed information on a specific product. The user can see the product price, picture, rating, tags from other users, and information about the online shops that sell the product, e.g., shop name and rating. Purchases can be made by following a link to a participating online shop. The latter activity is referred to as a 'click-out'. The operator of a SSC receives a fee from the participating online shops for each click-out. This is identical to the revenue model of shopbots.[26]

Only registered users may create user-generated content and interact directly with other users. Except for the information on whether a visitor is logged in or not, we do not have any personalized data on website visitors that could be merged with our clickstream data (see also section 6.1. for corresponding limitations).

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[24]　C.f. e.g. DENNIS/MERRILEES/JAYAWARDHENA/WRIGHT 2009; KIM/FORSYTHE 2009.

[25]　C.f. e.g. GOLDER/HUBERMAN 2006.

[26]　C.f. e.g. SMITH/BRYNJOLFSSON 2001.

3. Literature Review and Hypotheses Development

3.1. Clickstream Research in Marketing

The term "clickstream" denotes the recording of user actions while browsing through one or more websites. Clickstream data is used in various research fields, e.g., informatics, sociology, and marketing. Clickstream data typically contain information about, besides others, the date and time of request, the type of browser used, the previous URL (Uniform Resource Locator) visited, and other specific variables (e.g., prices, ratings, keywords).[27] There are several common clickstream data formats (e.g., Common Logfile Format (CLF), Combined Logfile Format (DLF), and Extended Logfile Format (ELF)), but there is yet no definition of what exactly will be contained in such a dataset.[28] In our study, we use a specific clickstream data format.

Clickstream data record a user's activities while navigating the Web

Several formats of clickstream data

Within the research field of online consumer behavior, clickstream studies can be categorized into three broad categories: (1) website usage and navigation, (2) advertising on the internet, and (3) online shopping and e-commerce.[29] One has to take into account that these categories could overlap in some cases. Figure 2 gives an overview of the three categories.

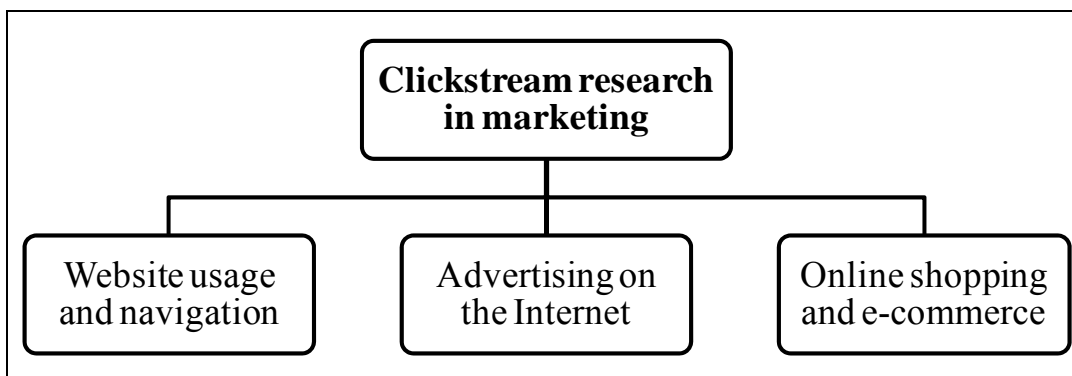*Three categories of clickstream studies in marketing research*

Figure 2: Categorization of Clickstream Research in Marketing

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[27] Cf. e.g. BUCKLIN/SISMEIRO 2009.

[28] For a graphical example of the DLF standard of the National Center for Supercomputing Applications (NCSA) see OLBRICH/SCHULTZ 2008.

[29] Cf. e.g. BUCKLIN/SISMEIRO 2009.

Website usage and navigation The category of *website usage and navigation* can be divided into within-site[30] and across-site[31] studies. Studies focusing on within-site behavior focus on single visits, multiple visits or visits of both types.[32] In our study, we use single visits. These "site-centric" data provide data from a single website. They can provide very detailed information on visitors' actions on a specific website. However, they lack the information regarding activities on other websites as well as user-specific information, e.g., demographics.

Across-site studies generally use data from providers of syndicated Internet panel data[33]. User-centric panel data contain the activities of users on all websites visited as well as demographic profiles. Nevertheless, panel data also suffer from several problems, e.g., sampling problems.[34] Particularly, the high sample size of within-site data is one major advantage. Because we are interested in detailed information about the page content and specific user activities, we use site-centric data.[35]

Advertising on the Internet *Advertising on the Internet* is another important research stream. Online marketing activities are becoming more and more popular and expenditures for internet advertising are growing fast. Therefore, analyzing, for example, the effectiveness of banner ads as well as paid search are research topics. With the advent of Web 2.0, research in the area of word-of-mouth and user-generated content has also become a fast growing area of interest.

Online shopping and e-commerce Within the category of *online shopping and e-commerce*, the research stream of understanding and predicting user behavior and purchase conversion is one of the most active areas. Furthermore, the understanding of auctions[36] as well as shopbots[37] is of great interest.

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[30] C.f. e.g. CHATTERJEE/HOFFMAN/NOVAK 2003; DANAHER/MULLARKEY/ESSEGAIER 2006; MOE 2006; MOE 2003; MONTGOMERY ET AL. 2004; SISMEIRO/BUCKLIN 2004.

[31] C.f. e.g. HUANG/LURIE/MITRA 2009; JOHNSON/MOE/FADER/BELLMAN/LOHSE 2004; PARK/FADER 2004.

[32] C.f. e.g. BUCKLIN/SISMEIRO 2003; MOE/FADER 2004a; MOE/FADER 2004b.

[33] Providers are, for example, comScore, GfK WebScope, and Nielsen NetRatings.

[34] C.f. e.g. BUCKLIN/SISMEIRO 2009.

[35] Another possibility to collect clickstream data are experimental settings, in which the activities of study participants are recorded in laboratory settings or in the field.

[36] C.f. e.g. RESNICK/ZECKHAUSER 2001; SPANN/SKIERA/SCHÄFERS 2004.

In our study, we affect all three categories: we use within-site data for understanding and predicting the impact of user-generated content as well as conventional direct-search features on consumer behavior. In the following three chapters, we discuss several studies within the three categories in greater detail.

This study affects all three categories

3.2. Impact of Virtual Community Affiliation on Purchasing Behavior

Social shopping is about connecting consumers[38] and shopping together, e.g., recommending products and being inspired by the community. Therefore, a SSC is a 'virtual community of consumption', which is defined as a community that centers consumption-related interests.[39] Thus, the existence of a community could be regarded as a core element of social shopping. Previous research shows that consumers have several different motivations to participate in communities, e.g., belonging, entertainment, and prestige.[40] In general, resources offered by virtual communities can foster shopping needs-satisfaction.[41] For example, consumers can exchange opinions on company products and help each other with specific problems, which may lead to a more personal shopping experience[42]. The sharing of reviews of products and giving advice can increase trust, thus reducing perceived risk when purchasing online[43]. Despite this research, academic research has nothing to offer about the impact of community affiliation on purchasing behavior in SSC. We expect that logged-in visitors, i.e., registered community members, are very familiar with internet usage and experienced in online shopping. Hence, we expect registered members to

SSC: virtual community of consumption

Community foster shopping needs-satisfaction and reduces perceived risk

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[37]   C.f. e.g. SMITH/BRYNJOLFSSON 2001.

[38]   C.f. e.g. STEPHEN/TOUBIA 2010.

[39]   C.f. KOZINETS 1999.

[40]   C.f. e.g. ANDREWS/PREECE/TUROFF 2002; BAGOZZI/DHOLAKIA 2002; FLAVIAN/ GUINALIU 2005; ROTHERMAEL/SUGIYAMA 2001; WANG/WANG/FARN 2009; YANG/TANG 2005.

[41]   C.f. e.g. MACAULAY/KEELING/MCGOLDRICK/DAFOULAS/KALAITZAKIS/KEELING 2007.

[42]   C.f. e.g. FLAVIAN/GUINALIU 2005.

[43]   C.f. e.g. FLAVIAN/GUINALIU 2005; YANG/TANG 2005.

visit the SSC regularly to communicate, search, and purchase. This is in line with VAN DEN POEL AND BUCKINX 2005, who assumed registered clients to be among the most active ones.[44] Within the research stream of purchase conversion, MOE AND FADER 2004a and 2004b introduce stochastic models.[45] They show that the more often people visit a retail site, the more likely to buy. Thus, they predict conversion as a function of prior browsing behavior. Although our data does not measure repeat visits explicitly, because of data privacy concerns of the operator, we assume, that logged-in visitors are repeat visitors. Therefore, we expect logged-in visitors to have a higher probability of conversion, i.e., conducting a click-out, than non-logged-in visitors. Thus,

Hypothesis 1:

The trait of log-in will increase the likelihood of a click-out.

3.3.   Online Consumer Search Behavior and Purchase Conversion

Measuring conversion rates has become crucial

In general, measuring and managing website key performance metrics, such as the number of visitors, view time, and conversion rates, has become crucial to website managers.[46] Conversion rates in the online shopping environment are not limited only to purchases and may also entail signing up for a newsletter, generating leads, or, as in our study, a click-out. An understanding of what influences these metrics of success and how to improve them is thus of great interest to researchers and website managers.[47]

Across-site and within-site studies

Generally, studies in the research stream devoted to the analysis of browsing and purchasing behavior with clickstream data can be divided into across-site[48] and within-site[49] studies (see also section 2.1.). Studies

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[44]   C.f. VAN DEN POEL/BUCKINX 2005.

[45]   C.f. MOE/FADER 2004a and 2004b.

[46]   C.f. e.g. AYANSO/YOOGALINGAM 2009; BUCKLIN/SISMEIRO 2009; MOE/FADER 2004a.

[47]   C.f. e.g. BUCKLIN/SISMEIRO 2009.

[48]   C.f. e.g. HUANG/LURIE/MITRA 2009; JOHNSON/MOE/FADER/BELLMAN/LOHSE

focusing on within-site behavior focus on single visits, multiple visits or visits of both types.[50] In our study, we use single visits. There are several research directions, including information search and usage[51], consumer motives to continue browsing[52], identifying consumers' goals[53], investigating online decision-making processes[54], and identifying consumers with a high purchase probability[55].

Different research directions

These studies focus on several different types of websites, e.g., automotive website[56], retailer of nutritional products[57], or book shop[58]. Furthermore, the data volume is quite different. For example, within the sub-category of within-site studies, BUCKLIN AND SISMEIRO 2003 analyze 6,630 sessions, while MOE 2006 uses 300 sessions. Within the category of across-site studies, PARK AND CHUNG 2009 comprise 1,190 sessions, while DANAHER et al. 2006 analyze 23,264 sessions. These differences rely on varying research questions. For example, if a researcher is particularly interested in purchases, sessions without a purchase are eliminated from analysis. Furthermore, researchers depend on firm's willingness and ability to provide meaningful data.

Different types of websites

Data volume is quite different

Overall, this research stream is still in its infancy. As stated above, the studies focus on different research questions, different types of websites, and the data volume is often quite limited. Therefore, our study fills in a research gap. No other study has yet analyzed the purchasing in SSC. Moreover, one advantage of our study is the vast amount of data. In the following, we introduce our hypotheses regarding purchase conversion,

This study fills in a research gap

2004; PARK/FADER 2004.

[49]   C.f. e.g. CHATTERJEE/HOFFMAN/NOVAK 2003; DANAHER/MULLARKEY/ESSEGAIER 2006; HUANG/LURIE 2009; MOE 2006; MOE 2003; MONTGOMERY/LI/SRINIVA-SAN/LIECHTY 2004; SISMEIRO/BUCKLIN 2004.

[50]   C.f. e.g. BUCKLIN/SISMEIRO 2003, MOE/FADER 2004a, MOE/FADER 2004b.

[51]   C.f. e.g. MOE/FADER 2004a.

[52]   C.f. e.g. BUCKLIN/SISMEIRO 2003.

[53]   C.f. e.g. MOE/FADER 2004A, MOE/FADER 2004b.

[54]   C.f. e.g. SENECAL/KALCZYNSKI/NANTEL 2005.

[55]   C.f. e.g. MOE/FADER 2004b; MONTGOMERY/LI/SRINIVASAN/LIECHTY 2004.

[56]   C.f. BUCKLIN/SISMEIRO 2003.

[57]   C.f. MOE 2003 and 2006.

[58]   C.f. MONTGOMERY/LI/SRINIVASAN/LIECHTY 2004.

based on a broad literature review.

<div style="float:left; width:25%">Impact of involvement and view time</div>

Consumer involvement, i.e., personal relevance, has an important impact on information processing during searching and purchasing.[59] In general, involvement can be measured by the view time and number of products in the purchasing process.[60] View time is an important web-site performance metric and the research on factors affecting view time is quite limited.[61] PADMANABHAN, ZHENG, AND KIMBROUGH 2001 introduce the view time visitors spent at a specific website during one visit session.[62] The view time seems to be significant in their modeling approach and positively correlated with a potential purchase. Therefore, we expect a positive correlation between the view time and a click-out. Thus,

Hypothesis 2:

The view time will increase the likelihood of a click-out.

Goal-directedness and exploratory search

The goal-directedness of a search is another important factor affecting purchasing behavior. JANISZEWSKI 1998 classifies consumer search behavior in goal-directed and exploratory search.[63] Goal-directed searchers have a specific or planned purchase in mind. Therefore, the search patterns of these consumers focus on making a purchase decision.[64] In contrast, exploratory search is less focused and no purchase is planned. In this context, MOE 2003 used the content of the pages viewed to make distinctions between the purchase likelihood of consumers.[65] She found that visitors can be divided into four types of browsing behavior: directed buying, search/deliberation, hedonic browsers, and knowledge building. With respect to our study, the cluster of hedonic browsing is of particular interest. The visitors in this cluster seek new "stimuli", thus enhancing impulse buying. Styles and recommendation lists may serve as such a kind of stimulus. We expect that a high average view time per page is

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[59]   C.f. e.g. MOE 2003; WANG/FESENMAIER 2003.

[60]   C.f. e.g. ENGEL/BLACKWELL 1982.

[61]   C.f. e.g. BUCKLIN/SISMEIRO 2009; DANAHER/MULLARKEY/ESSEGAIER 2006.

[62]   C.f. PADMANABHAN/ZHENG/KIMBROUGH 2001.

[63]   C.f. JANISZEWSKI 1998.

[64]   C.f. JANISZEWSKI 1998; MOE 2003.

[65]   C.f. MOE 2003.

characteristic of hedonic visitors who like browsing, e.g., for relaxation purposes or as a moment-by-moment activity[66]. In this context, we assume that goal-directed consumers are more frequent shoppers, visit the SSC regularly and thus benefit from learning effects[67]. In contrast to hedonic visitors, we hypothesize that goal-directed visitors have a relatively low average view time per page (goal-directedness) and are thus more likely to conduct a click-out. Thus,

Hypothesis 3:

The average view time per page will decrease the likelihood of a click-out.

In general, goal-directed visitors plan to purchase a specific product. Therefore, they view more product-level than category-level pages.[68] We expect a high usage of product-detail sites to lower the likelihood of a click-out because of non-goal-directed search. Furthermore, we assume that goal-directed visitors intensively check the information given on a product-detail site, before conducting a click-out because of involvement. Thus,

Goal-directed visitors view more product-level pages

Hypothesis 4:

The number of product-detail sites will decrease the likelihood of on a click-out.

Hypothesis 5:

The average view time per product-detail site will increase the likelihood of a click-out.

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[66]   C.f. e.g. WANG/WANG/FARN 2009.

[67]   C.f. e.g. DENNIS/MERRILEES/JAYAWARDHENA/WRIGHT 2009; JOHNSON/BELLMAN/ LOHSE 2003. JOHNSON/BELLMAN/LOHSE 2003 show that visitors of a website spend less time per visiting session the more they visit the same website. BUCKLIN/SISMEIRO 2003 confirm their finding but show, at least for the case of a specific automotive website, that repeat visits lead to fewer pages viewed but do not affect the average view time per page.

[68]   C.f. e.g. MOE 2003.

Direct-search
features can
increase search
efficiency

Direct-search mechanisms could ease information processing and increase search efficiency.[69] Specifically, direct buyer and searchers[70] use these features to access the required information quickly. Because the search for information yields benefits, but also causes costs, consumers will not search endlessly for information.[71] In general, transaction-related activities are

Transaction costs

called transaction costs.[72] Such transaction costs as searching for information, negotiating, and ordering, play an important role in searching and purchasing, because consumers choose transactions that minimize their transaction costs.[73] If several filtering stages are needed to find the right product, transaction costs rise, i.e., high information costs measured in time. Therefore, high transaction costs could lead to a termination of the purchasing process. In this way, user purchasing behavior is rational, involving time constraints and cost-benefit trade-offs.[74]

Information
overload

Moreover, although the web is often regarded as useful in searching and reducing transaction costs,[75] it is often argued that the web and the vast amount of information can also lead to information overload.[76] Despite the high use of filtering features, it remains possible that consumers do not find the right product or are confronted with too much information. Therefore, consumers are overloaded with information and abandon the session because of confusion or frustration.[77]

Pre-purchase
deliberations

Furthermore, the goal of consumers may be to acquire information during their pre-purchase deliberations[78] and to form a set of products for consideration.[79] The actual purchase is planned for the next visit. This

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[69]   C.f. e.g. JAYAWARDHENA/WRIGHT 2009.

[70]   C.f. e.g. MOE 2003.

[71]   C.f. e.g. SU 2007.

[72]   C.f. e.g. WILLIAMSON 1985.

[73]   C.f. e.g. LIANG/HUANG 1998. For a detailed overview of transaction theory, see RINDFLEISCH/HEIDE 1997.

[74]   C.f. e.g. BUCKLIN/SISMEIRO 2009; LIANG/HUANG 1998.

[75]   C.f. e.g. ALBA/LYNCH/WEITZ/JANISZEWSKI/LUTZ/SAWYER/WOOD 1997; BAKOS 1996; LIANG/HUANG 1998; SU 2007.

[76]   C.f. e.g. CHEN/SHANG/KAO 2009; SU 2008.

[77]   C.f. e.g. CHEN/SHANG/KAO 2009; KALCZYNSKI/SENECAL/NANTEL 2006; SU 2008.

[78]   C.f. e.g. MOE 2003; WU/RANGASWAMY 2003.

[79]   C.f. e.g. ALBA/LYNCH/WEITZ/JANISZEWSKI/LUTZ/SAWYER/WOOD 1997.

could be a reason for the high usage of direct-search features. This assumption has also been confirmed indirectly by studies demonstrating that users who click relatively infrequently, search in a very goal-orientated manner and purchase relatively frequently.[80]

Summarizing the above mentioned assumptions, we expect a high usage of direct search features to lower the likelihood of a click-out. In our study, we analyze the following direct-search features: a) brand, b) category, c) search field, d) gender, e) price, f) sales, and g) shop. Thus,

Hypothesis 6a-g:

The number of each direct-search feature (a-g) will decrease the likelihood of a click-out.

In addition, we assume that a high usage of the home page site within a session could indicate information overload. The home page could serve as an orientation in situations of information overload. Therefore, we expect the number of home pages to correlate negatively with the probability of a click-out. Thus,

Home page as an orientation

Hypothesis 7:

The number of home pages will decrease the likelihood of a click-out.

3.4.   Impact of User-generated Content and Electronic Word-of-Mouth on Purchasing Behavior

Long before the days of the internet, consumers shared opinions about products with their family and friends through word-of-mouth.[81] Nowadays, the 'social media' enable consumers to extend their connections very substantially and conduct shopping in new ways.[82] Therefore, since the internet provides many opportunities for creating and sharing UGC, it

Internet stimulates research in the field of word-of-mouth

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80   C.f. e.g. PARK/LEE/HAN 2007.

81   C.f. e.g. KATZ/LAZARSFELD 1955.

82   C.f. e.g. GHOSE/IPEIROTIS 2009; STEPHEN/TOUBIA 2010.

has stimulated research in the field of eWOM communication.[83]

Analyzing
economic impact
of UGC on
performance
measures is in its
infancy

Despite the high value of UGC within the consumer information-seeking and purchase-decision process, the impact of UGC and eWOM on consumer behavior has only recently become the subject of research.[84] In particular, empirical studies on the influence of UGC on performance measures are few in number and an economic evaluation has yet to be conducted.[85]

Impact of Ratings

A large proportion of the studies in this area have investigated user-provided ratings and reviews. For example, LIU 2006 finds out that both negative and positive eWOM increase the box office revenues,[86] while CHEVALIER AND MAYZLIN 2006 find that online book reviews exert a positive impact on online book sales.[87] Therefore, we hypothesize that the overall average product rating, as well as the overall average shop rating, will have a positive impact on click-out behavior. Thus,

Hypothesis 8a:

The overall average product rating will increase the likelihood of a click-out.

Hypothesis 8b:

The overall average shop rating will increase the likelihood of a click-out.

Lists and styles as
new forms of
UGC

In general, UGC is being integrated steadily into e-commerce.[88] UGC is applied, with amongst others, the aim of serving as a sales assistant[89], to increase the purchase price and promote consumer confidence. Because UGC is faded in by the website provider and the contents can be varied, UGC can be considered as situational factor which potentially influences

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[83]   C.f. e.g. BUCKLIN/SISMEIRO 2009.

[84]   C.f. e.g. CHEVALIER/MAYZLIN 2006; DELLAROCAS/ZHANG/AWAD 2007; DHAR/ CHANG 2007; GODES/MAYZLIN 2004; TRUSOV/BUCKLIN/PAUWELS 2009; VILLA-NUEVA/YOO/HANSSENS 2008.

[85]   C.f. e.g. GHOSE/IPEIROTIS 2009.

[86]   C.f. LIU 2006.

[87]   C.f. CHEVALIER/MAYZLIN 2006.

[88]   C.f. e.g. BUCKLIN/SISMEIRO 2009; CHEUNG/LEE/RABJOHN 2008.

[89]   C.f. e.g. CHEN/XIE 2008.

consumer behavior. Fade-ins, particularly graphic ones, may, however, distract users from their originally intended searches.[90] Taking into account Elaboration Likelihood Model, PARK/CHUNG 2009 refer in this case to a peripheral route which distracts the user.[91] WANG/WANG/FARN 2009 mentions that the visual system takes effect when one is not conducting a goal-directed search.[92] Non-goal-directed searchers, using the peripheral route and UGC, may be hedonically motivated consumers,[93] enjoying the shopping process itself.[94] For non-goal-directed consumers, search choices are often intuitive and spontaneous. For such consumers, the satisfaction of needs unrelated to the product is the most important goal. Therefore, UGC is important for marketing managers wishing to attract these consumers and to gain competitive advantages.[95] Nonetheless, novel shopping features are also unlikely to be familiar at this point and may lead to adverse reactions on the part of some users, who feel overwhelmed or undesirably influenced by the provider. Such a reaction can occur particularly in the case of inexperienced online consumers. On the other hand, there are also experienced users who specifically want new functions. This behavior is called 'novelty seeking'.[96] We assume that most online consumers are not familiar with novel social-shopping features, so that most focus their attention on functional aspects of shopping motivation. Hence, we assume that UGC in the form of lists and styles lower the likelihood of a click-out. Thus,

Adverse reactions vs. novelty seeking

Hypothesis 9a:

The number of lists will decrease the likelihood of a click-out.

Hypothesis 9b:

The number of styles will decrease the likelihood of a click-out.

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[90] C.f. e.g. ALBA/LYNCH/WEITZ/JANISZEWSKI/LUTZ/SAWYER/WOOD 1997.

[91] C.f. PARK/CHUNG 2009.

[92] C.f. WANG/WANG/FARN 2009.

[93] C.f. e.g. ARNOLD/REYNOLDS 2003; JAYAWARDHENA/WRIGHT 2009; PARSONS 2002; VAZQUEZ/XU 2009.

[94] C.f. e.g. HOFFMAN/NOVAK 1996.

[95] C.f. e.g. PARSONS 2002.

[96] C.f. e.g. CHEN/SHANG/KAO 2009.

User-generated tags

Furthermore, collaborative tagging is a new form of UGC.[97] Tags are used to annotate different kinds of content, e.g., news, photos, and videos.[98] The collaborative tagging of products has also become very popular for consumers because consumers could benefit from effective sharing and organization of large amounts of information.[99] Therefore, tags could be useful in a goal-directed search for products and let consumers find what they are looking for. Thus,

Hypothesis 10:

The number of tags will increase the likelihood of a click-out.

User profiles for social activities

As stated above, user profiles are an important element of social networks as well as SSC. Therefore, we assume that user profiles are relevant for a specific fraction of the visitors. Of course, user profiles are not directly relevant to shopping, but aim to enhance connection and social activities. Thus,

Hypothesis 11:

The number of user profiles will decrease the likelihood of a click-out.

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[97]   C.f. e.g. GOLDER/HUBERMAN 2006.

[98]   C.f. e.g. GOLDER/HUBERMAN 2006; NOV/YE 2010.

[99]   C.f. e.g. CATTUTO/LORETO/PIETRONERO 2007.

4. Data Analysis and Modeling Approach

4.1. Clickstream Data Collection and Pre-Processing

Our study uses consumer clickstream data from a high-traffic SSC (name undisclosed at the request of the operator). In addition to the tracking of transactions, such as purchases or, in this case, click-out, clickstream data also facilitates tracking earlier consumer actions, such as browsing and searching. Using clickstream data confronts researchers with a number of difficulties.[100] Capturing the purchasing environment of consumers and the associated pre-processing of clickstream data is often something of a challenge, so that few studies in fact use such data. Particularly clickstream analysis in marketing research is in the early phase of its life cycle.[101]

Clickstream data still in its infancy in marketing research

Our data spans six months from May 1, 2009 to October 31, 2009. For each session, the pages viewed and the viewing duration of the pages are recorded. Visitor actions are also recorded, such as whether a user viewing a product-detail site or conducts a click-out to a participating online shop. Because we are interested in shopping-related visitor actions, sites that do not relate to shopping, e.g., the imprint or the job-offer page, are not included. Demographic information on registered users was not available. Several data pre-processing tasks are necessary in order to obtain a useful dataset. For this purpose, we use, amongst others, PHP and mySQL. In line with COOLEY 1999, requests from web crawlers and web spiders are eliminated.[102] The most important step in pre-processing the data is to link all data from different visitors and transform them into unique sessions.[103] The resulting user sessions are then transformed into an analytical base table. Because of the specific collection method, there are no missing values. Consistent with existing approaches, we removed single-page sessions from further analysis.[104] This is crucial, because sessions with only a one-page view do not constitute a real "browsing" session. After

Data base and pre-processing

Using PHP and mySQL

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[100] C.f. e.g. BUCKLIN/LATTIN/ANSARI/GUPTA/BELL/COUPEY/LITTLE/MELA/MONTGO-MERY/STECKEL 2002; MOE/FADER 2004a.

[101] C.f. e.g. BUCKLIN/SISMEIRO 2009.

[102] C.f. COOLEY/MOBASHER/SRIVASTAVA 1999.

[103] C.f. e.g. VAN DEN POEL/BUCKINX 2005.

[104] C.f. e.g. BUCKLIN/SISMEIRO 2003; MONTGOMERY/LI/SRINIVASAN/LIECHTY 2004.

these pre-processing steps, the overall number of sessions decreases from 7.842.591 to 2.951.198. We aggregate the page-level data to the session level, by using various different measures that we introduce below. Therefore, we describe the nature of visitor actions within each session. The data volume in our study is very high, in comparison with existing studies.[105]

4.2.   Session Measures

Characterizing
visiting sessionsThe aim of our study is to characterize sessions rather than the page-to-page decisions of a particular visitor, for example, by applying the methodology of "path analysis"[106]. Therefore, we use the page-to-page information to generate more general session-level measures that characterize the search and purchasing behavior of visitors. Hence, we develop five variable categories, which correspond to our hypotheses: general, search, social, rating, and transaction. Existing studies have already incorporated some of our presented predictors, e.g., view time[107], so as to examine the impact on purchase propensity. However, these studies considered only a relatively small selection of input variables. This present study adds several new input variables to those proposed in existing studies, particularly social-shopping features have never been conducted before. Furthermore, in contrast to most other in clickstream studies, ours takes the content of the pages into account. As VAN DEN POEL/BUCKINX 2005 found, detailed clickstream variables generate the best predictive performance.[108] We incorporate this by using detailed information on direct-search and social-shopping features. Figure 3 describes the session measures.

Five variable categories

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[105]   C.f. e.g. BUCKLIN/SISMEIRO 2009. See also section 3.3.

[106]   C.f. e.g. BUCKLIN/LATTIN/ANSARI/GUPTA/BELL/COUPEY/LITTLE/MELA/MONTGO-MERY/STECKEL 2002.

[107]   C.f. e.g. JOHNSON/BELLMAN/LOHSE 2004; MOE 2003.

[108]   C.f. VAN DEN POEL/BUCKINX 2005.

General session measures:

LOG_IN	Indicator variable for log-in of a visitor
PROD_VIEW	Total number of product-detail sites viewed
PROD_VIEW_TIME	Average view time per product-detail site in seconds
VIEW_TIME	Total view time in minutes
VIEW_TIME_AVG	Average view time per page in seconds
START	Total number of index sites viewed

Search session measures:

SEARCH_BRAND	Total number of usages of filter brand
SEARCH_CAT	Total number of usages of filter category
SEARCH_FIELD	Total number of usages of the search field
SEARCH_GENDER	Total number of usages of filter gender
SEARCH_PRICE	Total number of usages of filter price
SEARCH_SALES	Total number of usages of filter sales
SEARCH_SHOP	Total number of usages of filter shop

Ratings:

PROD_RATING	Average rating for all products viewed within a session
PROD_SHOP_RATING	Average rating for all top-tip shops viewed on a product detail site within a session

Social session measures:

LIST_VIEW	Total number of lists viewed
PROFILE_VIEW	Total number of profiles viewed
STYLE_VIEW	Total number of styles viewed
TAG_VIEW	Total number of usages of a user-generated tag

Transactional:

CLICK_OUT	Indicator variable for click-out to an online shop

Figure 3: Session Measures

The variable category *general* contains typical web-site metrics. The variable VIEW_TIME measures the total time in seconds spent on the site. VIEW_TIME_AVG measures the average time in seconds per page. The variable LOG_IN indicates whether a visitor is logged into the site by his user name and password. PROD_VIEW gives the total number of viewed product-detail sites during the session. The data lack by the fact that the actual number of different considered products cannot be recorded. It is not possible to determine whether, for example, accessing five product-detail sites entails five different products or fewer. PROD_VIEW_TIME is the average view time in seconds on product-detail sites. The variable HOME reveals how often the home page, i.e., the index site, is conducted.

Variable category general

Variable category
search

The *search*-category variables reflect the way a visitor uses conventional, direct-search features. SEARCH_CAT is the total number of pages that were result pages from filtering products via the product category filter (fashion, living, and lifestyle). Further direct-search measures are SEARCH_BRAND, SEARCH_GENDER, SEARCH_PRICE, SEARCH_ SALES, and SEARCH_SHOP, which count the use of the filters brand, gender, price, sales, and shop. The search field is another direct-search feature. The total number of uses of the search field is counted by the variable SEARCH_FIELD.

Variable category
ratings

User-generated *ratings* are an important website feature, e.g., product ratings. The ratings on this site are on a 5-star-scale, with 1 as the lowest and 5 as the highest value. We measure the average percentage of all products viewed by a visitor within a session, by the variable PROD_RATING. This variable ranges from 0% (no ratings) to 100% (all viewed products have a 5-star-rating). We do the same for the top-tip shops (shop at position one on a product-detail site, i.e., placed directly near the product) appearing on a product-detail site with the variable PROD_SHOP_RATING.

Variable category
social

In addition to the more rational direct-search possibilities, particular attention is paid to the variable category *social*. This summarizes the user-generated social-shopping features that can be used by the visitor. LIST_VIEW counts the total number of lists viewed by the visitor, while STYLE_VIEW counts the number of styles viewed. TAG_VIEW measures the total number of pages resulting from a search action by clicking on a user-generated tag. User-generated tags can be found on product-detail sites, in lists and styles, and on user profiles. The variable PROFILE_VIEW counts the total number of pages related to a user profile, e.g., profile with photo, a friends list, or the guestbook of the profile.

Variable category
transaction

Finally, the *transaction* category contains the variable CLICK_OUT, which indicates whether or not the user has performed a click-out to a participating online shop within the session. In our study, we regard this variable as an indicator for actual purchases.

4.3.   Descriptive Statistics

Figure 4 shows the descriptive statistics (mean, standard deviation, minimum, maximum, and median) of the variables used.

Variable	Mean	SD	Minimum	Maximum	Median
General session measures:					
LOG_IN	.0122	.1099	.0000	1	-
PROD_VIEW	.9475	2.2305	.0000	368.0000	0.0634
PROD_VIEW_TIME	17.3917	60.3684	.0000	2546.0000	.0000
START	.0888	.4703	.0000	130.0000	.0000
VIEW_TIME	3.5418	6.5593	.0000	235.0500	1.2022
VIEW_TIME_AVG	34.1010	58.3515	.0000	2350.0000	16.9477
Search session measures:					
SEARCH_BRAND	.3183	2.711	.0000	423.0000	.0000
SEARCH_CAT	1.6345	8.2149	.0000	563.0000	.0000
SEARCH_FIELD	1.1701	2.7147	.0000	520.0000	.2864
SEARCH_GENDER	.7868	4.8198	.0000	494.0000	.0000
SEARCH_PRICE	.1267	1.9944	.0000	490.0000	.0000
SEARCH_SALES	.0523	1.0704	.0000	234.0000	.0000
SEARCH_SHOP	.1238	1.0792	.0000	283.0000	.0000
Ratings:					
PROD_RATING	14.4577	31.8897	.0000	100.0000	.0000
PROD_SHOP_RATING	13.4174	30.8686	.0000	100.0000	.0000
Social session measures:					
LIST_VIEW	.0163	.2104	.0000	112.0000	.0000
PROFILE_VIEW	.0104	.2393	.0000	121.0000	.0000
STYLE_VIEW	.0112	.1828	.0000	95.0000	.0000
TAG_VIEW	.0453	.7548	.0000	191.0000	.0000
Transactional:					
CLICK_OUT	.4092	.4917	.0000	1	-

Figure 4: Descriptive Statistics

The mean view time per session is 3.54 minutes. The mean number of pages visited per session is 6.23. Therefore, the average view time per page is 34.1 seconds. The log-in rate is 1.22 percent, i.e., in 1.22 percent of the sessions, the visitors are logged-in. On average, 0.95 product-detail sites are considered. The click-out rate, that is, following a link to a participating online shop, is 40.92 percent. In contrast to direct-search features, the use of social-shopping features (lists, styles, and tags) is relatively low. For example, the mean of the variable indicating the average number of lists is just 0.0163.

High click-out rate and low usage of social-shopping features

4.4.   Logit Modeling Approach (Objective: Click-Out)

The objective of our modeling is to determine the dependent variable CLICK_OUT. This variable is binary coded. Therefore, we run a logistic regression.[109] Logit modeling is conceptually simple and frequently used in marketing.[110] SAS Enterprise Miner 9.2 was used to estimate the logit-model. The procedure PROC LOGISTIC uses the maximum likelihood estimation to generate relative weights for each independent variable.[111] Our logit model, in which $\Lambda(\bullet)$ is the inverse of logit function, is formulated as follows:

Logit modeling with SAS Enterprise Miner

(1)

$$P\,(CLICK\;OUT = 1) = \Lambda[\beta_0 + \beta_1(LOG\_IN) + \beta_2 log(x_2) + \ldots + \beta_{19} log(x_{19})].$$

In Equation 1, β_0 is the intercept. The β's (from 1 to 19) are the regression coefficients of the nineteen predictor variables (variable categories general, search, ratings, and social; see Figure 3). The variable LOG_IN is the only binary coded predictor variable. Because the distributions of the eighteen metric predictor variables (x_2 to x_{19}) are positively skewed, we use log-transforms of all metric predictor variables.[112]

Using concept of odds ratios for interpretation

The interpretation of the regression coefficients is somewhat tricky. Therefore, we interpret the logistic regression results using the concept of odds ratio.[113] The odds of an event occuring is the probability that the event will occur, divided by the probability that it will not. An odds ratio is computed by exponentiating the parameter estimate for the predictor variable, and can be interpreted as the multiplicative change in the odds for a one unit change in the predictor variable.[114]

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[109] C.f. e.g. HOSMER/LEMESHOW 2000.

[110] C.f. e.g. BUCKLIN/GUPTA 1992; HUANG/LURIE/MITRA 2009.

[111] C.f. SAS 2009.

[112] C.f. e.g. GREENE 2003.

[113] C.f. e.g. AGRESTI 1996; HOSMER/LEMESHOW 2000.

[114] C.f. e.g. ALLISON 1999.

4.5.   Results of Logit Regression Analysis

Figure 5 shows the result of the logistic regression.

Variable	Coefficient	Standard error	*p*-value	Odds ratio
Intercept	2.9687	.0098		
General session measures:				
LOG_IN (0 vs 1)	-1.3710	.0075	<.0001	.064
PROD_VIEW	-.9769	.0045	<.0001	.377
PROD_VIEW_TIME	.2896	.0013	<.0001	1.336
START	-1.8197	.0085	<.0001	.162
VIEW_TIME	1.8504	.0038	<.0001	6.363
VIEW_TIME_AVG	-1.1043	.0027	<.0001	.331
Search session measures:				
SEARCH_BRAND	-.2032	.0038	<.0001	.816
SEARCH_CAT	-.5530	.0022	<.0001	.575
SEARCH_FIELD	-.7180	.0024	<.0001	.488
SEARCH_GENDER	-.1236	.0026	<.0001	.884
SEARCH_PRICE	.0556	.0060	<.0001	1.057
SEARCH_SALES	-.1018	.0083	<.0001	.903
SEARCH_SHOP	-.0734	.0055	<.0001	.929
Ratings:				
PROD_RATING	.0137	.0010	<.0001	1.014
PROD_SHOP_RATING	.1503	.0010	<.0001	1.162
Social session measures:				
LIST_VIEW	-.9749	.0160	<.0001	.377
PROFILE_VIEW	-1.7584	.0242	<.0001	.172
STYLE_VIEW	-.4539	.0186	<.0001	.635
TAG_VIEW	.1588	.0088	<.0001	1.172
Observations	2,951,198			
McFadden Pseudo R^2	0.1162			

Figure 5: Results Logistic Regression

The overall goodness-of-fit is considered using McFaddens Pseudo R^2.[115] This is the percentage fall in log likelihood, compared with a random effects model with a consistent term only. A value of the Pseudo R^2 between 0.2 and 0.4 indicates a good model fit.[116] Therefore, the value of

Pseudo R^2 shows satisfactory model fit

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[115]   C.f. e.g. HOSMER/LEMESHOW 2000.

[116]   C.f. e.g. LOUVIERE/HENSHER/SWAIT 2000.

the Pseudo R^2 in our model (0.1145) demonstrates a satisfactory fit between the estimated model and the observed empirical data.

At the variable level, all variables are highly statistically significant at the .0001 level (see column p-value). According to the magnitude of the variables, the view time (VIEW_TIME, see Hypothesis 2) is the most important. When interpreting quantitative variables, it is useful to do the following: subtract one from the odds ratio and multiply by 100. In this way, one obtains the percentage increase or decrease associated with a one-unit increase in the independent variable.[117] Hence, the odds ratio of 6.362 of VIEW_TIME means as follows: The odds of a click-out are 536.2% higher per additional minute on the site. In contrast, the higher the average view time per page, the lower the likelihood of a click-out. This negative impact is indicated by an odds ratio below 1 for the variable VIEW_TIME_AVG (0.331). Thus, Hypothesis 3 is supported.

Hypothesis 4 is also supported. The more product-detail sites a consumer accesses, the lower the likelihood of a click-out. This result may indicate a goal-directed visit to the site, in which the consumer has already built his consideration set. The average view time per product-detail site (Hypothesis 5) has a positive impact. The odds ratio is 1.336, i.e., the odds of a click-out are 33.6% higher per additional second on a product-detail site.

In agreement with Hypothesis 7, the odds of a click-out are 84.0% lower per additional viewed home page. This implies the importance of the home page as a tool for visitor orientation.

The result regarding the variable LOG_IN (Hypothesis 1) is of considerable interest. The binary coded variable LOG_IN has a significant effect on click-out. The value 0 stands for not logged-in, the value 1 for logged-in. The odds ratio is 0.064 for value 0 versus value 1. This means that the probability of a click-out occuring, i.e., CLICK_OUT = 1, is lower for the value 0 than for the value 1. In other words, logged-in visitors have a higher tendency to make a click-out in comparison to non-logged-in visitors.

Consistent with Hypotheses 9a and 9b, the frequent use of lists and styles lowers the likelihood for a click-out. The variable LIST_VIEW has an odds ratio of 0.377, i.e., only a high usage of the home page is more negatively

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[117] C.f. e.g. ALLISON 1999.

correlated to the likelihood of a click-out. This is similar to the variable STYLE_VIEW, which has an odds ratio of 0.635. This finding may indicate that lists and styles could lead to reactance and information overload, or support browsing and inspiration. Although not driven by the motivation to buy immediately, exploratory search, such as with lists and styles, may also lead to a purchase in the future.[118]

According to the odds ratio of 1.172, tags have a positive impact. The more user-generated tags are used, the higher the likelihood of conducting a click-out. Therefore, Hypothesis 10 is accepted.

Also in line with our assumption in Hypotheses H8a and H8b, is the positive impact of the variables PROD_SHOP_RATING (odds ratio: 1.162) and PROD_RATING (odds ratio: 1.014). Therefore, user-provided ratings for shops and products play an important role in the decision-making process of visitors and increase the likelihood of a click-out. As described above, both variables are heavily aggregated measures within a session. Therefore, these variables should be considered carefully. However, they may be useful to provide some initial insight into their direction of impact.

The odds ratio for user profiles (PROFILE_VIEW) is 0.172, i.e., the more user profiles are used within a session, the lower the likelihood of conducting a click-out. Hence, Hypothesis 11 is accepted.

The use of the direct-search feature for price (H6e, SEARCH_PRICE) is the only such feature with a positive impact on click-out. The more this feature is used, the higher the likelihood of a click-out. This implies the importance of price within the purchasing process. Accordingly, our hypotheses regarding the direct-search features (Hypothesis 6) are supported for six of the seven direct-search features, i.e., the more a visitor uses conventional direct-search features, the lower is the number of click-outs. Increasing transaction cost and information overload could be potential reasons. Furthermore, in the case of knowledge-building, a consumers' ongoing search is motivated by the desire to acquire a bank of product knowledge which is potentially useful in the future. Therefore, a consumer uses several features, but does not conduct a click-out.

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[118] C.f. e.g. MOE 2003.

All but one hypothesis can be regarded as proved statements

Finally, Figure 6 summarizes the results of the hypotheses. As can be seen, all but one of the odds ratios demonstrates the expected sign. Only Hypothesis 6e (SEARCH_PRICE: direct-search feature price) is not supported.

Hypothesis	Variable	Expected sign	Supported
	General session measures:		
H1	LOG_IN	+	YES
H4	PROD_VIEW	-	YES
H5	PROD_VIEW_TIME	+	YES
H7	START	-	YES
H2	VIEW_TIME	+	YES
H3	VIEW_TIME_AVG	-	YES
	Search session measures:		
H6a	SEARCH_BRAND	-	YES
H6b	SEARCH_CAT	-	YES
H6c	SEARCH_FIELD	-	YES
H6d	SEARCH_GENDER	-	YES
H6e	SEARCH_PRICE	-	NO
H6f	SEARCH_SALES	-	YES
H6g	SEARCH_SHOP	-	YES
	Ratings:		
H8a	PROD_RATING	+	YES
H8b	PROD_SHOP_RATING	+	YES
	Social session measures:		
H9a	LIST_VIEW	-	YES
H11	PROFILE_VIEW	-	YES
H9b	STYLE_VIEW	-	YES
H10	TAG_VIEW	+	YES

Figure 6: Summary of Hypotheses

5.   Discussion and Implications

5.1.   Implications for Researchers

Previous research has established that UGC exerts a significant impact on economic outcomes.[119] However, one has to take into account that the situational influence, in which UGC occurs, is moderated by consumer involvement[120], and both product and consumer characteristics[121]. We enhance the research by analyzing several user-generated social-shopping features, as well as ratings and direct-search features. In comparison to existing studies, the data volume in our study is extremely high. Therefore, our results are of high representativeness.

Study enhances research field of UGC and purchase conversion

We show that social-shopping features have a low level of usage. Their novelty constitute a possible explanation. Despite the low usage, we found that user-generated social-shopping features have a significant impact on purchasing behavior, both negative and positive. In line with existing studies, we found that ratings for shops and products exert a positive impact on a click-out.[122] In contrast, lists and styles lower the likelihood of a click-out. Reactance and information overload could be potential reasons. Therefore, each innovative website feature should to be tested in advance. In conclusion, the monetization of user-generated content is a challenge for website operators and a target-group-specific adoption is necessary.

Empirical results indicate strong impact of UGC – both negative and positive

Monetization of UGC is challenging

Moreover, our results show that user behavior is consistent with rational considerations involving time constraints and cost-benefit trade-offs.[123] The more direct-search features that are used within a session, the lower the probability of a click-out. Moreover, consumer focus on functional aspects and goal-directedness is also confirmed by our result that a high average view time per page correlates negative with a click-out.

Rational considerations of consumers

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[119] C.f. e.g. CHEVALIER/MAYZLIN 2006; DHAR/CHANG 2007; LIU 2006.

[120] C.f. e.g. PARK/LEE/HAN 2007.

[121] C.f. e.g. NIKOLAEVA/SRIRAM 2007.

[122] C.f. e.g. CHEVALIER/MAYZLIN 2006; DELLAROCAS/ZHANG/AWAD 2007.

[123] C.f. e.g. BUCKLIN/SISMEIRO 2009; LIU 2006.

Logit modeling approach as basis for analyzing other online shopping channels

In general, our modelling approach could not only be used to predict consumer behaviour, but to understand the impact of website features on purchase conversion. Therefore, our model could be enhanced by further input variables, i.e., features and consumer traits, to build more holistic models of consumer behavior, e.g., in other online shopping channels.

5.2.   Implications for Operators of a Social Shopping Community

Enhancing community-building

It was found that logged-in visitors have a higher probability of making a click-out than non-logged-in visitors. Logged-in visitors are few in number, but, at the same time, they generally have a high value. It is well-known that a relatively small share of customers is responsible for a relatively large share of profit.[124] Moreover, it is often stated that it is more important to care about existing customers, than to acquire new ones.[125] In this context, following the strategy of community-building may be an appropriate way to boost revenue. Therefore, paying attention to their behavior and developing tools to increase their loyalty, may be a prudent tactic.

Providing effective search tools

Our results clearly indicate that a cost-benefit perspective may be useful for understanding and predicting purchasing behavior in SSC. Therefore, an operator should provide effective search tools to visitors in order to increase their benefit. Otherwise, a visitor could easily abandon the session. Potential explanations could be information overload and high transaction costs. This is shown by the result that a high usage of direct-search features lowers the likelihood of a click-out. In this regard, our analysis shows that

Product prices seem to be important

the direct-search feature for price is the only one that correlates positively with a click-out. Not surprisingly, product prices seem to be an important factor in the decision-making process.

UGC is a fundamental part of the business model of SSC, because consumers add value to the operator by generating UGC. Moreover, social-shopping features may increase the site "stickiness", thereby enhancing the business-consumer relationship, purchases, and loyalty rates[126]. However,

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124   C.f. e.g. NIRAJ/YE 2001.

125   C.f. e.g. MOZER/WOLNIEWICZ/GRIMES/JOHNSON/KAUSHANSKY 2000.

126   C.f. e.g. FARQUHAR/ROWLEY 2006; FLAVIAN/GUINALIU 200; HAGEL/ARMSTRONG

our results do not generally confirm this, at least with regard to purchase conversion.

According to our findings, user-provided ratings for online shops and products play a significant role in the decision-making process of consumers. A high rating seems to be a significant generator of click-outs.

Animate visitors to rate products and shops

Likewise, the use of user-generated tags exerts a positive influence on click-outs. Presumably, providing tags supports goal-directed searching and lets consumers find what they are looking for. An operator should, therefore, animate visitors to rate products and shops and generate tags, in order to maximize the number of click-outs.

Animate visitors to tag products and shops

Lists and styles are novel features that are used to enhance the stickiness of a website, stimulate browsing, enhance inspiration, and thus increasing the likelihood of a purchase. Contrarily, our results show that the use of lists and styles is negatively correlated with a click-out. This could be explained by the novelty of these features and therefore with consumer reactance. Furthermore, consumers may be confronted with information overload. Despite the negative impact on a click-out, lists and styles could lead to positive long-term effects on the click-out rate. As a consumer may be in the pre-purchase phase, i.e., knowledge-building[127], a purchase is not intended. Nonetheless, lists and styles may stimulate the examination of a product. Thus, a product could enter into consumers' considered set of products. Moreover, social shopping could be regarded as a form of entertainment.[128] Therefore, lists and styles may be an important element of website design and could lead to a more emotional shopping experience.[129] To avoid consumer reactance and information overload, as well as stimulate the usage of social-shopping features, an operator could explain the concept of a SSC, especially within the group of inexperienced consumers. The explanation of social-shopping elements on a separate site may be an appropriate way of achieving this.

Lists and styles could cause consumer reactance and information overload

Lists and styles for pre-purchase phase, entertainment, and emotionality

Explain novel features like lists and styles

1997; LEA/YU/MAGULURU 2006.

[127] C.f. e.g. MOE 2003.

[128] C.f. e.g. JAYAWARDHENA/WRIGHT 2009.

[129] Especially, this may be important for websites focusing on women. In this context, HANSEN/JENSEN 2009 found that women, in comparison to men, are more "shopping for fun".

Providing relevant
information,
search tools, and
support on the
home page

Furthermore, we found that frequent usage of the home page exerts a strong negative impact on a click-out. This may be explained by a non-goal-directed search of a consumer, or as an indicator of information overload. Thus, providing visitors with relevant information and effective search and support tools on the home page could stimulate the visitor to continue searching.

Providing detailed
transactional
information on
product detail
sites

Providing all relevant information regarding the purchase transaction may also be important for the product-detail sites. We found that a high average view time per product-detail site correlates positively with a click-out. This indicates that consumers intensively check all the information given there, because this is relevant for purchasing.

Besides
clickstream
analysis,
conducting
usability studies

Overall, improving website features and usability could improve conversion rates.[130] Besides the general analysis of clickstream data, an operator may conduct usability studies, e.g., such as by randomly delivering different features and content on the site (e.g., A/B test), or by applying controlled experiments in laboratory that manipulate website design.

5.3.   Implications for Online Retailers and Manufacturers

SSC as
component of
marketing strategy

In general, more and more consumers use infomediaries[131], as well as new shopping channels in Web 2.0.[132] Therefore, online retailers, as well as manufacturers with their own online shop, must integrate this development into their marketing strategy. SSC could be one important component.

Enhancing rating

High ratings could enhance the trustworthiness of online shops. Our results show that, the higher the overall average shop ratings on product-detail sites, the higher the likelihood of conducting a click-out to a participating online shop. Therefore, online retailers should encourage consumers (their customers), to rate their shop. The situation is the same for product ratings. Manufacturers could animate consumers to rate their products and brands.

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[130] C.f. e.g. AYANSO/YOOGALINGAM 2009.

[131] C.f. e.g. SU 2007.

[132] C.f. e.g. PETERS/ALBERS/ASSELMANN/SCHÄFERS 2009; STEPHEN/TOUBIA 2010.

Tagging is an additional new form of UGC. The more user-generated tags used within a session, the greater the probability of a click-out. Hence, activating consumers to tag products with specific key words is another tactic that could draw attention to specific products.

Enhancing tagging

Lists and styles are also a very innovative marketing tool. Stimulating consumers to create recommendation lists and styles with specific manufacturers' products could lead to a high degree of awareness in SSC. For example, *Coach*, a USA-based apparel brand, is already experimenting in SSC. They conduct a "contest" on *Polyvore* ("How will you sparkle this season?"), in which consumers have to create a set (style) with products of *Coach*.[133] Within one week, *Coach* received 3,692 sets. The sets received 103,379 "likes", 13,006 comments, and an overall of 204,656 page views.[134] Therefore, this not only led to a high visibility on the SSC itself, but also increased brand and shop awareness in social media, e.g., when consumers, especially 'lead users', embed this content in their 'news feed' on Facebook. Thus, it encourages user participation and the creating of emotional links that enhance shop and product loyalty.[135] Furthermore, as our results indicate, the community members in particular, should be activated, so that the retailers and manufacturers benefit from the high click-out rate.

Brand and shop awareness through contests

Activate members of community

Moreover, manufacturers could upload images of a new collection before deciding to produce them, so as to obtain input from fashion-savvy users. For this purpose, manufacturers could organize a contest, too. A manufacturer could use it as a forecasting tool, that is, base their order or product quantities on how often their products are included in styles. In this context, online retailers and manufacturers could also license the SSC technology for use on their own websites, for just such market-research questions. Moreover, it is entirely conceivable that such integration could strengthen the involvement with their own shop and also act as purchasing stimuli.

Styles as forecasting-tool

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[133] C.f. POLYVOREC 2010.

[134] C.f. GOULD-SIMON 2010.

[135] C.f. e.g. FARQUHAR/ROWLEY 2006; FLAVIAN/GUINALIU 2005.

Incorporating
specific pricing
strategies

Last but not least, the price of products is an important component in consumer decision-making processes. As our analysis shows, the direct-search filter mechanism for price correlates positively with a click-out. Thus, online shop managers should take this into account and create the appropriately specific pricing strategies.

Overall, our findings yield preliminary insights for marketers, as well as researchers, so that they can better assess the purchasing behavior in SSC. In particular, our results suggest that UGC within the new business model of SSC should be taken into account seriously by online retailers and manufacturers, in order to boost brand or shop awareness, as well as sales.

6.   Limitations and Further Research

Our study makes the first contribution to modeling consumer purchasing behavior in SSC with the aid of clickstream data. Nevertheless, our study does have some limitations, and some research questions still remain open.

6.1.   Limitations

Loss of textual
and graphic
information

First, we were unable to determine whether the significance of the measures is due to the nature of result presentation by the site operator, or the way the information is processed by the visitor. Furthermore, we abstracted the website by categorizing pages, which resulted in the loss of much textual and graphic information in terms of page content.

Aggregated
measures

Second, we use aggregated measures in our models. This inevitably entails a degree of lost information, in comparison to page-to-page level data.

Data from early
developmental
phase

Third, it should be noted that the data was obtained from an early developmental phase of the SSC. Thus, consumers are often unfamiliar with the various facilities. Observation over time would therefore be useful, in order to integrate a more representative sample into the modeling process.

6.2.   Future Research

Despite our original findings, a number of interesting research questions remain open. It would be useful to investigate the behavior of registered users in greater detail. An investigation of interaction behavior with other registered users and the use of their own, self-created UGC, would be of substantial benefit. In this manner, a website manager could more accurately determine the economic value of a particular registered user. In this respect, the use of created content by other users and the associated revenues, through, for instance, a click-out, could be allocated to a specific registered user. Therefore, a combination of clickstream data with additional sources, e.g., demographic user data or revenue, could yield additional findings. An investigation of other detailed information beyond that which, can be found on the website would similarly be worth conducting. In this manner, a text mining analysis of the tags could be used.

Analyzing behavior of community members in greater detail

Integration of demographic profiles or revenue

The present study investigates the product groups of fashion, living and lifestyle. An investigation of other product groups, such as consumer electronics, could usefully extend our results. In addition, the integration of information from actions that take place on the pages of participating online shops would provide a more complete picture of visitor behavior. For instance, this would enable capturing actual product purchases, so that the purchasing behavior in the final stage could be researched. Moreover, an investigation of embedded lists and styles on social networks like *facebook* or *Twitter* would be of great interest, e.g., their impact on conversion rates, in comparison to other online marketing activities.

Investigate further product groups

Integrating actions in participating online shops and social networks

Moreover, many studies indicate that the so-called 'm-commerce'[136], i.e., mobile e-commerce, will grow exponentially.[137] Within this context, users will purchase via their mobile phones, with iPhones, for instance. Mobile phones will be used to access the internet and to support purchases in bricks-and-mortar stores (e.g., via location-based services). For our investigation, only a few accesses to the SSC through mobile appliances could be observed. With the introduction of additional services (barcode readers, visual search, etc.), an increase can be expected.[138] The impact of

Social shopping via mobile phones

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[136] C.f. e.g. GUNASEKARAN/MCGAUGHEY 2009; SIAU/SHEN 2003.

[137] C.f. e.g. DMC 2009; FENG/HOEGLER/STUCKY 2006.

[138] Cf. e.g. HOLSING/SCHÄFERS 2010.

direct search and social-shopping features in the context of these modes of use will raise new research questions.

Applying other data mining methodologies, e.g., Decision Trees or Neural Networks

With respect to the methodology used in our study, it would be useful to apply further methodologies. For example, one could use advanced data mining techniques such as Decision Trees or Neural Networks. It is of great interest to proof the significance of the results presented in this study. We let this work for future research.

In conclusion, there are many unacknowledged research questions in the fast emerging area of social commerce, especially in social shopping channels. We hope that our preliminary research will initiate further studies.

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