ONLINE VS. IN-STORE SHOPPING: HOW PROBLEM SOLVING STRATEGIES OF DECISION SUPPORT SYSTEMS INFLUENCE CONFIDENCE IN PURCHASE DECISIONS

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Abstract

Several studies have investigated the relevance of Decision Support Systems (DSS) on purchase behaviour. Even though these studies show several aspects of the utility of DSS, they are limited to online purchase situations, the use of one decision making strategy and one DSS technology. In this paper, we therefore develop a theoretical model that measures the impact of DSS strategies relative to a given purchase problem and an adequate use of DSS technology on consumers' perceived confidence in purchase decisions for both online and in-store purchase situations. Further, three mediating decision process variables are considered: perceived personalization of a DSS, perceived relevance of recommendations, and cognitive trust in DSS competence. As this paper represents a work in progress, the theoretical model has still to be tested empirically with regard to the proposed method. But as a result, we expect that the model not only allows evaluating different kinds of purchase-directed DSS but let researchers also draw conclusions on the appropriate use of technology and decision strategies of one individual DSS, which in turn has practical implications for the design of DSS-enabled future shopping environments.

Keywords: Decision support system, consumer decision-making, empirical model.

1 INTRODUCTION

Prevalent use of mobile technologies, increasing integration of low-cost sensor technologies in any environment, e.g., RFID technologies, and global information networks, such as the World Wide Web, are increasingly considered for the design of purchase environments (Rigby and Vishwanath 2006). Early adopters on the consumer side start to use decision support systems (DSS) on mobile phones and smart phones with the goal to improve their purchase decisions. For example, mobile devices may provide access to web-based product recommendation services such as DooYoo.co.uk, eOpinions.com, or Ask.com. But also shopping environments already provide DSS in the form of online terminals and smart displays (e.g., Prada store in Manhattan or Inamo restaurant in London) or even by robotic assistants (e.g., Fujitsu's Enon). In general, users tend to accept the trade-off between advanced capabilities of desktop-based computing technologies versus mobility and flexibility of mobile technologies. Accordingly, consumers enrich their shopping experience by taking advantage of instant Internet access on their mobile devices (Lee and Benbasat 2004, Lee and Benbasat 2003).

Within the context of these technological and behavioural developments, new forms of purchase-directed DSS are being developed (e.g., the Mobile Prosumer by Resatsch et al. 2008, see below for further applications). The key question is whether these mobile-based DSS (mDSS) for in-store purchase decisions differ from desktop-based DSS (dDSS) for online purchase decisions in terms of perceived characteristics such as personalization, relevance of recommendations and trust considerations or in their potential to influence purchase decisions. These differences would inform us on how to design and implement future mDSS in contrast to dDSS, such that consumers will adopt them as widely for in-store purchase situations in the future as dDSS are adopted for online purchase situations today.

Up until now, many studies have investigated the impact of dDSS on purchase behaviour (Bo and Benbasat 2007, Gregor and Benbasat 1999, Häubl and Murray 2003, Häubl and Trifts 2000, Kamis et al. 2008, Komiak and Benbasat 2006, Pereira 2001, Senecal and Nantel 2004, Swaminathan 2003, Todd and Benbasat 1999) and some have investigated mDSS (Kleijnen et al. 2007, Maass and Kowatsch 2008, van der Heijden 2006). But to the best of our knowledge, a comparison of dDSS and mDSS relative to purchase situations is still missing. In particular, the value of product information, which strongly influences purchase behaviour as found by marketing research for in-store purchase situations (Tellis and Gaeth 1990), can be increased with the use of DSS as they "elicit the interest or preferences of individual users for products either explicitly or implicitly, and make recommendations accordingly" (Bo and Benbasat 2007). In this sense, product information provided by DSS becomes adaptive and therefore more relevant to individual consumers' information needs than static product information on printed product labels in retail stores. The utility of DSS has been shown in several studies. For example, they help to reduce search complexity and customer's information overload (Häubl and Trifts 2000, Todd and Benbasat 1999), improve decision quality (Pereira 2001), increase trust in decisions (Gregor and Benbasat 1999), or influence consumer behaviour and purchase intentions (Bo and Benbasat 2007, Kamis et al. 2008, Komiak and Benbasat 2006). Even though these studies prove several aspects of the utility of DSS, they are limited to online purchase situations, the use of one DSS strategy (usually the weighted adding strategy), and one DSS technology (usually a desktop-based website).

Because unprecedented, we investigate how different problem-solving strategies supported by both DSS types (dDSS and mDSS) influence consumers' confidence in purchase decisions within online and in-store purchase situations. Two normalizations are required for comparing the utility of DSS in both purchase situations: (1) the fit between a purchase problem and the decision strategy implemented by a DSS and (2) perceived fit between a purchase situation and the DSS technology. Both normalizations are discussed in the following.

First, Mobile Commerce (Mennecke and Strader 2002) and Ubiquitous Commerce (Sheng et al. 2008) allow the use of DSS in in-store shopping situations on mobile devices. Correspondingly, first applications are being developed for consumers to communicate with physical products (Maass and Varshney 2008) such as Shoppers Eye (Fano 1998), Impulse (Youll et al. 2000), MyGrocer (Kourouthanassis and Roussos 2003), MASSI (Metro AG), the Tip'n Tell client (Kowatsch et al. 2008, Maass and Filler 2006), the Mobile Prosumer (Resatsch et al. 2008), Easishop (Keegan et al. 2008) or APriori (von Reischach et al. 2009). All of them allow consumers to request product information directly at the point of sale. In that case, physical products can be enriched with new kinds of product services such as product recommendation services provided by mDSS. As physical surroundings, i.e. the existence of physical products, differentiate online and in-store purchase situations (Bitner 1992), they may also have an impact on consumers using a DSS as more information is available for the product in question. Similarly, consumers might use different purchase strategies in online and in-store purchase situations. Inline with information processing theory, preferences for products and decision strategies applied by consumers may change according to purchase problems, thus are constructed on the spot (Bettman 1979, Bettman et al. 1998, Bettman and Park 1980, Payne et al. 1992, Slovic 1995, Tversky et al. 1988). As a result, we assume that the fit of an initial purchase decision problem with adequate support of decision strategies implemented by DSS influences purchase decision-making.

Second, after more than a decade of online shopping, consumers in purchase situations might rate the fit of graphical desktop applications on standard PCs with broadband Internet access higher than the fit of a web-based application on a low-end mobile phone with a slow Internet connection. But consumers may find dDSS provided in in-store situations as not being adequate. For example, they may expect to use a DSS at any place such as in front of products they are interested in, or at any time without waiting for other consumers that use a dDSS such as in crowded stores (Eroglu et al. 2005, Junglas and Watson 2006). Therefore, we assume that technologies used for DSS implementations differ with their perceived fit with online or in-store situations.

As a result, the contribution of this paper is to propose a research model that measures the impact of DSS on consumers' confidence in purchase decisions from a holistic perspective that considers two aspects primarily: use of DSS strategies relative to a given purchase problem and second, use of DSS technology relative to a given purchase situation. In particular, online and in-store purchase situations are being considered. For a deeper understanding of the utility of DSS, we additionally use three mediating decision process variables in our research model, whereby perceived DSS personalization predicts both perceived relevance of recommendations and cognitive trust in DSS competence. The overall motivation of the current work is to provide an empirical framework for user studies, from which practical implications can be drawn for the design and implementation of future DSS.

In the following, we develop our research model based on information processing choice theory (Bettman et al. 1998). Thus, we focus rather on the consumers' perceptions of product information and their effects on the confidence in purchase decisions than on the adoption or diffusion of new DSS technologies which can be investigated appropriately with the Technology Acceptance Model (TAM, Davis 1989), Unified Theory of Acceptance and Use of Technology (UTAUT, Venkatesh et al. 2003) or the DeLone and McLean Model of Information Systems Success (DeLone and McLean 2003). Then, after we have developed the research model, we present the methodology and the design of the empirical study, which will be used to test our model. Finally, we conclude this work in progress by a short summary.

2 RESEARCH MODEL AND HYPOTHESES

The theoretical model of our study is shown in Figure 1. The model suggests that the impact of fit between a purchase problem and DSS strategy on perceived confidence in purchase decision is mediated by three decision process variables, namely perceived DSS personalization, perceived relevance of recommendations, and cognitive trust in DSS competence. Furthermore, perceived fit of purchase situation with DSS technology moderates the relation between the fit of purchase problem with DSS strategy and perceived DSS personalization. The latter relationship is suggested to be sensitive regarding in-store ad online shopping situations as different degrees of fit of purchase situations with DSS technologies are expected. We develop the rationale for these relationships below.

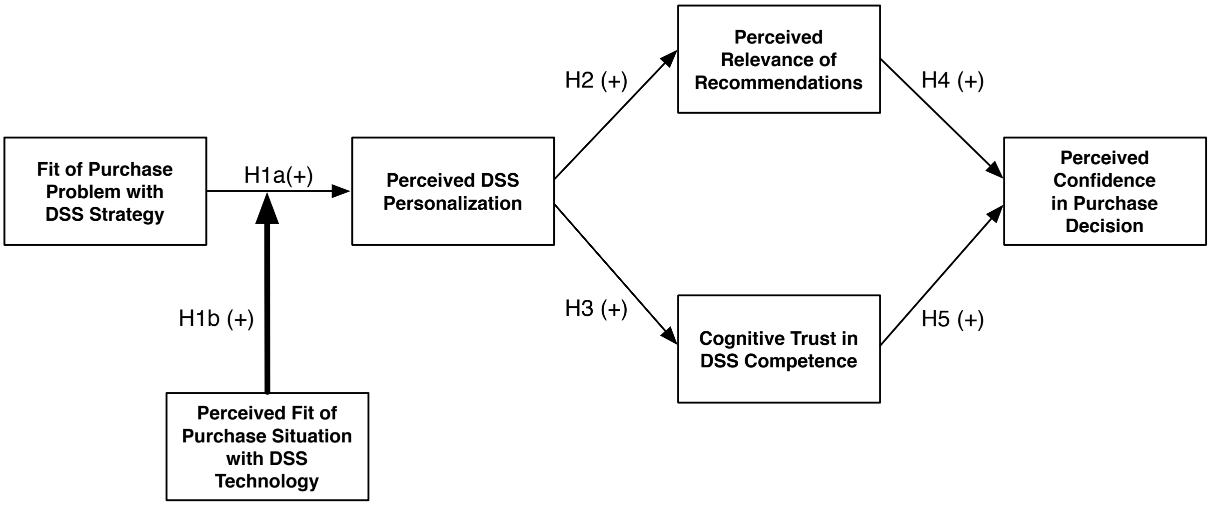

Figure 1. Research Model. Note: the path in bold is hypothesized to be sensitive regarding in-store and online shopping situations.

In general, the purchase problem of consumers is to decide on one product out of a given choice set. Consumer research has studied choice models that explain how consumers make purchase decisions. Within rational choice theory (Simon 1955), consumers are characterized as rational decision makers with well-defined preferences (Bettman et al. 1998). Each option within a choice set of products has a utility or a perceived subjective value. In this sense, rational consumers want to maximize the utility and their individual value of the outcome when making purchase decisions. Although rational choice theory has contributed greatly to the prediction of consumer decisions (Bettman et al. 1998), an alternative information-processing theory argued that rational choice theory is incomplete as consumers have limitations on processing information, which is denoted as bounded rationality (Simon 1955). In detail, consumers have limited working memory and limited computational capabilities and thus are not able to compute all attributes of products within a choice set with regard to their perceived utility. In addition, perceived utility and values are relative to products consumers compare and are therefore subject to changes (Tversky and Kahnemann 1991). Inline with the information processing approach, consumer behaviour such as purchase decision making is influenced by the relationship between properties of the human information-processing system and the properties of task environments (Simon 1990). Here, properties of consumer's information processing are experiences with decision strategies, memory and computational capabilities and task environments are purchase environments. Thus, preferences for products and corresponding decision strategies applied by consumers may change according to the complexity or stressfulness of a purchase problem and therefore are constructed on the spot (Bettman 1979, Bettman et al. 1998, Bettman and Park 1980, Payne et al. 1992, Slovic 1995, Tversky et al. 1988).

Consumers adopt a variety of decision strategies when making choices, e.g., weighted-adding and lexicographic strategies (Bettman et al. 1998), satisficing strategy (Simon 1955), elimination by aspects strategy (Tversky 1972), equal weight strategy (Dawes 1997), majority of confirming dimensions strategy (Russo and Dosher 1983) or by counting the number of good and bad features of products (Alba and Marmorstein 1987). Consumers may also use combinations of these strategies within one purchase decision process, but this is not within the scope of the current work (see Bettman et al. 1998). As consumers may use one of those decision strategies depending on their purchase problem, we assume a higher utility of a DSS when this DSS provides a decision strategy preferred by the consumer. This goes beyond the definition of DSS, because not only product preferences but also decision strategy preferences of consumers are elicited by DSS to make recommendations accordingly (see Bo and Benbasat 2007).

The fit between a consumer's purchase problem and the decision strategy implemented by a DSS may increase the utility of that DSS by means of higher degrees of DSS personalization. By stating that perceived personalization is the consumer's perception of an DSS's personalization, i.e., the degree to which the DSS understands and represents his or her personal needs (Komiak and Benbasat 2006), we assume a higher degree of perceived DSS personalization if it provides a decision strategy that fits to the consumer's purchase problem. In this sense, perceived DSS personalization measures the degree to which the DSS's product filtering strategy and ranking calculations, i.e., the availability of a human-computer-interface to control the filtering and ranking of products, are consistent with the consumer's personal shopping strategy. For example, a consumer that expects products to be ranked from low to high prices for his purchase decision requires an adequate DSS user interface to implement his decision strategy. We therefore formulate the first hypothesis as follows:

H1a: The fit between a purchase problem and the decision strategy provided by a DSS is positively related to perceived DSS personalization.

Consistent with task-technology-fit theory (Goodhue and Thompson 1995), online and in-store purchase situations require an appropriate use of DSS technology, such that personalized DSS can be perceived as such. In this sense, the right DSS technology is a necessary but not sufficient condition for a DSS to be perceived as a personalized one. For example, a consumer might perceive a DSS less personalized when the implementation of the DSS is not easy to use, the user is unfamiliar with, or it does not fit into in the current purchase situation regarding any time and any place considerations (Junglas and Watson 2006). For online purchase situations and DSS use, consumers are already familiar with desktop-based browser technologies, as a variety of research has shown (Bo and Benbasat 2007, Gregor and Benbasat 1999, Häubl and Murray 2003, Häubl and Trifts 2000, Kamis et al. 2008, Komiak and Benbasat 2006, Pereira 2001, Senecal and Nantel 2004, Swaminathan 2003, Todd and Benbasat 1999). But for in-store purchase situations, consumer knowledge on the use of DSS is suggested to be very low as reflected by limited research (Kleijnen et al. 2007, Maass and Kowatsch 2008, van der Heijden 2006). We therefore assume stronger moderating effects on perceived DSS personalization for in-store than for online purchase situations. Correspondingly, we propose the following hypothesis:

H1b: Perceived fit of a purchase situation with DSS technology will positively moderate the relation between the fit of a purchase problem with the decision strategy provided by DSS and perceived DSS personalization and will be stronger for in-store purchase situations than for online purchase situations.

Perceived DSS personalization will affect customers beliefs about product recommendations provided by that DSS (Komiak and Benbasat 2006). As higher degrees of DSS personalization require a higher fit of purchase problems with decision strategies, personal needs are better met by more personalized DSS. Therefore, perceptions of high DSS personalization are a rational reason for consumers to believe that products recommended by these DSS are more relevant to them than those products recommended by DSS that show low ratings of personalization. Accordingly, perceived relevance of recommendations reflects the degree, to which a consumer perceives the selection or ranking of products adequate relative to his or her purchase problem after the filter or ranking algorithm of the DSS is applied. We therefore formulate the following relationship:

H2: Perceived DSS personalization has a positive relationship with the perceived relevance of its recommendations.

A second important success factor in the use of DSS is the concept of trust (Wang and Benbasat 2007). Prior research on DSS has identified several dimensions of trust, namely cognitive trust in competence, cognitive trust in integrity and emotional trust (Komiak and Benbasat 2006). In the current work, we only consider cognitive trust in competence, which is defined as "a customer's rational expectation that a RA [here: DSS, the authors] has the capability to provide good product recommendations" (Komiak and Benbasat 2006). We choose cognitive trust in competence for three reasons. First, it can be directly linked to our definition of perceived DSS personalization. Accordingly, consumers may only trust in the competence of a DSS when it provides adequate product filtering strategies and ranking calculations. Second, cognitive trust in integrity – "a customer's rational expectation that an RA [here: DSS] will provide objective advice" and emotional trust – "a customer's feelings of security and comfort about relying on an RA [here: DSS] for the decision on what to buy" (for both definitions, see Komiak and Benbasat, ibid.) – would require the introduction of a new concept describing a trustee. This trustee could be a retailer that configures and provides a DSS with regard to his or her marketing objectives, which would influence both, trust in integrity and emotional trust of consumers. Although a trustee would be an important extension of the research model, it is not within the scope of the current work. And third, cognitive trust in competence represents a slightly different indicator for the utility of a DSS compared to perceived relevance of recommendations because it addresses the DSS itself. For example, a consumer may trust in the competence of a DSS because of its features (e.g., a particular product filter) even before any recommendations are provided. This applies also for scenarios, in which no recommendations are made at all and in which the perceived relevance of recommendations could not be measured.

All in all, if a consumer beliefs that a DSS meets his or her personal needs in terms of a user interface, which allows the application of an individual decision strategy, then he or she is likely to trust in that particular DSS's competence. In this sense, we rather consider cognitive trust in competence toward a DSS (Wang and Benbasat 2007) than toward a retailer (Lord et al. 1979), and thus formulate our third hypothesis as follows:

H3: Perceived DSS personalization has a positive relationship with consumers' cognitive trust in the competence of that DSS.

Finally, consumers' self-confidence in decision-making is the last construct that is applied in our research model to evaluate the utility of DSS. It is defined as "consumers' belief regarding their ability to make sound judgments" (Loibl et al. 2009). Here, consumers make purchase decisions with the help of product information provided by DSS, which consumers expect to result in outcomes that elicit personal feelings of satisfaction (Bearden et al. 2001). Accordingly, we assume that consumers are more likely to expect positive outcomes represented by high perceptions of confidence in purchase decisions when they perceive *relevant* recommendations provided by a *competent* DSS. Thus, we propose the last two hypotheses:

H4: Perceived relevance of recommendations has a positive relationship with a consumer's perceived confidence in his or her purchase decision.

H5: Consumers' cognitive trust in the competence of a DSS has a positive relationship with the perceived confidence in his or her purchase decision.

3 METHOD

A lab experiment will be conducted to test the theoretical model. We will employ a 2 x 2 x 2 factorial design as shown in Table 1. Accordingly, we use three experimental conditions, namely (1) fit between purchase problem and DSS strategy (high versus low), (2) purchase situation (online versus in-store) and (3) product type (digital camera versus wine). All three conditions are between-subject factors. We use two different products for greater generalizability of the results. Thus, the product condition in the factorial design is not part of our research model but is included in our data analysis to ensure that the results were the same for both products used. The treatments are discussed in the following.

First, a pre-test is required to select adequate DSS strategies for a given purchase problem. In order find high and low levels of fit between purchase problem and DSS strategy, subjects will be given a purchase task and are asked to think aloud when making their own decisions without the use of a DSS. Then, based on the resulting think aloud protocol (Ericsson and Simon 1980), the preferred decision strategies of the subjects can be assigned to the theoretical strategies as proposed by decision research (Alba and Marmorstein 1987, Bettman et al. 1998, Dawes 1997, Russo and Dosher 1983, Simon 1955, Tversky 1972). Finally, the decision strategies perceived as low and high will then be implemented by our DSS and manipulated according to the study design.

Second, we employ a DSS that is implemented as a web-based browser application on a fully featured personal computer for the online shopping situation. By contrast, we use a DSS for the in-store purchase situation that is implemented on a mobile device but also provides a web-based interface that slightly differs from the desktop version by considering the design guidelines for mobile devices (Lee and Benbasat 2004, Lee and Benbasat 2003). The use of both mDSS and dDSS technologies are consistent with prior work regarding online purchase situations (Bo and Benbasat 2007, Häubl and Murray 2003, Kamis et al. 2008, Komiak and Benbasat 2006, Pereira 2001, Senecal and Nantel 2004, Swaminathan 2003) and in-store purchase situations (Kleijnen et al. 2007, Maass and Kowatsch 2008, van der Heijden 2006).

Third, we choose digital cameras and wine for two reasons: the products belong to two different price segments and differ in their domains. This selection is also consistent with prior research (Jiang and Wang 2008). Both types of products can be consulting intensive thus requiring the use of a DSS. On the one hand, digital cameras are technical products that offer a variety of different features. Here, a consumer may want to know about the quality of these features. On the other hand, wine as nutrition good is also consulting sensitive for consumers who plan a dinner and want know which wine fits to a given meal.

Questionnaire items for the perceived constructs of our research model are either adapted from exiting scales for personalization, relevance, trust or confidence (Bearden et al. 2001, Komiak and Benbasat 2006, Loibl et al. 2009), or are newly developed according to the methodology described by Davis (1989) and Moore and Benbasat (1991).

		Fit of Purchase Problem with DSS Strategy	
		low	*high*
Purchase Situation	*Online and desktop-based DSS*		
	Digital Camera	Group 1	Group 2
	Wine	Group 3	Group 4
	In-store and mobile-based DSS		
	Digital Camera	Group 5	Group 6
	Wine	Group 7	Group 8

Table 2. Experimental Design.

Inline with current empirical research on DSS (Kamis et al. 2008, Komiak and Benbasat 2006), partial least squares (PLS) will be used for data analysis. PLS belonging to structural equation modelling (SEM) is chosen over regression analysis, because SEM can analyze all of the paths in one analysis (Barclay et al. 1995, Gefen et al. 2000). PLS provides the analysis of both the structural model (assessing relationships among theoretical constructs) and the measurement model (assessing the reliability and validity of measures) (Komiak and Benbasat 2006). In our research, all constructs – with the exception of the manipulation factor fit of purchase problem with DSS strategy – will be modelled as reflective constructs, because their measurement items are manifestations of these constructs (Barclay et al. 1995) and because these items covary (Chin 1998) (Komiak and Benbasat 2006).

Using G*Power3 (Faul et al. 2007), a sample size of 68 was calculated for a maximum of two predictors (Method: f-test, multiple regression – omnibus) which would be good enough to detect PLS path coefficients with medium effect sizes (f^2=.15). A statistical power of .80 was used for calculation, which is common in MIS research (Baroudi and Orlikowski 1989, Cohen 1977). As we compare online and in-store purchase situations for two different kinds of products, a sample size of 4 * 68 = 272 is required, such that 34 subjects can be assigned to each of the eight groups. The PLS analysis of between-group differences will be done with regard to the methodology proposed by Qureshi and Compeau (2009).

4 SUMMARY

The theoretical model proposed in this paper considers several limitations of prior research regarding the impact of decision support systems (DSS) on purchase decision-making. In general, the contribution of the current work is twofold. First, the model extends existing research as it introduces two new constructs that make comparisons of different kinds of purchase-directed DSS possible. DSS may therefore differ in their implementation of decision strategies (e.g., weighted adding, lexicographic or elimination by aspects) and technology (e.g., as desktop-based application on a PC or a mobile-based application on a smart phone), because both constructs, the fit of a purchase problem with a decision strategy provided by DSS and perceived fit of DSS technology with purchase situation normalize the impact of DSS on purchase decision-making. In this sense, not only a benchmarking of different purchase-directed DSS would be possible, but the researcher may also draw conclusions on the appropriate use of technology and decision strategies of one individual DSS.

Second, we expect that the model and the proposed study design will have practical implications as differences of desktop-based DSS and mobile-based DSS will reveal new requirements for the design of DSS-enabled future shopping environments. For example, the availability and an adequate use of DSS technology at any time and any place would not only change the way retail stores are perceived by consumers today, e.g., they might request product information for decision-making directly at the point of sale instead at home, but would also have managerial implications for retailers and providers of product information. For example, by providing access to purchase-directed DSS, retail stores may increase their operational agility with product recommendation services (Kowatsch et al. 2009) or personalized pricing services (Kowatsch and Maass 2009), in each case with the goal to increase customer satisfaction.

Nonetheless, a study is required according to the proposed method in order to test and empirically validate the research model and to complement this work in progress.

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