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Nour El Shamy

McMaster University, elshamyn@mcmaster.ca

Khaled Hassanein

McMaster University, hassank@mcmaster.ca

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The Influence of Cognitive Biases and Decision Making Styles on Older Adults' E-Commerce Decisions

Nour El Shamy

DeGroote School of Business, McMaster University, Hamilton, ON, Canada
elshamyn@mcmaster.ca

Khaled Hassanein

hassank@mcmaster.ca

ABSTRACT

Older adults are particularly susceptible to cognitive biases that could potentially impact the quality of their decisions in e-commerce environments. This may negatively affect their online experience, depriving them from reaping the full benefits of e-commerce. It is thus important to explore this domain with the objective of assisting older adults in making higher quality decisions in e-commerce contexts. This research-in-progress paper takes on this challenging inquiry through a two-stage study to (i) understand how the decision making styles of older adults interact with cognitive biases affecting their decisions' quality in e-commerce and how these interactions vary by product type; and (ii) understand the influence of decision aids in de-biasing older adults with different decision making styles under the stimuli of cognitive biases and how this varies by product type. We outline a detailed exploratory experimental methodology for this proposed research as well as potential contributions to theory and practice.

Keywords

Cognitive biases, de-biasing, decision making styles, decision support, e-commerce, older adults.

INTRODUCTION

Older adults, those who are 60 or more years old, are the fastest growing segment of Internet users (Lian and Yen 2014; Wagner et al. 2010). They comprise the fastest growing population age group, at almost triple the growth rate of the population as a whole (Department of Economic and Social Affairs 2014), a trend that is particularly evident in developed countries. It is also observed that older adults are becoming increasingly self-reliant and more involved in making their own everyday decisions (Mitzner et al. 2010; Peters et al. 2007).

Many features unique to e-commerce can be particularly appealing to older consumers including; reduced physical effort exerted when shopping, freedom from geographic constraints, ability to remotely access a wider range of vendors, and convenience of having purchases delivered to their residences. Nonetheless, this lucrative consumer segment has been under-appreciated for years (Lian and

Yen 2014), leading to lost vendor revenues and diminished opportunities for older adults (Lian and Yen 2014).

Older adults face various difficulties with online interfaces which limit their ability to make high quality decisions in e-commerce environments. These difficulties stem from the natural aging process and negatively affect this user group in two main areas. First, they suffer from the diminishing physical abilities of vision, hearing, and motor skills. Second, they also suffer from diminishing cognitive abilities which are not related to intelligence or willingness to learn; but include attention deficits, lower processing speeds, declines in spatial abilities, memory impairments, retention issues, and higher distraction by visual clutter, animation, and irrelevant information. These cognitive challenges act as a significant barrier to older adults' computer use (Wagner et al. 2010). Thus, there is a growing need to understand the impacts of such cognitive challenges faced by older adults in e-commerce environments and to consequently support them with the most appropriate decision aids to address these challenges.

THEORETICAL BACKGROUND AND RESEARCH MODEL

Decision making in online environments is a complex task for all consumers. The ever-growing plethora of product and vendor choices and the overabundance of detailed product information burden online consumers and complicate their decision making process. Additionally, the lack of physical interaction with tangible products in e-commerce environments prevents consumers from adequately assessing their features and quality which renders the decision making process even more difficult (Häubl and Trifts 2000). These limitations force consumers to resort to suboptimal strategies such as satisficing where they settle for satisfactory yet suboptimal decisions to conserve cognitive effort. These complex problems are even more exacerbated amongst older consumers given their diminishing cognitive abilities (Finucane et al. 2002). Particularly, they face higher levels of confusion caused by product complexity, choice proliferation, and information overload which can affect the cognitive process of decision making and

consequently, the decision outcome quality (Walsh and Mitchell 2005).

Decision making has been shown to be affected by three main factors (Appelt et al. 2011): decision features such as the framing or ordering of decision options; situational factors such as time pressure and social context; and individual differences which are specific characteristics of the decision maker such as decision making style and gender among others. The first two of these factors have been well studied and there is a general understanding and consensus as to their effects and impacts on decision making. However, there seems to be a lack of focus, understanding of, and consensus amongst the research community in regards to the individual differences, which warrants the need for research that focuses on these differences as well as on their interactions with other decision making factors such as decision features (Appelt et al. 2011).

Two important factors influence **Decision Quality (DQ)** including e-commerce decisions. The first are **Decision Making Styles (DMS)**, sometimes labelled Cognitive Styles, and are considered an individual difference factor. DMS are defined as a personality trait that shapes individuals approach to decisions (Sproles and Kendall 1986). The second are **Cognitive Biases (CB)**, sometimes labelled Decision Biases, and are considered a decision feature factor. CB are defined as common inherent reasoning prejudices that reduce the quality of a significant number of decisions (Arnott 2006). Evidence suggest that consumer DMS incorporate both cognitive and affective characteristics (Sproles and Kendall 1986), which suggests that CB can interact with DMS. Hence, it is expected that some consumers maybe more or less impacted by different CB due to the specific DMS they espouse. However, this is yet to be studied rigorously.

The decline of certain cognitive abilities (e.g. memory, attention, reasoning) as a natural result of ageing drives older consumers to rely more on heuristics to overcome deficits in these abilities (Fleischmann et al. 2014). Thus, it is logical to expect that this approach renders them more vulnerable to certain CB that are closely related to these diminishing cognitive abilities. One of these CB is the **Recall Bias** (Arnott 2006), sometimes described as the Vividness bias, which gravitates the decision maker towards alternatives that are rich in media and are consequently easier to remember. Additionally, the **Order Bias** (Arnott 2006), also referred to as the Sequential bias or Primacy effect, is a CB where the decision maker gravitates towards the first or last alternative in a set as a result of declining attention when evaluating multiple alternatives. Another bias that is related to memory and attention is the **Completeness bias** (Arnott 2006), where the decision maker perceives information as complete and is not attentive to important omissions that can potentially impact the decision. These three biases are selected to be focused on in this study as they are thought to be particularly salient for the older adults segment due to

their diminishing cognitive abilities including memory deficits (Fleischmann et al. 2014). Additionally, research indicates that these biases affect decisions within an e-commerce context (Fleischmann et al. 2014).

Evidence suggests that culture significantly shapes individuals' DMS (Dabić et al. 2015). Wickliffe (2004) identified three salient DMS specific to the American marketplace which we adopt here given the geographic focus of this research. Thus, the three DMS which will be examined are: **Brand Conscious** (shows concern for up-to-date, highly advertised, well-known, national, and designer brands products); **Perfectionist, High-Quality Conscious** (demonstrate high standard expectations and concern for quality, and price-value equity of products); and **Confused Impulsive** (reduces the cognitive load associated with the decision as a result of information overload by making impulsive decisions which can be regretful).

Decision aids have been shown to be effective in reducing or eliminating biases influencing decision makers who are prone to CB thus improving their DQ (Bhandari and Hassanein 2012), which is referred to as de-biasing. Online consumers have become much more reliant on decision aids to assist them with their online purchasing decisions as a result of the increasing complexity of decision making in online environments. Various decision aids such as content filters, intelligent agents, recommendation agents, comparison matrices, product reviews, expert chats have been available for many years and have been shown, in some cases, to positively affect decision making quality (Xiao and Benbasat 2014).

One of the unique affordances of the online environment is that it allows e-commerce vendors to create interactive and personalized interfaces for shoppers (Häubl and Trifts 2000). Such personalization of web sites has been shown to improve site brand loyalty, repeat site visits and to lower the likelihood of web site defection among other metrics. Unfortunately, available online decision aids are typically generic in nature and are generally not tailored to the varied individual differences of e-commerce consumers. In general, previous research has been inconclusive with respect to the effects of decision aids on consumers' DQ in online environments (Xiao and Benbasat 2014). Particularly, different decision aids have been shown to have contrasting effects on DQ in e-commerce (Häubl and Trifts 2000; Tan et al. 2010).

Based on the foregoing discussion, it becomes clear that there is a need to explore and understand whether and how different CB interact with different DMS, and how these interactions influence the ability of older adults to make high quality decisions in complex e-commerce environments. It is also important to investigate variances in this regard by product type (e.g. tangible and intangible products), as studies have shown product type as playing a role in shaping consumer experiences in e-commerce environments (Hassanein and Head 2006). Finally, it is important to investigate the potential of decision aids in

improving e-commerce decisions' quality with an emphasis on customizing such aids for the varied individual differences of the older adults' consumer segment.

There has been many calls to investigate the decision making of older adults under the influence of CB (Finucane et al. 2002); within the context of Information Systems; and particularly in e-commerce environments (Tan et al. 2010). While some studies have provided evidence of the presence of CB in e-commerce and shed some light on the utility of decision aids in de-biasing users, CB have been generally examined in isolation from cognitive style theory. Additionally, few studies have studied e-commerce under the DMS paradigm, although evidence suggests that DMS plays a significant role in this context. Moreover, there are no studies that investigate these relationships for the older adults' demographic, despite being considered the most susceptible and vulnerable group to CB influences (Peters et al. 2007). To address this gap, this two stage exploratory study attempts to exhume the complex interaction effects between CB and the different DMS to methodologically identify the combinations that exert a negative influence on the DQ of older adults in e-commerce tasks. Consequently, the second stage of the study aims to investigate the utility of different decision aids to support older adults in making higher quality decisions under such combinations. Thus, our overarching objectives are:

Objective 1: Identify the detrimental combinations of CB and DMS to the DQ of older adults in e-commerce tasks.

Objective 2: Investigate whether these effects vary by product type in this context.

Objective 3: Identify the decision aids that are most effective in de-biasing and improving DQ in this context.

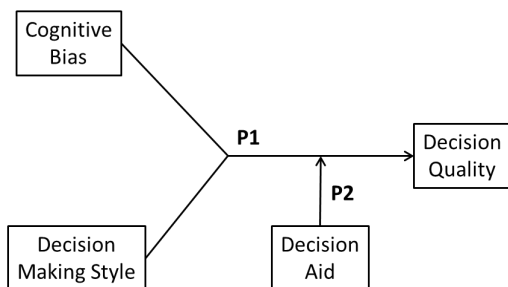


Figure 1. Research Model

Figure 1, above, shows a research model that captures the variables in this study and their interrelations. The basic premise of this model which is supported by the forgoing discussion and theory base is that older adults espousing different DMS will be susceptible to specific CB to different levels, such that their DQ will be influenced differently for certain combinations of CB and DMS (P1). Additionally, the model argues that different decision aids will be effective to different degrees in de-biasing CB for specific DMS (P2). We further argue that these

propositions are applicable in e-commerce tasks involving tangible as well as intangible products with the understanding that the effect of biases and their interactions with specific decision making styles may vary across these two product categories. The above propositions could more generally be stated as:

Proposition 1: The interaction of specific cognitive biases and certain decision making styles will influence the quality of older adults' decisions in e-commerce tasks while shopping for (a. tangible) and (b. intangible) products.

Proposition 2: Specific decision aids will improve the decision quality of older adults exhibiting certain combinations of decision making styles and cognitive biases in e-commerce tasks while shopping for (a. tangible) and (b. intangible) products.

METHODOLOGY

In this section we outline a detailed methodology for an exploratory experimental design in two phases to empirically test and validate the above propositions.

Phase 1: Investigating the Interaction Effects of Cognitive Biases and Decision Making Styles

Older adults will be invited to voluntarily partake in the study through the McMaster Gilbreath Centre for Studies in Aging and through a variety of other resources including a market research firm, and every effort will be made to ensure that the sample is representative of the population. Participants will be initially tested to determine their dominant DMS using the scale designed by Wickliffe (2004), then they will be asked to complete two controlled experimental e-commerce tasks (one involving a tangible product and another involving intangible product). Each task will be under a randomized induced influence of either one of the three CB mentioned earlier or a non-induced bias treatment. Both participant assignment to bias treatments and task order will be randomized. Thus, tasks will follow a four level (three induced CB treatments and a non-induced bias treatment) by three level (one for each DMS) by two level (tangible or intangible product) partially-repeated measures analysis of variance design (total of 24 matrix cells). The impact of product type will be measured within subjects to reduce the required number participants (12 matrix cells).

Each participant will be asked to complete their two controlled e-commerce tasks within a carefully designed website following a commonly accepted e-commerce experimental design (Häubl and Trifts 2000; Tan et al. 2010). The tasks will involve the selection of specific tangible (e.g. laptop computer)/intangible (e.g. airline ticket) products meeting a pre-determined set of criteria provided to them. Each of the experimental tasks will be carefully designed so as to have a single optimal choice as well as a range of sub-optimal choices while ensuring sufficient complexity. Each alternative will be assigned a

score based on the extent to which it meets the selection criteria outlined in the task with the optimal alternative having the highest score. The design will be validated in a pre-test (with faculty, staff, and graduate students) and a pilot study (using a convenience sample). The experimental design will ensure that each studied CB is isolated so that participants are only exposed to one CB at a time. To induce specific biases, each bias treatment task will be slightly different. For example, the order of presented choices will be controlled in the Order bias induced tasks but will be randomized for the others. Similarly, all alternatives will be presented in the same way and will be described with full information except when they are manipulated for the Recall bias and Completeness bias induced tasks respectively.

A one-tail t-tests will be used to analyze the differences in proportions of optimal decisions made between groups of subjects espousing different DMS completing their e-commerce tasks under specific induced biases versus the group completing the same tasks without induced bias. Group differences across product types for the same bias will also be analyzed. Mean score differences in deviation from the optimal decision score will also be compared across the same groups. Additionally, ANOVA statistical methods will be used to compare the results down each of the treatments' matrix column in order to understand which CB are most salient for each DMS, and across each treatments' matrix row in order to understand how the impact of a CB varies across DMS. Comparison between corresponding cells under the two tasks (tangible and intangible) will also facilitate an understanding of how the interaction effects of DMS and CB vary by product type. Demographic balance between the different cells in the treatments' matrix will be maintained and other relevant variables, such as education, prior experience with the tasks, etc. will be controlled for. In order to detect a medium effect size at a power of 0.8 and α of .05, this phase will require of 26 participants for each cell (Tan et al. 2010). To account for possible incomplete experiments and data spoilage, we will use 30 participants per cell for a total of 360 participants. Phase 1 of the research will reveal the most detrimental combinations of DMS and CB in terms of the severity of their combined effect on DQ of older adults in e-commerce tasks.

Phase 2: Understanding the Utility of Customized Decision Aids for De-Biasing Older Adults in E-Commerce Environments

Two types of decision aids have been selected for this phase: **Recommendation Agents (RA)**, which filter out alternatives not meeting the criteria of the user; and **Comparison Matrices (CM)**, which provide the user with a detailed matrix of product criteria for each alternative. These decision aids were selected as they are the standard aids provided on most e-commerce websites (Xiao and Benbasat 2014) and they transform the way consumers seek information and make decisions in an e-commerce context (Häubl and Trifts 2000). Applying

these decision aids individually or combined will provide additional insights into how individual aids or a combination of them influences DQ.

The experimental design in this phase follows the design in the previous phase. New participants will first be tested to determine their dominant DMS, and then potentially assigned to the same two controlled experimental e-commerce tasks under the randomized induced influence of either one of the three CB or the non-induced bias treatment. Participants will be randomly assigned to one of four groups receiving different decision aids as follows: CM only, RA only, both CM and RM together, or no decision aids (this last group results will be imported from the corresponding cells in Phase 1). Thus, the experiment will follow a four level (three induced CB treatments and a non-induced bias treatment) by three level (one for each DMS) by four level (different decision aids outlined above) by two level (tangible or intangible product) partially-repeated measures analysis of variance design (total of 96 possible matrix cells). The impact of product type will be measured within subjects to reduce the required number participants where appropriate. As the number of significant detrimental combinations of DMS and CB propagated from Phase 1 is unknown at this point, it is not possible to determine the exact number of matrix cells or the total number of required participants in Phase 2 until Phase 1 is complete. For each cell propagated from Phase 1, 30 participants will be needed using the same sample size logic as outlined in Phase 1 above. Participants' performance on their assigned tasks will be scored using the same methods used in Phase 1. Results of this second phase of the research will provide an understanding of which individual or combination of decision aids are most effective in de-biasing e-commerce shoppers with specific DMS who are susceptible to certain CB.

POTENTIAL CONTRIBUTIONS, LIMITATIONS AND FUTURE RESEARCH

This research promises to make important theoretical and practical contributions. From a theoretical perspective: first, it will advance our understanding of how CB influence the DQ from a cognitive style theory perspective. Specifically, it will clarify whether interactions of specific CB with certain consumer DMS might have a negative influence on the DQ of older adults in e-commerce tasks. Second, it will explore the potential de-biasing role of different decision aids in enhancing the DQ of older adults in e-commerce tasks while under the influence of specific identified detrimental combinations of CB and DMS.

From a practical perspective: online vendors could leverage the findings and guidelines developed under this research program to improve their websites' accessibility for older adults. More specifically, it will allow vendors to provide the appropriate decision aids to support their older adult consumers, affording them substantially

enhanced online shopping experiences and thus potentially improving their satisfaction and loyalty.

As with any research endeavour, there are some limitations. First, given the differentiating influence of culture, results of this research, which is focused on a Canadian and U.S. demographic, must be validated with samples from other cultures before generalizing them to those cultures. Second, this study focuses on specific biases that are suspected of affecting our population of interest. Additional research can examine numerous other biases across different populations and contexts. Finally, in this study we will only explore two types of decision aids. Various other decision aids exist and their utility in supporting older adults in e-commerce environments should be explored in future research.

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