DESIGNING RECOMMENDATION AGENTS FOR OLDER ADULTS

ONLINE PRODUCT RECOMMENDATION AGENTS DESIGN: THE ROLE OF COGNITIVE AGE AND AGENT COMPREHENSIVENESS

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Abstract

The quantity and variety of product information available online today has increased significantly in recent years. This situation has exacerbated user information overload perceptions and made it difficult for online shoppers to choose between various online products and services. This is especially true for older adults, who typically have limitations in cognitive abilities due to the natural aging process and, as such, may perceive additional difficulties processing large amounts of information online. In response, Recommendation Agents (RAs) have become popular as decision support tools for online consumers in general, and older adults in particular. However, in the information systems literature, there is a lack of understanding regarding the design of RAs to suit the needs of different segments of the population, including older adults. Grounded in the theory of planned behaviour, and the "aging and IS adoption" literatures, this study investigates the impact of cognitive age and RA comprehensiveness on user perceptions towards the complexity of the input and output stages of an RA, and their subsequent impact on the antecedents of a user's intention to utilize the RA for online shopping.

This experimental study finds that: (i) an individual's cognitive age significantly increases perceived RA input and output complexity perceptions; (ii) higher levels of RA comprehensiveness increases a user's RA input and output complexity perceptions significantly; (iii) RA output complexity plays a more critical role than RA input complexity in shaping user perceptions of the overall complexity of an RA; and, (iv) increased levels of RA comprehensiveness increases individual perceptions of RA usefulness. Additionally, and as expected, cognitive age moderates the relationship between RA comprehensiveness and input/output complexity such that the effect is stronger for older adults. Surprisingly, however, cognitive age also moderates the relationship between RA comprehensiveness and perceived RA usefulness such that it is stronger for older adults. Theoretically, this study helps us to better understand how different levels of RA comprehensiveness, in terms of both the input and output stages of the RA operation, impact the intention of users of different cognitive ages to use online RAs. For practitioners, the results highlight the importance of customizing the design of RAs, in both their input and output stages, for consumers with different cognitive ages.

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Chapter 1: Introduction

This research integrates the theory of planned behaviour, and the aging and information systems adoption literatures to understand an individual's intention to use online Recommendation Agents (RAs) while shopping for online products. Specifically, this research examines the impact of cognitive age and RA comprehensiveness on the antecedents of an individual's intention to use an online RA. Although older adults are the fastest growing segment of users on the Internet and have a strong interest in making online purchases, they face cognitive limitations, and thus may perceive difficulties in making online decisions not experienced by younger adults (Nam et al., 2007; Lian & Yen, 2014). Therefore, online RAs could help older adults make better decisions while shopping for online products. However, in the IS literature, there is a lack of understanding on the design of online RAs for different segments of the population (e.g., older adults). Therefore, this study takes into account the impact of cognitive age and RA comprehensiveness, in terms of both the input and output stages of an RA, on a user's intention to use an online RA while shopping online.

1.1 Research Motivation

Online shopping has increased dramatically in the last few years (Shobeiri, Mazaheri, & Laroche, 2015). The quantity and variety of product information available online have also increased significantly, enhancing information overload perceptions and making it difficult for consumers to choose the right products or services (Xu, Benbasat,

& Cenfetelli, 2014). This is especially true for older adults as they have limitations in their cognitive abilities and may perceive additional difficulties in processing large amounts of information online (Becker, 2004).

The United Nations reports that while in 1950 5.2% of the population were over the age of 65, this percentage is projected to increase to 15.9%, 27.5%, and 32.3% by the years 2050, 2150, and 2300 respectively (Baecker, Moffatt, & Massimi, 2012). Studies have reported that older adults are the fastest growing segment of Internet users (Lian & Yen, 2014). Hence, they are an important segment for online retailers to consider. However, although older adults have a strong interest in making purchases through the online environment, they have been neglected for years by retailers. The lack of attention to this important and rapidly growing consumer segment has led to decreased purchasing opportunities for older adults and loss of potential revenues for retailers (Nam et al., 2007; Lian & Yen, 2014).

In the online environment, Recommendation Agents (RAs) are online-based software tools that support online shoppers by eliciting their preferences for products and making appropriate recommendations that satisfy consumer preferences (Ansari, Essegaier, & Kohli, 2000; Xiao & Benbasat, 2007, Ricci & Werthner, 2006; Xu et al. 2014). RAs operate in three stages: i) an input stage where consumers' preferences are elicited; ii) a processing stage where recommendations are generated; and iii) an output stage where recommendations are presented and the user makes a decision (Xiao & Benbasat, 2007). Each of these stages is considered as a critical success factor for online

RA vendors, especially those confronted with increasingly competitive pressures (Kamis & Stohr, 2006; Palanivel & Sivakumar, 2010; Xu et al. 2014). A poorly designed RA, however, could result in frustrated consumers. Specifically, the RA's user interface experienced by users in the input and output stages of the RA's operation has been discussed by practitioners and researchers to be a critical factor to attract customers to use them in their online shopping decision makings (Leavitt, 2006; Gretzel & Fesenmaier, 2006). Given this, the impact of an RA's user interface on consumer online decision making, especially for older adults, is still not well understood.

Studies show that consumers have become much more reliant on RAs to help them with their shopping decisions (Xiao & Benbasat, 2007). Online RAs could especially be helpful for older adults in making better online decisions given the additional difficulties they face due to the natural aging process. However, as RAs vary in the amount of detail (or comprehensiveness) of their input and output stages (Xiao & Benbasat, 2007), some consumers may perceive difficulties due to the increased complexity associated with using highly comprehensive RAs, characterized in terms of the number of the product attributes in the input stage and the number of recommendations and the level of detail associated with these recommendations in the output stage. This could particularly be the case for older adults experiencing limitations in their cognitive abilities which are expected to manifest the most during the input and output stages of RA use, as individuals have the most interaction with RAs in these stages (Ghasemaghaei, Hassanein, & Benbasat, 2014). Thus, this study seeks to investigate the impact of age and RA comprehensiveness on an individual's intention to use an online RA.

In the IS literature, age has been usually measured as the number of years from birth (i.e,. chronological age) without much attention to individual self-perceptions of age (Hong et al. 2013; Ghasemaghaei et al. 2014). However, according to Sherman, Schiffman, & Mathur (2001), "[A]ge is revealing itself to be more a state of mind than a physical state (p. 188)." Hong et al. (2013) found that it is the self-perception of one's own age (i.e., cognitive age) rather than one's chronological age that impacts behaviours towards using technology. For example, in a study of American elderly consumers, Eastman & Iyer (2005) found that seniors with the same chronological age, who exhibited lower perceived age, were more willing to use the Internet compared to those whose self-perceived age was higher. Thus, in this study, an individual's cognitive age is used to understand how RAs should be best designed and a person's intention to use an online RA.

1.2 Research Objectives

Previous studies have examined the effects of RAs on consumer experiences in online shopping environments. For example, Komiak & Benbasat (2006) explored the effects of perceived familiarity and personalization on the intention to adopt an RA. Swaminathan (2003) studied the impact of RAs on consumer decision making while considering the moderating roles of product complexity, category risk, and consumer knowledge. However, no studies have examined the role of consumers' age on their online shopping experience while using online RAs. Therefore, there is a need for additional research in this area, particularly in terms of customizing these agents for specific e-commerce consumer segments such as older adults. Thus, the first objective of this paper is to use aging theories to understand the influence of cognitive age on the RA user experience and its ultimate impact on the intentions to use RAs for online decision making. This age consideration is a novel addition to the online RA design literature.

Xiao & Benbasat (2007) show that users perceive RAs to be useful when they perceive high utility for RAs. However, although different levels of RA comprehensiveness could impact user perceptions regarding RA usefulness in shopping decisions, it has been overlooked in the online RA research literature. Thus, the second objective of this study is to understand the influence of the level of RA comprehensiveness on the RA user experience and its ultimate impact on intentions to use RAs to support online decision making. Towards that end, this study draws on cognitive complexity theory and cognitive load theory to predict the influence of RA comprehensiveness on individual perceptions regarding RA complexity. This perspective recognizes that increased RA comprehensiveness could be useful up to a point beyond where it becomes a burden to users (depending on their cognitive abilities) making the RA difficult to use.

The IS literature has been mostly focused on the design of the input stage of online RAs (e.g., Komiak & Benbasat, 2006; Wang & Benbasat, 2009). This overlooks the importance of the output stage where users closely interact with online RAs

(Ghasemaghaei et al. 2014). Thus, the third objective of this paper is to understand the individual roles of RA input and output stages' complexity level on the RA users' experience and its ultimate impact on their intentions to use RAs to support their online decision making. Hence, this study focuses on the design of RAs in both the input and output stages where individuals have the most interaction with RAs.

According to aging theories, older adults face limitations in their cognitive abilities (Kooij et al. 2008). Thus, when RAs exhibit different levels of comprehensiveness, in their input and output stages, older adults may have different online shopping experiences compared to younger adults. Such differences could necessitate different RA design guidelines for the increasingly growing older adult segment of Internet users. Thus, the fourth objective of this study is to understand the differences in the perceptions of cognitively older and younger adults while using RAs of different comprehensiveness levels.

Based on the above four main research objectives, there are four main research questions for this study:

RQ1: How does RA comprehensiveness impact the antecedents of user intentions to use online RAs?

RQ2: How does cognitive age impact the antecedents of user intentions to use online RAs?

RQ3: How do complexity and usefulness perceptions of users of RAs with different levels of comprehensiveness vary between younger and older adults?

RQ4: How does RA input and output complexity impact the RA user experience?

To address these research objectives and associated research questions, this study proposes and empirically validates a research model grounded in the Theory of Planned Behaviour (TBP) (Ajzen, 1991) and leveraged in Aging, Cognitive Load and Complexity theories. The empirical findings of this study will provide guidelines for practitioners on how to better design online RAs with different levels of comprehensiveness to suit the cognitive abilities of different customer segments.

1.3 Outline of Dissertation

The remainder of this dissertation document is organized as follows. Chapter 2 provides a literature review of the studies conducted in the area of aging and online RAs. Chapter 3 presents the theoretical background for this research and details the research model and hypotheses that were tested with the research methodology described in Chapter 4. In Chapter 5, the results of data analyses conducted are presented. Finally, Chapter 6 provides a discussion of findings and outlines this study's contributions and limitations, as well as recommendations for future research directions.

Chapter 2: Literature Review

The purpose of this chapter is to provide a review of the studies on aging and online RAs in order to understand the current state of research in these areas. To fulfil this purpose, the chapter is organized as follows: Section 2.1 presents the different mechanisms that have been suggested to describe the age-related declines in cognitive performances specifically related to technology use with emphasis on online shopping in particular. This section also outlines the different methods used to measure age in the literature. Section 2.2 introduces online RAs and their various types and examines the previous research on online RAs. Finally, Section 2.3 summarizes the findings of this literature review.

2.1 Aging

The number of older adults population has increased significantly during the last century and it is expected to continue to rise. As shown in Figure 2.1, the United Nations report that in 1950 5.2% of the population were over 65. This percentage is projected to increase to 15.9% by the year 2050 (Baecker et al., 2012). As illustrated in Figure 2.2, the number of Canadians aged over 65 is projected to increase to more than 10 million by 2036.

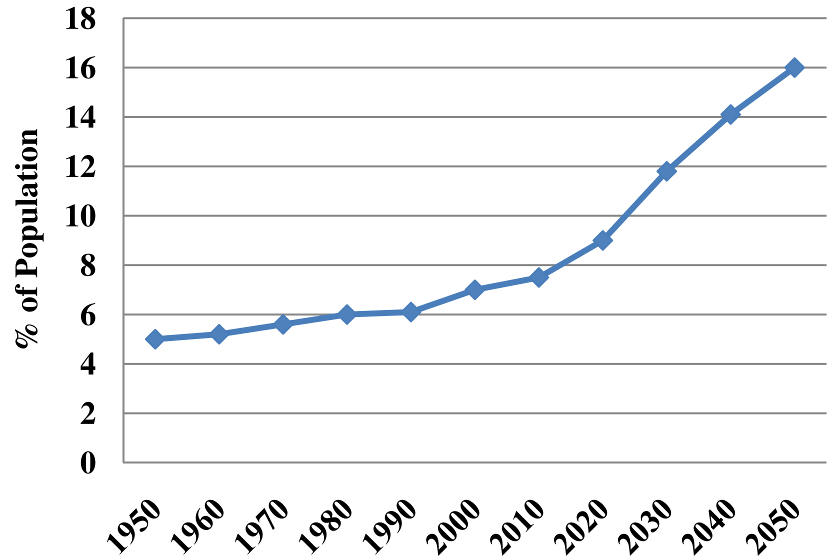


Figure 2.1 Percentage of the World Population Over 65 (United Nations, 2010)

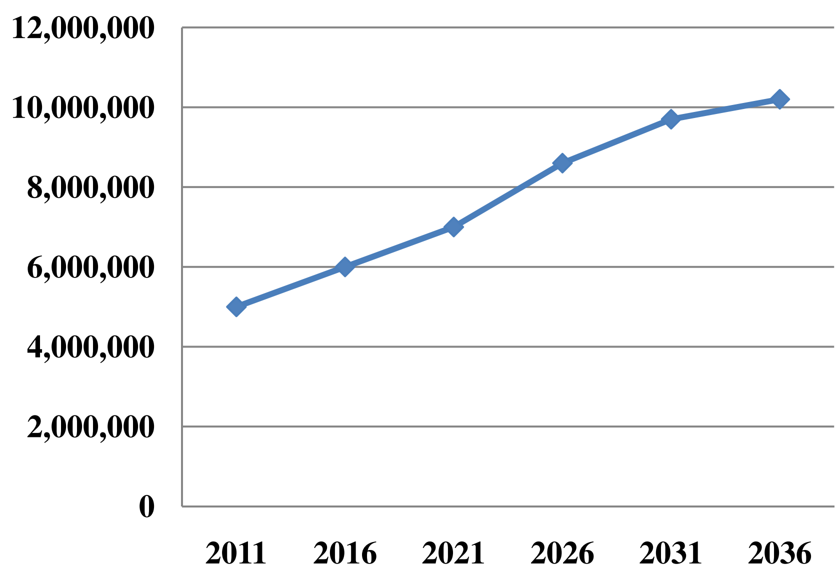


Figure 2.2 Number of Canadian Population Over 65 (http://www.c21canada.org/2013)

It is generally accepted that as people become older, there will be decline across multiple cognitive abilities (Kooij et al. 2008). Thus, although older adults have a strong interest in purchasing online products, the age-related decline in cognitive functions has decreased purchasing opportunities for older adults (Nam et al., 2007; Lian & Yen, 2014). Different mechanisms have been suggested to describe the age-related declines in cognitive performances while shopping for online products. These mechanisms include issues related to attention, memory, processing speed, spatial ability, and navigation as explained below.

Attention: Most websites contain a large quantity of information, much of which is irrelevant or unnecessary to complete the required task. Thus, it becomes important for the user to be able to focus his/her attention on the task at hand. Studies show that compared to younger adults, older adults are affected to a greater extent by irrelevant information (Connelly & Hasher, 1993; Sjölinder, 2006).

Memory: Many older adults have difficulties in remembering and learning (Namazi & McClintic, 2003). For example, compared to younger adults, older adults often have difficulties in remembering the context of the information particularly if the message is too lengthy (Hawthorn, 2000). When the information consists of a large amount of text, older adults become confused and remember less (Gregor, Newell, & Zajicek, 2002).

Processing speed: Increased age is associated with longer reaction times and slower responses, which contributes to age-related differences in performance on different tasks. Compared to younger adults, mental operations are slower for older adults (Salthouse, 1996). The slower processing speed makes it difficult for older adults to respond to different stimuli in the online environment and makes it more difficult for them to select, process, and remember information (Sjölinder, 2006).

Spatial ability: Online environments are often designed around spatial structures. The individual's spatial ability influences their ability to navigate in the online environment (Sjölinder, 2006). Many studies have studied spatial ability and have found that it impacts the performance of individual's performance on computer tasks, including website navigation (Benyon & Murray, 1993; Höök, Sjölinder, & Dahlbäck, 1996; Wagner, Hassanein, & Head, 2014). As people become older, there is a decline in their spatial ability which is one explanation for the increased difficulties older adults face when purchasing online products (Kelley & Charness, 1995; Wagner, Hassanein, & Head, 2014).

Navigation: Compared to younger adults, older adults are more likely to lose track of where they have navigated and return back to the pages that they have already visited, which is related to age-related decline in memory (Sjölinder, 2006). In addition, older adults tend to scroll through more pages and follow more hypertext links to find the information they are looking for (Mead, Sit, Rogers, Jamieson, & Rousseau, 2000). In their online shopping experience, many older users have been found to become disoriented on a website (Chadwick-Dias, McNulty, & Tullis, 2003). Furthermore, older adults have more difficulties in remembering the location of information they have already viewed. Many of them are also unaware of which items are clickable. Moreso than younger adults, they often click on items that are not links such as bullets, headings, and icons (Chadwick-Dias et al., 2003). Difficulties in knowing which actions to take to get the information they are looking for contribute to confusion in navigation in older adults.

Hence, although older adults are interested in purchasing online products, the different mechanisms, explained above, decrease purchasing opportunities for them.

2.1.1 Age Measurement

Chronological age which refers to the number of years a person has lived is a useful age measure (e.g., Phillips & Sternthal, 1977; Visvabharathy, 1982). However, it is no longer considered a good predictor of factors such as mental outlook and cognitive ability (Barak & Gould, 1985). Thus, despite the great popularity of chronological age, the use of it is problematic for researchers interested in age-related research that evaluates the behavioural patterns of individuals (Morris & Venkatesh 2000).

Czaja et al. (2001) and Lindberg et al. (2006) suggest that as computer performance among individuals has been shown to vary widely, predictions regarding user performance should not be based solely on chronological age. As such, some research attention has focused on the subjective perception of how old one feels (Barak, 2009; Guido et al. 2014). Barak & Schiffman (1981) suggest that an individual's behaviour may be based on perceived or felt age rather than their chronological age.

Three main concepts of self-perceived age can be identified from the literature on aging: i) *cognitive age*, which refers to how old individuals are based on their self-perceptions regarding their looks, feelings, actions, and interests (Barak & Gould, 1985; Barak & Schiffman, 1981); ii) *comparative or relative age*, which refers to whether individuals feel the same, older, or younger than most people with the same chronological age; and iii) *ideal age*, which refers to "an individual's ideal age-role self-concept: the age he/she considers to be a person's ideal age, expressed in years" (Barak & Gould, 1985). These alternative measurements of age enable a better understanding of the individual's attitudes and behaviours. Among these self-perceived age concepts, cognitive age has been most commonly used in consumer research and it has been found to impact consumer;s behaviours (Barak & Gould, 1985; Johnson, 1996; Guiot, 2001; Sherman et al., 2001; Goulding & Shankar, 2004). To measure an individual's cognitive age, Barak & Schiffman (1981) asked subjects to indicate which age decade (e.g., 20s, 30s, 40s, 50s, 60s, 70s, 80s, or 90s) best described their perception of themselves in terms of do-age (how involved a person is in doing "things" that are favored by members of a certain age group), feel-age (how old a person feels), interest-age (how similar an individual's interests are to members of a certain age group), and look-age (how old a person looks). Schwall et al. (2012) suggest that there are three subcategories of individual aging: biological (i.e., individual's physiological capabilities which captures sensing, the aging of the body), social (i.e., social roles and habits), and psychological (i.e., individual's ability to adapt behaviour to the demands of the environment (e.g., expectation to retire)).

They noted that cognitive age is a type of subjective age which considers all these subcategories in computing one's individual age.

Cognitive age has been used and validated in consumer research (Underhill & Cadwell, 1984; Wilkes, 1992; Hong et al., 2013) as well as in aging research (Neugarten & Hagestad, 1976; Baum & Boxley, 1983). Aging research suggests that most adults tend to feel younger than their chronological age and such tendencies become more pronounced as individuals get older (Kastenbaum et al. 1972). This suggestion is supported by many studies (Barak & Gould, 1985; Clark et al. 1999). In addition, consumer research has shown that cognitive age influences an individual's purchasing behaviours (Sherman et al., 2001; Goulding & Shankar, 2004; Hong et al., 2013). For example, Yoon et al. (2005) found that compared to chronological age, cognitive age can provide better insight into consumer behaviours, as it can affect decision processes more than chronological age. Iyer et al. (2008) found that older consumers whose cognitive age is significantly lower than their chronological age are an attractive segment for online purchasing. Research has also shown that cognitive age can be more effective in capturing older adult lifestyles (Cleaver & Muller, 2002; Iyer et al. 2008), explaining their choices (Ying & Yao, 2010), and predicting their purchases (Myers & Lumbers, 2008), than other widely used variables such as education, income, and health (Gwinner & Stephens, 2001; Guido et al., 2014).

As online RAs are increasingly becoming available to consumers to facilitate their online shopping decision making (Leavitt, 2006; Xiao & Benbasat, 2007; Wang &

Benbasat, 2009), it is important to understand the influence of an individual's self-perceptions with regard to aging on the use of these agents. Thus, in this study, the impact of self-perceived age on user's behavioural intentions to use online RAs to support their decision making in online shopping tasks is considered. As cognitive age provides better insights into a consumer's behaviours, it is utilized as an effective measure of self-perceived age.

2.2 Recommendation Agents (RAs)

Having access to the vast amount of product information online may allow consumers to make better purchasing decisions. However, consumers may be unable to adequately process such large amounts of information due to their limited cognitive capacity, particularly older adults who have more limitations in their cognitive abilities. A response to the problem of information overload in the online shopping environment is the emergence of online RAs (Häubl & Murray, 2003; Detlor & Arsenault, 2002; Serenko, 2008).

RAs are software agents that elicit the preferences or interests of consumers for products and make recommendations accordingly (Xiao & Benbasat, 2007). With the help of RAs, consumers can evaluate their options, deal with information overload, and enhance the quality of their online decision making (Lee & Lee, 2009). RAs operate in three stages: (i) an input stage, where user preferences are elicited; (ii) a process stage, where recommendations are generated; and (iii) an output stage, where recommendations are presented to the user. Research on RAs has focused mostly on the process stage, which consists of evaluating and developing the different algorithms that generate recommendations (Swearingen & Sinha, 2002; Cosley et al., 2003), while failing to sufficiently investigate the user experience in the input and output stages. From the user perspective, the usefulness of RAs is determined by many factors other than the algorithms (Swearingen & Sinha, 2002), such as the characteristics of an RA's input and output stages (Xiao & Benbasat, 2007).

As seen in Table 2.1, there are different types of RAs such as attribute-based RAs; collaborative RAs; need-based RAs, and compensatory RAs. Some websites have used hybrid RAs that combine different types of RAs to utilize the advantages of each type. For example, Tango, an online RA for newspaper articles, combines an attribute-based RA and a collaborative-based RA. A definition and example of different RA types are shown in Table 2.1.

In this study, the focus is on the attribute-based RAs as they are an integral component of many of the online shopping sites and vendors can design them in such complex ways (in terms of the input and output stages) that could make it rather difficult for consumers, particularly older adults, to use.

Table 2.1 RA Types

RA Types	Definition	Example
Attribute-based RAs	Attribute-based RAs elicit user preferences based on different product attributes and based on that generate different alternatives (Xiao & Benbasat, 2007).	Toyota.ca
Needs-based RAs	Needs-based RAs ask users to provide information about how they want to use the	windows.microsoft.com

	product and then generate alternatives from which the user can make a choice. These types of RAs identify the needs of a user based on the intended use of a product and then make recommendations that meet those needs (Komiak & Benbasat, 2004).	
Collaborative filtering RAs	Collaborative filtering RAs utilize the opinions of like-minded consumers to generate product recommendations (Xiao & Benbasat, 2007).	amazon.com
Compensatory RAs	Compensatory RAs allow tradeoffs between product attributes. These types of RAs ask individuals to rate the importance of each product feature (Xiao & Benbasat, 2007).	MyProductAdvisor.com

2.2.1 RA Comprehensiveness

Xiao & Benbasat (2007) argue that RAs vary in the amount of detail (or comprehensiveness) in their input and output stages. In this study, RA comprehensiveness is defined as the number of the product attributes in the input stage and the number of recommendations and the level of detail associated with these recommendations in the output stage. RAs with low levels of comprehensiveness ask consumers about only a few numbers of product attributes in the input stage and produce only a low number of recommended products for customers to compare simultaneously in the output stage with low levels of detail associated with these recommendations. On the other hand, RAs with high levels of comprehensiveness gather large amounts of information about consumer product attribute preferences in the input stage and produce several recommendations for consumers to compare in the output stage with high levels of detail associated with these recommendations.

Figures 2.3, 2.4, 2.5 and 2.6 show different RAs that help customers purchase cars. Figures 2.3 and 2.4 show examples of the input and output stages of RAs with low level of comprehensiveness, while Figure 2.5 and 2.6 show examples of the input and output stages of RAs with high level of comprehensiveness. As can be seen in these figures, RAs with low level of comprehensiveness only ask consumers about a few numbers of product attributes in the input stage and produce only a low number of recommended products for customers to compare simultaneously in the output stage with low levels of detail associated with these recommendations. On the other hand, RAs with high level of comprehensiveness gather large amounts of information about consumer product attribute preferences (e.g., brand, body type & size, safety, appearance & capacity, price, quality & ownership, driving & performance) in the input stage and produce several recommendations for consumers to compare in the output stage with high levels of detail associated with these recommendations.

Figure 2.3 RA with Low Level of Comprehensiveness (Input Stage) (Source: AutoTempest.com)

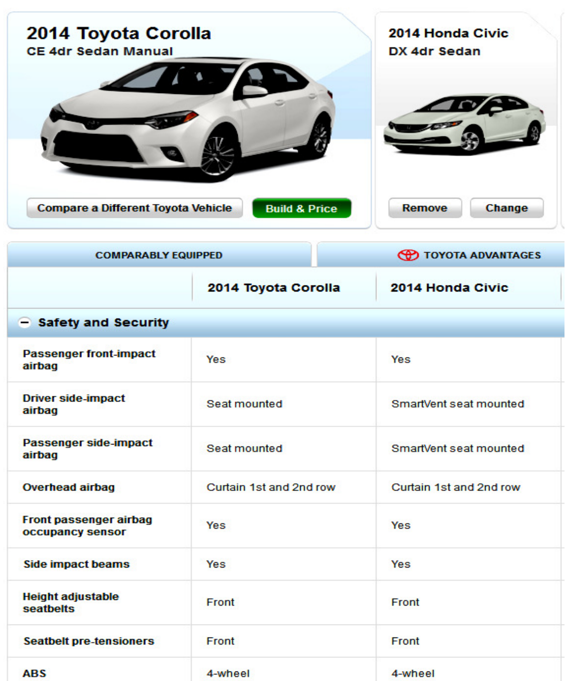


Figure 2.4 RA with Low Level of Comprehensiveness (Output Stage) (Source: http://www.Toyota.ca)

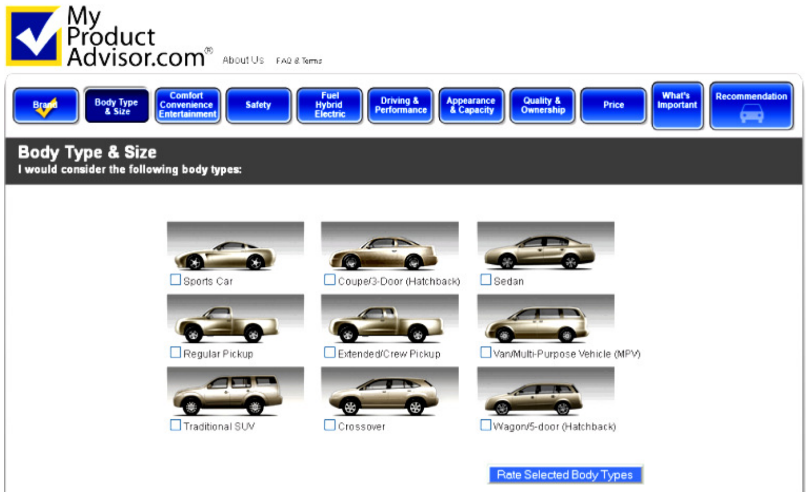
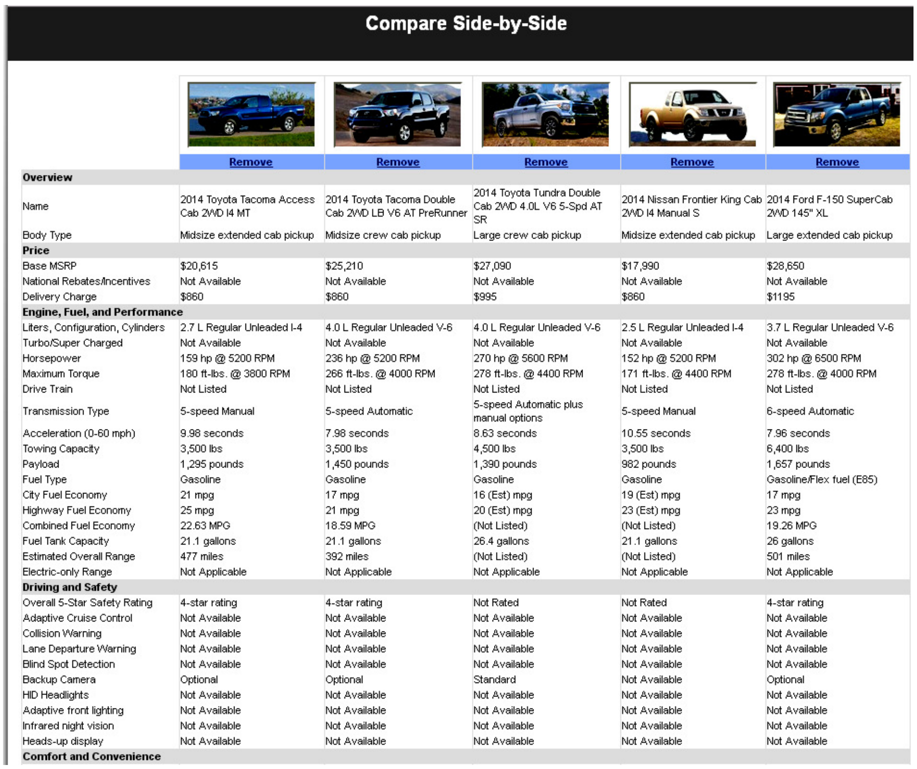


Figure 2.5 RA with High Level of Comprehensiveness (Input Stage) (Source: MyProductAdvisor.com)



Compare Side-by-Side

	Remove	Remove	Remove	Remove	Remove
Overview					
Name	2014 Toyota Tacoma Access Cab 2WD I4 MT	2014 Toyota Tacoma Double Cab 2WD LB V6 AT PreRunner	2014 Toyota Tundra Double Cab 2WD 4.0L V6 5-Spd AT SR	2014 Nissan Frontier King Cab 2WD I4 Manual S	2014 Ford F-150 SuperCab 2WD 145" XL
Body Type	Midsize extended cab pickup	Midsize crew cab pickup	Large crew cab pickup	Midsize extended cab pickup	Large extended cab pickup
Price					
Base MSRP	$20,615	$25,210	$27,090	$17,990	$28,650
National Rebates/Incentives	Not Available	Not Available	Not Available	Not Available	Not Available
Delivery Charge	$860	$860	$995	$860	$1195
Engine, Fuel, and Performance					
Liters, Configuration, Cylinders	2.7 L Regular Unleaded I-4	4.0 L Regular Unleaded V-6	4.0 L Regular Unleaded V-6	2.5 L Regular Unleaded I-4	3.7 L Regular Unleaded V-6
Turbo/Super Charged	Not Available	Not Available	Not Available	Not Available	Not Available
Horsepower	159 hp @ 5200 RPM	236 hp @ 5200 RPM	270 hp @ 5600 RPM	152 hp @ 5200 RPM	302 hp @ 6500 RPM
Maximum Torque	180 ft-lbs. @ 3800 RPM	266 ft-lbs. @ 4000 RPM	278 ft-lbs. @ 4400 RPM	171 ft-lbs. @ 4400 RPM	278 ft-lbs. @ 4000 RPM
Drive Train	Not Listed	Not Listed	Not Listed	Not Listed	Not Listed
Transmission Type	5-speed Manual	5-speed Automatic	5-speed Automatic plus manual options	5-speed Manual	6-speed Automatic
Acceleration (0-60 mph)	9.98 seconds	7.98 seconds	8.63 seconds	10.55 seconds	7.96 seconds
Towing Capacity	3,500 lbs	3,500 lbs	4,500 lbs	3,500 lbs	6,400 lbs
Payload	1,295 pounds	1,450 pounds	1,390 pounds	982 pounds	1,657 pounds
Fuel Type	Gasoline	Gasoline	Gasoline	Gasoline	Gasoline/Flex fuel (E85)
City Fuel Economy	21 mpg	17 mpg	16 (Est) mpg	19 (Est) mpg	17 mpg
Highway Fuel Economy	25 mpg	21 mpg	20 (Est) mpg	23 (Est) mpg	23 mpg
Combined Fuel Economy	22.63 MPG	18.59 MPG	(Not Listed)	(Not Listed)	19.26 MPG
Fuel Tank Capacity	21.1 gallons	21.1 gallons	26.4 gallons	21.1 gallons	26 gallons
Estimated Overall Range	477 miles	392 miles	(Not Listed)	(Not Listed)	501 miles
Electric-only Range	Not Applicable	Not Applicable	Not Applicable	Not Applicable	Not Applicable
Driving and Safety					
Overall 5-Star Safety Rating	4-star rating	4-star rating	Not Rated	Not Rated	4-star rating
Adaptive Cruise Control	Not Available	Not Available	Not Available	Not Available	Not Available
Collision Warning	Not Available	Not Available	Not Available	Not Available	Not Available
Lane Departure Warning	Not Available	Not Available	Not Available	Not Available	Not Available
Blind Spot Detection	Not Available	Not Available	Not Available	Not Available	Not Available
Backup Camera	Optional	Optional	Standard	Not Available	Optional
HID Headlights	Not Available	Not Available	Not Available	Not Available	Not Available
Adaptive front lighting	Not Available	Not Available	Not Available	Not Available	Not Available
Infrared night vision	Not Available	Not Available	Not Available	Not Available	Not Available
Heads-up display	Not Available	Not Available	Not Available	Not Available	Not Available
Comfort and Convenience					

Figure 2.6 RA with High Level of Comprehensiveness (Output Stage) (Source: MyProductAdvisor.com)

Examples of two types of RAs with different levels of comprehensiveness in both the input and output stages that were designed for this study are provided in the methodology section. As individuals have limitations in their memory capacity, increasing the amount of information presented to them in a given context could increase their perceptions of information overload (Alvarez and Cavanagh, 2004). This could particularly be the case for older adults who experience limitations in their cognitive abilities (Kooij et al., 2008).

2.2.2 Previous Research on Online RAs

Recently, there has been a surge in research on online RAs. As can be seen in Table 2.2, existing studies on online RAs can be categorized into five categories: definitions and descriptions, input stage, process stage, decision making and adoption.

Table 2.2 Existing RA Research Publications

Category	Publications
Definitions and Descriptions	(Todd & Benbasat, 1992), (Leavitt, 2006), (Ricci & Werthner, 2006), (Xiao & Benbasat, 2007), (Adomavicius & Tuzhilin, 2003), (Aggarwal & Vaidyanathan, 2003), (Ansari et al., 2000), (Detlor & Arsenault, 2002), (Gregor & Benbasat, 1999), (Häubl & Murray, 2006), (Jiang, Wang, & Benbasat, 2005), (King & Hill, 1994), (Maes, Guttman, & Moukas, 1999), (Montaner, López, & De La Rosa, 2003), (Moore & Punj, 2001), (Patrick, 2002), (Patton, 1999), (Punj & Rapp, 2003), (Schafer, Konstan, & Riedl, 2001), (Spiekermann & Paraschiv, 2002), (Stolze & Nart, 2004), (Urban, Sultan, & Qualls, 1999), (West et al., 1999), (Iacobucci, Arabie, & Bodapati, 2000), (Murray & Häubl, 2009), (Pfeiffer & Benbasat, 2012), (Xiao & Benbasat, 2014), (Aljukhadar & Senecal, 2011), (Wan &

Category	Publications
	Fasli, 2010), (Martínez-López et al., 2010), (Chen & McLeod, 2005), (Basu, Hirsh, Cohen, & others, 1998), (Sobecki, 2008), (Sheng, Li, & Zolfagharian, 2014)
Input Stage	(Gretzel & Fesenmaier, 2006), (Häubl & Murray, 2003), (Hess, Fuller, & Campbell, 2009), (Hess, Fuller, & Mathew, 2006), (Komiak & Benbasat, 2006), (Mao & Benbasat, 2000), (Schafer, Konstan, & Riedl, 2002a), (Wang & Benbasat, 2009), (McNee, Lam, Konstan, & Riedl, 2003), (Qiu & Benbasat, 2009)
Process Stage	(Ahn, 2006), (Benbasat & Todd, 1996), (Palanivel & Sivakumar, 2010), (Weiquan Wang & Benbasat, 2009), (Ariely, Lynch, & Aparicio, 2004), (Balabanović & Shoham, 1997), (Breese, Heckerman, & Kadie, 1998), (Claypool et al., 1999), (Diehl, Kornish, & Lynch Jr, 2003), (Good et al., 1999), (Herlocker, Konstan, & Riedl, 2000), (Herlocker et al., 2000), (Kottemann, Davis, & Remus, 1994), (Sarwar, Karypis, Konstan, & Riedl, 2000), (Schein, Popescul, Ungar, & Pennock, 2002), (Swearingen & Sinha, 2001), (Swearingen & Sinha, 2002), (Papagelis & Plexousakis, 2005), (Ying, Feinberg, & Wedel, 2006), (Miao, Yang, Fang, & Goh, 2007), (Miao, Yang, Fang, & Goh, 2002), (Chai et al., 2002), (Yang, Guo, & Liu, 2013), (Young Eun Lee & Benbasat, 2011), (Li et al., 2012), (Papagelis, Rousidis, Plexousakis, & Theoharopoulos, 2005)¸ (Felfernig et al., 2007), (Li & Khosla, 2003), (Kwon, Cho, & Park, 2009), (Sarwar et al., 2000), (Shih, Chiu, Hsu, & Lin, 2002), (Budalakoti, DeAngelis, & Barber, 2009), (Mohanraj & Chandrasekaran, 2011), (Andersen et al., 2008), (Wang, 2012), (Qian, Zhang, & Duan, 2013), (Sekozawa, Mitsuhashi, & Ozawa, 2011), (Bing, Fei, & Chunming, 2010), (Kim, Kim, & Choi, 2009), (Kwon, 2003), (Birukov, Blanzieri, & Giorgini, 2005), (Knijnenburg, Kobsa, Moritz, & Svensson, 2011), (Velásquez & Palade, 2007), (Zhang, Lin, Xiao, & Zhang, 2009), (Modi & Narvekar, 2015), (Li, Lv, Shang, & Gu, 2014)
Decision Making	(Häubl & Trifts, 2000), (Hess et al., 2006), (Hostler, Yoon, & Guimaraes, 2005), (Bechwati & Xia, 2003), (Cooke,

Category	Publications
	(Sujan, Sujan, & Weitz, 2002), (Cosley, Lam, Albert, Konstan, & Riedl, 2003), (Fitzsimons & Lehmann, 2004), (Gershoff, Mukherjee, & Mukhopadhyay, 2003), (Kamis & Davern, 2004), (Kramer, 2007), (Olson & Widing, 2002), (Pedersen, 2000), (Pereira, 2001), (Schafer, Konstan, & Riedl, 2002) (Senecal & Nantel, 2004), (R. R. Sinha & Swearingen, 2001), (Sinha & Swearingen, 2002) (Swaminathan, 2003), (Todd & Benbasat, 1994), (van der Heijden & Sørensen, 2002), (Vijayasarathy & Jones, 2001), (Punj & Moore, 2007), (Aksoy, Bloom, Lurie, & Cooil, 2006), (Lee & Kwon, 2008), (Aksoy, Cooil, & Lurie, 2011), (Kwon & Chung, 2010),(Aljukhadar, Senecal, & Daoust, 2012), (Hostler, Yoon, & Guimaraes, 2012), (Taylor, Brown, & from Fiction, 2009), (Aggarwal & Vaidyanathan, 2005)¸ (Ju Jeong & Lee, 2013)
Adoption	(Komiak & Benbasat, 2006), (Lee & Benbasat, 2011), (Weiquan Wang & Benbasat, 2009), (Brown & Jones, 1998), (Komiak, 2003), (Komiak & Benbasat, 2004), (Massa & Bhattacharjee, 2004), (Weiquan Wang & Benbasat, 2004), (Benbasat & Wang, 2005), (Dabholkar & Sheng, 2012), (Weiquan Wang & Benbasat, 2007), (G. Lee & Lee, 2009), (Wang & Doong, 2010), (Wang & Benbasat, 2008), (Qiu & Benbasat, 2010), (Su, Comer, & Lee, 2008), (Komiak & Benbasat, 2008), (Xiao & Benbasat, 2003), (Yoon, Hostler, Guo, & Guimaraes, 2013), (Benbasat, Dimoka, Pavlou, & Qiu, 2010), (Knijnenburg, Willemsen, Gantner, Soncu, & Newell, 2012), (Sheng, 2009), (Chen, 2012), (Zhu, Chang, Luo, & Li, 2014), (Sheng & Zolfagharian, 2014)

As shown in the above table, a large number of RA studies have focused on the process stage of the RAs. For example, Ahn (2006) presents a novel approach to automated online RAs based on the popularity characteristics of products. Studies in this category provide taxonomies of available RAs in terms of the underlying techniques and algorithms without paying much attention to the other design issues (e.g., issues related to the design of RA output stage).

Many studies have focused on the definitions and descriptions category. In this category, studies have focused on providing the definitions and explanations for different types of online RAs as well as their usefulness in helping consumers to have a better online shopping experience. For example, Xiao & Benbasat did a literature review on online RAs and identified their different important aspects.

Many studies have also focused on the impact of online RAs on consumer online shopping decision-making. For example, Hess et al. (2006) conducted an experiment to evaluate the impact of RA vividness (text, voice, and animation) on consumer online shopping decision-making.

There are also a few studies that have focused on the adoption of online RAs. For example, Wang & Benbasat (2005) found that consumer's initial trust in an online RA is an important factor that impacts their intention to use the RA in their online shopping.

A few studies have looked at the design of the RAs in terms of the input stage. For instance, Komiak & Benbasat (2006) found that different levels of RA personalization in the input stage impact an individual's intention to use online RA while shopping for online products.

To the best of my knowledge, no studies have focused on how the design of the RA output stage could impact a consumer's intention to use online RAs. In addition, none of the existing studies that focused on the design of the RA input stage have considered the impact of RA comprehensiveness on an individual's online RA adoption. Thus, this study addresses these gaps by trying to understand the impact of the design of the online RAs in both input and output stages in terms of comprehensiveness on an individual's intention to use them while shopping online.

2.3 Summary of the Literature Review

This dissertation builds, in part, on the existing studies done on online RAs in order to develop and validate an adoption model for online RAs. Although there are several studies focused on the design of online RAs (Komiak & Benbasat, 2006; Wang & Benbasat, 2009), no studies have examined the impact of consumer age on an individual's shopping experience while using online RAs. To the best of my knowledge, this is the first study to focus on the impact of an individual's age on their intention to use online agents to support their online shopping decision. Therefore, this age consideration is a novel addition to the online RA design and adoption literature.

A few studies have examined the effects of different factors (e.g., personalization, and restrictiveness) in the design of RAs on intention to adopt online RAs. However, no studies have examined the impact of RA comprehensiveness on individual intention to use online RAs while shopping online. This is an important factor considered in this research as RA comprehensiveness could be useful up to a point beyond which it becomes an overburden to users making the RA difficult for them to use. This could be the case specifically for older adults, as they perceive some limitations in their cognitive abilities.

Since the advent of the first RA more than a decade ago, many studies have focused on the RA process stage, which focuses on developing and evaluating the underlying algorithms that generate recommendations (Swearingen and Sinha 2002), while failing to focus on understanding the input and output stage's design strategies. Similarly, the majority of the articles on online RAs provide taxonomies of available RAs (mostly in terms of the underlying techniques and algorithms), without paying much attention to other design issues. Xiao & Benbasat (2007) argue that the effectiveness of RAs is determined by many factors other than the algorithms, including the characteristics of RA input and output stages. Recently, a few studies (Komiak & Benbasat, 2006; Wang & Benbasat, 2009) focused on the design of the online RAs. However, they primarily focused on the design of the input stage of online RA. As individuals have the most interaction with RAs in both the input and output stages, the output stage of the online RAs is also considered to be critical on impacting a user's intention to use online RAs. Hence, this study focuses on the design of both input and output stages of RAs and its impact on the user experience.

Chapter 3: Theoretical Development

To address the main research objectives of this study, this chapter presents relevant theories to develop an appropriate research model. In the research model, the impact of individuals' cognitive age and RA comprehensiveness on their intention to use online RAs while shopping online is explored. Section 3.1 explains the relevant theoretical background of the research model. Section 3.2 presents the proposed theoretical model, along with the associated hypotheses and theoretical support. Finally, section 3.3 summarizes this chapter.

3.1 Theoretical Background

When individuals become older, they experience some limitations in their physical and cognitive abilities (Kooij et al. 2008). As such, they may face difficulties in making decisions in purchasing online products (Becker, 2004). Thus, this study drew on the most important aging theories to analyze the effect of an individual's cognitive age on their perceptions regarding the complexity of using online RAs during their online shopping. There are three popular aging theories that explain the cognitive difficulties that older adults experience: the Resources, Speed, and Inhibition Theories (Cabeza, 2002). These theories are used in this research to study the impact of an individual's cognitive age on the antecedents of their intention to use online RAs while shopping for online product.

Dean (2008) suggests that users sometimes experience difficulty and extraneous cognitive load in using new technologies. As explained in Chapter 2, RAs can be designed with different levels of comprehensiveness which may impact a users perceptions of the complexity of these decision support tools. Therefore, a theoretical model is needed to evaluate a user's experience with RAs to understand the impact of different levels of RA comprehensiveness on a user's complexity perceptions. Cognitive Complexity Theory (Kieras & Polson, 1985) and Cognitive Load Theory (WM Van Gerven, 2000) have been used to study the cognitive complexity of the interaction between the technology and the user and the extraneous cognitive load that users experience with a new technology. Thus, these theories are also employed in this study to understand how different levels of online RA comprehensiveness impact on an individual's perceptions of complexity in terms of both input and output stages of online RAs.

The main focus of this study is to understand the impact of cognitive age and RA comprehensiveness on an individual's intention to use RAs in their online shopping experience, the research model draws its theoretical foundation from the Theory of Planned Behaviour (TPB) (Ajzen, 1991). A brief review of these theories is presented below.

3.1.1 Aging Theories

Theories of psychological aging emphasize that older adults face limitations in their cognitive abilities (Kooij et al. 2008). Such limitations may result in difficulties for older adults in making high quality decisions, including those made in online environments (Becker, 2004). There are three popular aging theories: the Resources, Speed, and Inhibition Theories (Cabeza, 2002). This study utilizes these aging theories to understand the impact of an individual's cognitive age based on their perceptions regarding the complexity of using the online RAs in their online shopping experience. These theories are briefly explained below.

First, the notion of reduced processing resources, which sometimes is referred to as attentional capacity, refers to the limited amount of cognitive resources available for allocation for a given cognitive task (Kahneman, 1973; Balota et al. 2000). Studies show that reduced attentional resources decrease older adult's ability to engage in more complex and cognitive demanding tasks (Craik & Byrd, 1982; Salthouse, 1982).

Second, according to the speed of processing theory, aging is associated with a decline in the speed with which processing can be executed and this decrease in speed leads to impairments in cognitive functioning (Birren et al. 1980; Cerella, 1985; Salthouse, 1996). Therefore, cognitive performance is degraded when information processing is slow because the products of early processing may no longer be available when later processing is complete. Studies show that the mean response times of older adults is much longer than the mean response times of younger adults in accomplishing different tasks (Brinley, 1965).

Third, age related deficits in cognitive performance also may arise from a reduced efficiency in the ability to inhibit irrelevant information to the current task demands (Hasher et al. 1991; Hartman & Hasher, 1991; Hamm & Hasher, 1992; Duchek et al. 1995; Spieler & Balota, 1996; Salthouse, 1996; Balota et al. 2000). Zacks (1989) suggest that older adults are more distracted by irrelevant information (i.e., they have less ability to allow relevant information to enter working memory and to suppress activation of irrelevant information in working memory).

3.1.2 Complexity & Cognitive Load Theories

Complexity is defined as "the degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers & Shoemaker, 1971). Kieras & Polson (1985) proposed a cognitive complexity theory, which considers the cognitive complexity of the interaction between the technology and user. Dean (2008) suggests that cognitive complexity theory helps explain user difficulty in accepting and using new technology.

One important issue throughout the discussion of human-centered design principles is the focus on reducing perceived complexity and the extraneous cognitive load that users experience with a new technology. Cognitive load refers to "the mental resources a person has available for solving problems or completing tasks at a given time" (Oviatt, 2006). Thus, if the amount of information processing exceeds an individual's cognitive capacity, his/her attention to the task may get diluted (Kahneman, 1973). Furthermore, cognitive load theory (WM Van Gerven, 2000) which is mainly concerned with the limitations of human working-memory capacity suggests optimizing "schema acquisition by stimulating an efficient use of working memory" (WM Van Gerven, 2000, p. 16). Therfore, in this study, the impact of RA comprehensiveness on user perceptions regarding the RA complexity is investigated. Moreover, this study investigates if RA comprehensiveness impacts differently on RA input and output complexity perceptions in individuals with different cognitive ages.

3.1.3 Theory of Planned Behaviour (TPB)

The research model draws its theoretical foundation from the Theory of Planned Behaviour (TPB) (Ajzen, 1991) which extends the Theory of Reasoned Action to explain situations in which individuals do not have full control over a situation. TPB has been widely used by Information IS researchers to understand user intentions to use information technologies (IT) (e.g., Technology Acceptance Model (TAM)). Several studies (Morris & Venkatesh, 2000; Morris et al., 2005) have used TPB as their base framework to evaluate individual behavioural intention.

As shown in Figure 3.1, according to TPB (Ajzen, 1991), human actions are based on three kinds of considerations: (i) behavioural beliefs which refers to the possible outcomes of the behaviour and the evaluations of these outcomes; (ii) normative beliefs which refers to an individual's perceptions of the opinions of significant others about her/his performing a specific behaviour and her/his motivation to conform with them; and (iii) control beliefs which refers to the perception of the availability of resources, skills, and opportunities for the individual to carry out a behaviour (Ajzen, 1991; Yousafzai et al. 2010).

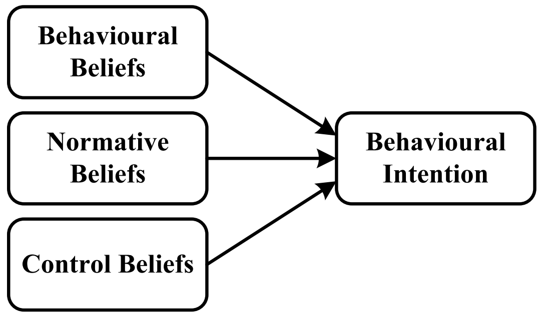


Figure 3.1 Theory of Planned Behaviour

In the context of IT adoption, the impact of normative beliefs on individual's intention is more significant when IT use is mandatory rather than voluntary (Miller and Hartwick, 2002). According to Komiak & Benbasat (2006), the impact of normative beliefs on the intention to adopt is greater in the absence of any experience with an IT. As individuals gain first-hand experience with an IT, normative beliefs have less of an impact on intention (Karahanna et al. 1999). This study focuses on voluntary use of an online RA by individuals who are given an opportunity to have a first-hand experience with the agent. Thus, the research model focuses on behavioural beliefs and control beliefs, not normative beliefs. This is consistent with prior IS research (Wei & Zhang, 2008).

Accordingly, TPB is utilized as the main research framework for the theoretical development of a model to understand the influence of cognitive age and RA comprehensiveness on antecedents of individual's intentions to use RAs (an information technology).

TPB suggests that salient beliefs about an individual's attitude toward a specific behaviour be considered as relevant to the particular behaviour. Salient beliefs are those behavioural beliefs that first come to mind when respondents are asked questions such as "What do you think would be the advantages for you of performing behaviour X?" (Higgins, 1996; Sutton et al., 2003, p. 235). Davis (1989) proposed two constructs in the TAM as salient behavioural beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to the "degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). PEOU refers to "the degree to which a person believes that using a particular system would be free of effort (Davis, 1989, p. 320)." Davis (1989) found a positive correlation between PEOU and behavioural intentions. Most of the root constructs of PEOU relate to the effort that is required to learn how to operate a system. For example, one of the items of the measurement scale for the PEOU construct is "Learning to operate the system would be easy for me" (Davis 1989). However, using online RAs entails efforts beyond just learning to operate the system. Users spend a lot of time entering their preferences regarding the product attributes during the RA input stage. Therefore, for the context of this study, a construct and associated measurement scale that captures the time dimension of the effort involved in using online RAs is more appropriate. In this regard, the Complexity construct from the model of personal computer use (Thompson, Higgins, & Howell, 1991) captures not only how to learn to operate a system and how easy is the system to use, but also the amount of time users need to spend when using a system.

Thus, this study considers the complexity of RA use, when assessing RA user's beliefs regarding the effort they have to expend in using an RA.

3.2 Research Model and Hypotheses Development

The research model which is grounded in the Theory of Planned Behaviour (TBP) (Ajzen, 1991) while leveraging the Aging, Cognitive Load and Complexity theories is shown in Figure 3.2. The model describes the causal chain from cognitive age and RA comprehensiveness to perceived RA input and output complexity to overall RA complexity perception to the antecedents of intention to use online RAs. The target behaviour in this study is intention to use online RAs to support online shopping decision-making as opposed to the actual use of the RA, as measuring the latter is difficult given the experimental manipulations needed in this study. The role of intention as a strong predictor of behaviour has been well established in IS literature (Davis 1989; Venkatesh, Morris, Davis, & Davis, 2003; Komiak & Benbasat, 2006).

The proposed research model is shown in Figure 3.2. As can be seen in this figure, some arrows are shown in bold type to demonstrate the main focus of this study. The relations shown in dashed lines on the right side of the model are included for statistical testing but they are not specifically hypothesized as they have been repeatedly established in the IS literature. Ajzen (1991) argues that the central factor in TPB is the individual's intention to perform a given behaviour. Many studies have found that this factor is influenced directly by PU (Agarwal & Karahanna, 2000; Srite & Karahanna, 2006; Limayem, Hirt, & Cheung, 2007) and an individual's behavioural control (Taylor

& Todd, 1995; Bulgurcu, Cavusoglu, & Benbasat, 2010; Tsai & Bagozzi, 2014). Moreover, studies show that an individual's behavioural control perception influences their behavioural intention indirectly mediated through PU (Agarwal & Karahanna, 2000; Horst, Kuttschreuter, & Gutteling, 2007). The definition of all the constructs in the model is shown in Table 3.1. In the rest of this section, the relationships in Figure 3.2, as well as the development of hypotheses, are explained in detail.

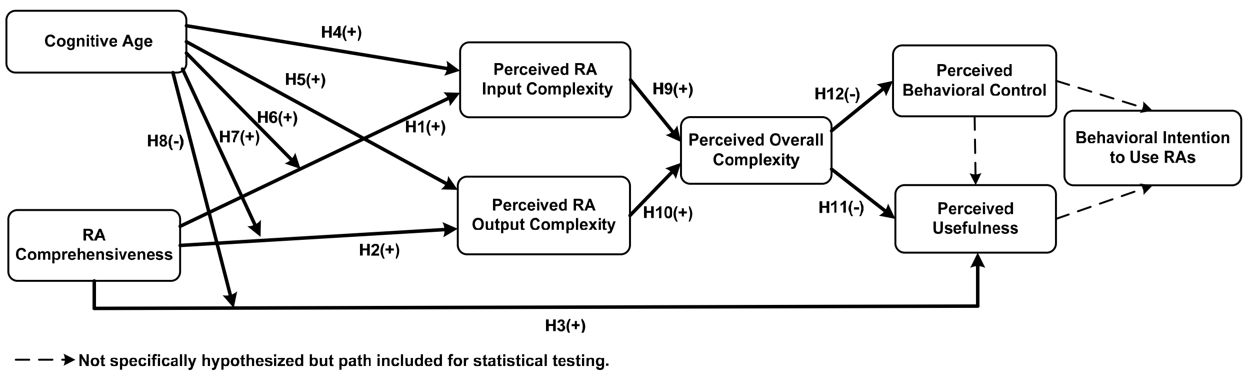


Figure 3.2 Research Model

Table 3.1 Construct Definition

Construct	Definition
Cognitive Age	How old individuals are based on their self-perceptions regarding their looks, feelings, actions, and interests (Barak & Schiffman, 1981; Barak & Gould, 1985).
RA Comprehensiveness	The number of the product attributes in the input stage and the number of recommendations and the level of detail associated with these recommendations in the output stage.
Complexity	The degree to which using a technology is perceived as being difficult to understand and use (Rogers Everett, 1995).
RA Input Complexity	The degree to which using an RA is perceived as being difficult to understand and use in the input stage.
RA Output Complexity	The degree to which using an RA is perceived as being difficult to understand and use in the output stage.
Behavioural Control	The perception of the availability of resources, skills, and

	opportunities for the individual to carry out a behaviour (Ajzen 1991; Yousafzai et al. 2010).
Usefulness	The degree to which an individual believes that using a specific system would enhance her/his job performance (Davis, 1989). In the context of this study, perceived usefulness refers to the degree to which a user believes an RA to be useful for his/her online shopping task.
Behavioural Intention	The motivational factors that capture how hard an individual is willing to try to perform a behaviour (Ajzen, 1991). Behavioural intention in this paper is a measure of the strength of a user's willingness to use RAs while shopping online.

3.2.1 Impact of RA Comprehensiveness on RA Input Complexity, RA Output Complexity, and Usefulness

In this study, as defined in Table 3.1, RA comprehensiveness is defined as the number of the product attributes in the input stage and the number of recommendations and the level of detail associated with these recommendations in the output stage. RAs may exhibit various degrees of comprehensiveness in the input and output stages of their operation. Users may perceive high or low RA comprehensiveness in the input stage based on the amount of information RAs gather about their product attribute preferences. Similarly, in the output stage of the RA operation, users may perceive high or low RA comprehensiveness based on the number of recommendations produced by the RA as well as the level of detail associated with these recommendations.

According to Alvarez & Cavanagh (2004), increasing the information load per object as well as the number of objects would increase complexity as individuals have limitations in their memory capacity. In addition, according to Cognitive Complexity

Theory (Kieras & Polson, 1985), and Cognitive Load Theory (WM Van Gerven, 2000), it is logical to expect that consumers will experience a higher sense of complexity in using more comprehensive RAs. Asking users about a large number of product attributes in the input stage may increase their perceptions of RA input complexity. Likewise, providing too many product recommendations along with their associated details in the output stage may induce users to compare a larger number of alternatives which may increase their perceptions of RA output complexity. As such, although, in a sorted recommendation list, the most promising options are at the top of the list, simultaneously considering a large number of options in the recommendation list increases RA complexity by diverting a user's attention from the better options to the less preferred ones (Xiao and Benbasat 2007). Thus, it is hypothesized that:

H1: *Higher levels of RA comprehensiveness lead to higher perceptions of RA input complexity*

H2: *Higher levels of RA comprehensiveness lead to higher perceptions of RA output complexity*

On the other hand, more comprehensive RAs provide consumers with more complete information and expand a consumer's choices regarding their preferred product attributes, and provide them with more recommendations with sufficient details. In so doing they allow consumers to play a more active role in decision-making. By providing detailed information in the input stage, the comprehensive RAs better inform users about different product attributes and allow for better fit with one's overall needs. Likewise, by presenting a large number of recommendations and a high level of detail in the output stage, RAs better inform users about the particular product in general and the recommended alternatives. The more detailed information provided by comprehensive RAs leads consumers to perceive higher utility for the RA and also to be more actively involved in the decision-making both of which lead to higher perception of RA usefulness (Xiao & Benbasat 2007). Thus, it is hypothesized that:

H3: *Higher levels of RA comprehensiveness lead to higher perceptions of RA usefulness*

3.2.2 Impact of Cognitive Age on RA Input Complexity, RA Output Complexity, and RA Usefulness

As explained in Table 3.1, cognitive age refers to how old individuals are based on their self-perceptions regarding their looks, feelings, actions, and interests (Barak & Schiffman, 1981; Barak & Gould, 1985). Studies show that as people get older, younger age perceptions among them (i.e., perceiving lower cognitive age compared to their chronological age) become more noticeable (Peters, 1971). However, the cognitive age of older adults is still usually higher than that of chronologically younger adults (Wei, 2005). Thus, it is reasonable to expect that the aging theories discussed above are also applicable to cognitive aging.

Welford (1980) found deficits in working memory to be more pronounced in older adults when the information presented is complex and difficult to understand and use. Researchers have suggested that technologies would be beneficial for older adults when they reduce requirements to maintain information in working memory (Morris and Venkatesh, 2000). Based on the above, and the resources, speed, and inhibition theories of aging, it is argued that older adults with higher cognitive age will perceive higher levels of complexity. Moreover, beliefs that people may become slower and forgetful with age have been supported in the literature (Heckhausen et al., 1989). To the extent that older adults believe that these characteristics decline with age, these beliefs may contribute to judgments that they are not capable of processing information appropriately (Warr and Pennington, 1993). Hence, it is logical to expect that older adults will experience more RA complexity in both RA input and output stages. Thus, it is hypothesized that:

H4: *Higher cognitive age leads to higher perceptions of input complexity while using an RA*

H5: *Higher cognitive age leads to higher perceptions of output complexity while using an RA*

In addition, as discussed above, RAs with a high level of comprehensiveness that involve users more fully in the input and output stages of the RA operation (i.e., asking users to input a higher number of product attributes in the input stage as well as providing a large number of recommendations and level of detail associated with these recommendations in the output stage) are thought to result in higher user perceptions of complexity in both the RA input and output stages. This would be more significant for older adults, since aging is associated with declines in physical and cognitive functioning.

These changes develop feelings of cognitive challenges among older adults, which increases their perception of complexity (Ghasemaghaei et al., 2014). On the other hand, RAs that involve users more fully in the input and output stages of the RA operation are thought to better inform users about the particular product in question and the recommended alternatives which lead consumers to perceive higher usefulness of the RA. However, this may not be the case for older adults, since aging is associated with declines in physical and cognitive functioning. Hardy et al. (1999) found that in decision-making, as many older adults have diminishing cognitive abilities, they prefer not to be presented with different choices, but instead having decisions taken from them. Likewise, Barnes and Prior (1995) suggest that offering different choices can increase information overload perceptions and cause confusion for older adults. Thus, they may not be able to fully process all the detailed information provided by highly comprehensive RAs and perceive them to be less useful compared to younger adults who are able to process the detailed information and consequently are more appreciative of the value provided by the RA. Thus, it is hypothesized that:

H6*: Cognitive age moderates the effect of RA comprehensiveness on perceived RA input complexity, such that the effect is stronger for older adults.*

H7: *Cognitive age moderates the effect of RA comprehensiveness on perceived RA output complexity, such that the effect is stronger for older adults.*

H8: *Cognitive age moderates the effect of RA comprehensiveness on perceived RA usefulness, such that the effect is stronger for younger adults.*

3.2.3 Impact of RA Input Complexity and RA Output Complexity on Overall Complexity

Individuals may perceive high complexity in the RA input stage if it attempts to elicit their preferences regarding a large number of product attributes. Similarly, users may perceive higher complexity in the RA output stage if it provides them with a large number of recommendations along with a large amount of details associated with each of these recommendations. As individuals interact with RAs only in the input and output stages (Ghasemaghaei et al., 2014), it is both expected and logical that higher complexity perceptions in either of these stages will significantly impact an individual's overall RA complexity perceptions. Thus, it is hypothesized that:

H9: *Higher RA input complexity leads to higher perceptions of RA overall complexity*

H10: *Higher RA output complexity leads to higher perceptions of RA overall complexity*

3.2.4 Impact of Overall Complexity on Usefulness and Behavioural Control

As shown in Table 3.1, complexity refers to the degree to which using a technology is perceived as being difficult to understand and use (Rogers Everett, 1995). There is a negative relation between perceived complexity of using a technology and an individual's perceived usefulness of that technology (Igbaria, Parasuraman, & Baroudi, 1996; Hasan, 2007). Hasan (2007) suggests that as using a technology becomes more complex, achieving the outcomes associated with a particular task becomes less likely. Accordingly, individuals who perceive a technology to be complex to use are likely to doubt their abilities to apply the system successfullywhich is expected to have negative effects on the user's judgments about the usefulness of the system (Hasan, 2007). In addition, Davis (1989) found that when individuals perceive using a new system to be free of effort (which is more likely to be the case with less complex systems), they would perceive it to be more useful. Hence, RA overall complexity perception is posited to have a negative effect on perceptions of usefulness. Thus, it is hypothesized that:

H11: *Higher RA overall complexity leads to lower perceptions of RA usefulness.*

As defined in Table 3.1, according to Ajzen (1991), behavioural control refers to the perception of the availability of resources, skills, and opportunities for the individual to carry out a behaviour. Pavlou and Fygenson (2006) indicate that the PEOU positively impacts an individual's behavioural control. Davis (1989) argues that self-efficacy and controllability (dimensions of perceived behavioural control) are the means by which PEOU influences an individual's behaviour. In the context of this study, an RA that is perceived to be not easy to use (i.e., complex), is likely to decrease a consumer's confidence and ability to use that RA in their online shopping decision-making (Pavlou & Fygenson, 2006). Particularly, the perception of the RAs overall higher complexity increases the user's cognitive impediments of using it, and leads them to have higher perception that the RA is difficult to use. This, in turn, leads to decreased user perceptions of their control over their online shopping decision-making task. This is consistent with Cognitive Complexity Theory which argues that when users perceive difficulty in using new technologies, they would perceive that it would be difficult for them to perform the behaviour enabled through the use of that technology (Dean 2008). Thus, it is hypothesized that:

H12: *Higher RA overall complexity leads to lower perceptions of users' behavioural control in making online shopping decisions while using that RA.*

3.3 Summary

This chapter presented the development of a theoretical research model to answer the research questions of this study, based on the aging theories, cognitive complexity theory, cognitive load theory, and TPB. The model was designed to address how an individual's cognitive age and RA comprehensiveness impact their intention to use online RAs in their online shopping experience. The next chapter discusses the methodology employed in this study to evaluate the proposed theoretical model.

Chapter 4: Research Methodology

This chapter discusses the research methodology employed to validate the research model presented in Chapter 3. The chapter is organized as follows: Section 4.1 describes the general experimental procedures, followed by Section 4.2 that provides some details of the research stages that were performed including a pilot and main study. Section 4.3 presents the details of the measurement instrument used in the study's questionnaire. Section 4.4 introduces the procedures followed to validate the proposed research model, followed by Section 4.5 which provides a brief summary of the post hoc analyses conducted in this study. Finally, Section 4.6 explains the manipulation check conducted for this study, and Section 4.7 summarizes the chapter.

4.1 Experimental Procedure

The experimental procedures were as follows: After reading and signing an initial consent form, participants were provided a link to use an online recommendation agent which helped them shop for a car from Toyota. They were randomly assigned to one of the two experimental RA treatments (i.e., low or high RA comprehensiveness) and an online survey tool was used to link participants to their assigned RA to complete the car shopping task. Participants were then directed to respond to the cognitive age questions and complete the survey instrument. An open-ended question was used to gather details about participant experiences using their assigned RAs. In the open-ended question section, participants were asked to justify how they reached a decision (i.e., selecting a specific recommended car). Finally, participants were asked to complete the measures of the manipulation check.

4.1.2 Recommendation Agents

In this study, experimental RAs were designed to help participants in choosing a car to purchase. This product was selected because it has many product attributes, requires strong consumer involvement in the purchasing process, and is a product of interest to both younger and older adults (Lambert- Pandraud et al., 2005).

Based on a survey of commercial RAs online, a pre-test involving 15 participants and a pilot test involving 50 participants (both explained below), two RAs were designed. These two RAs were similar in many aspects. Both were attribute-based RAs, in which agents obtained input regarding preferences for each product attribute and produced suitable recommendations based on these preferences (Ansari et al., 2000). The two RAs used the same strategy to filter all the product data available in the database. In addition, to minimize any confounding effects due to brand or design elements, both RAs focused only on the Toyota brand. However, they exhibited different levels of comprehensiveness in their input and output stages. As shown in Table 4.1, the low and high RA comprehensiveness treatments differed in the number of product attributes in the input stage of the RA and the number of recommendations/details in the output stage of the RA operation. Miller (1956) found that people can concurrently hold 7±2 chunks of information in their working memory. Thus, it is expected that subjects will experience significantly different perceptions regarding RA comprehensiveness between the low and high treatments in the Table 4.1.

Table 4.1 RA Design

	Low Comprehensiveness RA	High Comprehensiveness RA
• Number of product attributes elicited in the input stage	• 8 attributes	• 29 attributes
• Number of recommendations & number of associated attributes in the output stage	• 5 recommendations & 8 attributes for each recommendation	• 8 recommendations & 29 attributes for each recommendation

The screen-shots in Figure 4.1 and 4.2 show the input stages of the low comprehensiveness and high comprehensiveness RAs respectively while the screen-shots in Figure 4.3 and 4.4 show the output stages of the low comprehensiveness and high comprehensiveness RAs respectively.

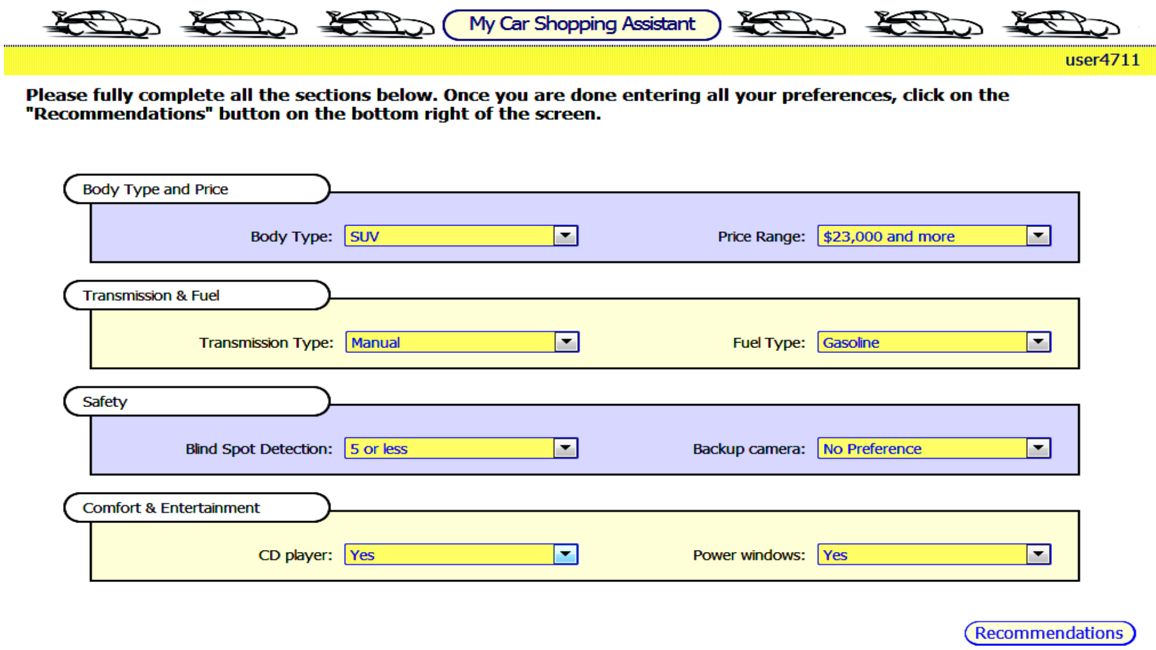


Figure 4.1 Screen Shot of the Low-Comprehensive RA in the Input Stage

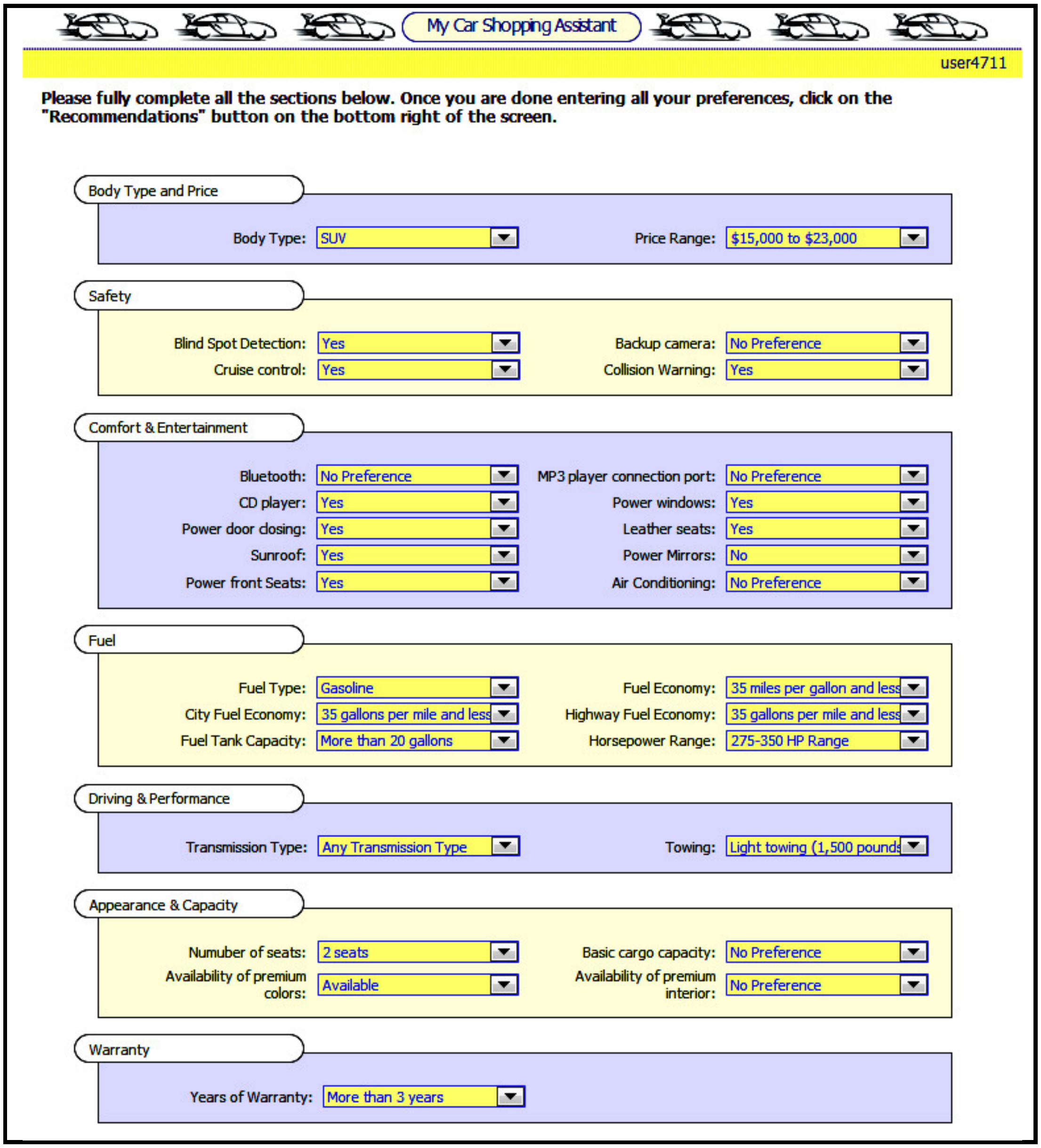
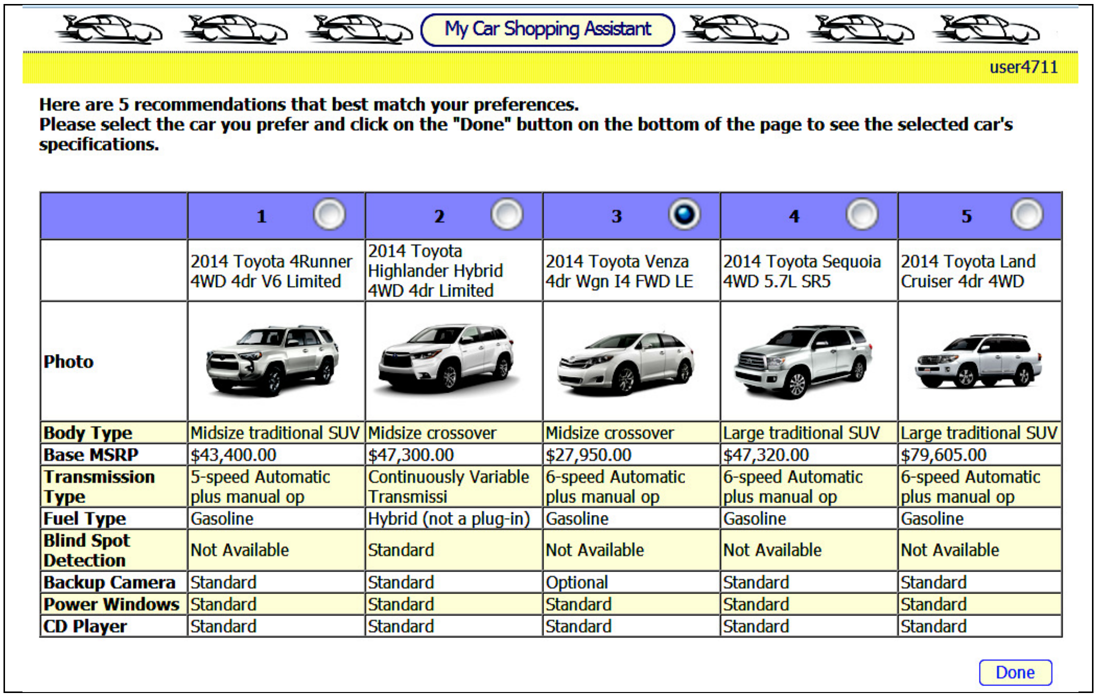


Figure 4.2 Screen Shot of the High-Comprehensive RA in the Input Stage



My Car Shopping Assistant

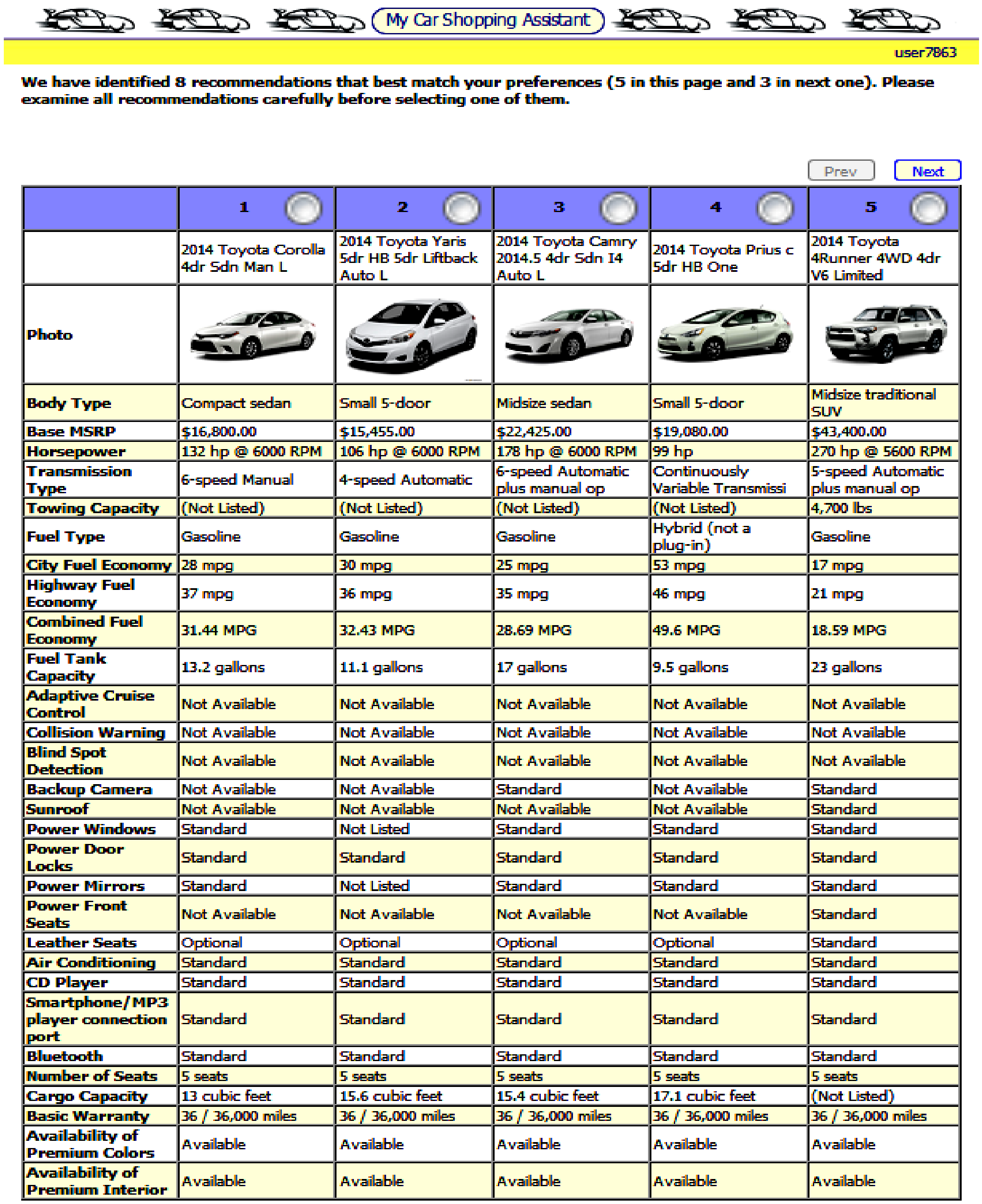
user4711

Here are 5 recommendations that best match your preferences.
Please select the car you prefer and click on the "Done" button on the bottom of the page to see the selected car's specifications.

	1	2	3	4	5
	2014 Toyota 4Runner 4WD 4dr V6 Limited	2014 Toyota Highlander Hybrid 4WD 4dr Limited	2014 Toyota Venza 4dr Wgn I4 FWD LE	2014 Toyota Sequoia 4WD 5.7L SR5	2014 Toyota Land Cruiser 4dr 4WD
Photo					
Body Type	Midsize traditional SUV	Midsize crossover	Midsize crossover	Large traditional SUV	Large traditional SUV
Base MSRP	$43,400.00	$47,300.00	$27,950.00	$47,320.00	$79,605.00
Transmission Type	5-speed Automatic plus manual op	Continuously Variable Transmissi	6-speed Automatic plus manual op	6-speed Automatic plus manual op	6-speed Automatic plus manual op
Fuel Type	Gasoline	Hybrid (not a plug-in)	Gasoline	Gasoline	Gasoline
Blind Spot Detection	Not Available	Standard	Not Available	Not Available	Not Available
Backup Camera	Standard	Standard	Optional	Standard	Standard
Power Windows	Standard	Standard	Standard	Standard	Standard
CD Player	Standard	Standard	Standard	Standard	Standard

Done

Figure 4.3 Screen Shot of the Low-Comprehensive RA in the Output Stage



My Car Shopping Assistant

user7863

We have identified 8 recommendations that best match your preferences (5 in this page and 3 in next one). Please examine all recommendations carefully before selecting one of them.

Prev Next

	1	2	3	4	5
	2014 Toyota Corolla 4dr Sdn Man L	2014 Toyota Yaris 5dr HB 5dr Liftback Auto L	2014 Toyota Camry 2014.5 4dr Sdn I4 Auto L	2014 Toyota Prius c 5dr HB One	2014 Toyota 4Runner 4WD 4dr V6 Limited
Photo					
Body Type	Compact sedan	Small 5-door	Midsize sedan	Small 5-door	Midsize traditional SUV
Base MSRP	$16,800.00	$15,455.00	$22,425.00	$19,080.00	$43,400.00
Horsepower	132 hp @ 6000 RPM	106 hp @ 6000 RPM	178 hp @ 6000 RPM	99 hp	270 hp @ 5600 RPM
Transmission Type	6-speed Manual	4-speed Automatic	6-speed Automatic plus manual op	Continuously Variable Transmissi	5-speed Automatic plus manual op
Towing Capacity	(Not Listed)	(Not Listed)	(Not Listed)	(Not Listed)	4,700 lbs
Fuel Type	Gasoline	Gasoline	Gasoline	Hybrid (not a plug-in)	Gasoline
City Fuel Economy	28 mpg	30 mpg	25 mpg	53 mpg	17 mpg
Highway Fuel Economy	37 mpg	36 mpg	35 mpg	46 mpg	21 mpg
Combined Fuel Economy	31.44 MPG	32.43 MPG	28.69 MPG	49.6 MPG	18.59 MPG
Fuel Tank Capacity	13.2 gallons	11.1 gallons	17 gallons	9.5 gallons	23 gallons
Adaptive Cruise Control	Not Available	Not Available	Not Available	Not Available	Not Available
Collision Warning	Not Available	Not Available	Not Available	Not Available	Not Available
Blind Spot Detection	Not Available	Not Available	Not Available	Not Available	Not Available
Backup Camera	Not Available	Not Available	Standard	Not Available	Standard
Sunroof	Not Available	Not Available	Not Available	Not Available	Standard
Power Windows	Standard	Not Listed	Standard	Standard	Standard
Power Door Locks	Standard	Standard	Standard	Standard	Standard
Power Mirrors	Standard	Not Listed	Standard	Standard	Standard
Power Front Seats	Not Available	Not Available	Not Available	Not Available	Standard
Leather Seats	Optional	Optional	Optional	Optional	Standard
Air Conditioning	Standard	Standard	Standard	Standard	Standard
CD Player	Standard	Standard	Standard	Standard	Standard
Smartphone/MP3 player connection port	Standard	Standard	Standard	Standard	Standard
Bluetooth	Standard	Standard	Standard	Standard	Standard
Number of Seats	5 seats	5 seats	5 seats	5 seats	5 seats
Cargo Capacity	13 cubic feet	15.6 cubic feet	15.4 cubic feet	17.1 cubic feet	(Not Listed)
Basic Warranty	36 / 36,000 miles	36 / 36,000 miles	36 / 36,000 miles	36 / 36,000 miles	36 / 36,000 miles
Availability of Premium Colors	Available	Available	Available	Available	Available
Availability of Premium Interior	Available	Available	Available	Available	Available

Figure 4.4 Screen Shot of the High-Comprehensive RA in the Output Stage

My Car Shopping Assistant

We have identified 8 recommendations that best match your preferences (3 in this page and 5 in previous one). Please examine all recommendations carefully before selecting one of them.
Please select the car you prefer and click on the "Done" button on the bottom of the page to see the selected car's specifications.

* indicates that a product exceeds your maximum price, but may be a good match otherwise.

Prev Next

	6	7	8
	2014 Toyota Venza 4dr Wgn I4 FWD LE	2014 Toyota Sequoia 4WD 5.7L SR5	2014 Toyota Land Cruiser 4dr 4WD
Photo			
Body Type	Midsize crossover	Large traditional SUV	Large traditional SUV
Base MSRP	$27,950.00*	$47,320.00*	$79,605.00*
Horsepower	181 hp @ 5800 RPM	381 hp @ 5600 RPM	381 hp @ 5600 RPM
Transmission Type	6-speed Automatic plus manual op	6-speed Automatic plus manual op	6-speed Automatic plus manual op
Towing Capacity	1,000 lbs	7,100 lbs	8,500 lbs
Fuel Type	Gasoline	Gasoline	Gasoline
City Fuel Economy	20 mpg	13 mpg	13 mpg
Highway Fuel Economy	26 mpg	17 mpg	18 mpg
Combined Fuel Economy	22.32 MPG	14.54 MPG	14.86 MPG
Fuel Tank Capacity	17.7 gallons	26.4 gallons	24.6 gallons
Adaptive Cruise Control	Not Available	Not Available	Not Available
Collision Warning	Not Available	Not Available	Not Available
Blind Spot Detection	Not Available	Not Available	Not Available
Backup Camera	Optional	Standard	Standard
Sunroof	Optional	Standard	Standard
Power Windows	Standard	Standard	Standard
Power Door Locks	Standard	Standard	Standard
Power Mirrors	Standard	Standard	Standard
Power Front Seats	Not Available	Not Available	Standard
Leather Seats	Optional	Optional	Standard
Air Conditioning	Standard	Standard	Standard
CD Player	Standard	Standard	Standard
Smartphone/MP3 player connection port	Standard	Standard	Standard
Bluetooth	Standard	Standard	Standard
Number of Seats	5 seats	8 seats	8 seats
Cargo Capacity	70.2 cubic feet	18.9 cubic feet	16.1 cubic feet
Basic Warranty	36 / 36,000 miles	36 / 36,000 miles	36 / 36,000 miles
Availability of Premium Colors	Available	Available	Available
Availability of Premium Interior	Available	Available	Available

Figure 4.5 (Continue). Screen Shot of the High-Comprehensive RA in the Output Stage

4.2 Research Stages

This dissertation was completed in two stages: a pilot study and a main study, as described below.

4.2.1 Pilot Study

A pre-test and a pilot test were conducted prior to data collection. As explained above, two RAs were designed with different levels of comprehensiveness in the input and output stages of the RA, based on the survey of commercial RAs online and a pre-test with 15 participants. Prior to any data collection, ethics approval was secured from the McMaster Research Ethics Board (MREB). As the RAs were designed to help users make a decision related to purchasing a car, participants were asked to rate the car attributes that are most important to them when purchasing a car in a pre-test. The five most important car attributes that were common among participants were used for both low and high comprehensive RAs in this study. The rest of the attributes provided by the pre-test study participants were only used for the design of the high comprehensive RA.

A pilot study was conducted with the purpose of refining the RA designs, experimental procedures and survey instrument. For the pilot study, 50 participants were recruited through Research Now, a commercial market research firm. Participants of the pilot study were asked to shop for a car using an online RA, respond to the cognitive age questions, fill out a survey containing the model's measures, and then respond to demographic and an open-ended question about their experience using their assigned RA.

To ensure that the selected RAs are significantly different in terms of their comprehensiveness, pilot study participants were asked to rate the RA they used as being high or low in terms of input, output and overall comprehensiveness. Results from the pilot study were used to make sure that the RA with the high level of comprehensiveness was perceived as being significantly more comprehensive than the RA with the low level of comprehensiveness. Results from the pilot study helped to refine the RA design. For example, more car attributes were added for the RA with the high level of comprehensiveness. The pilot study did not result in any changes in the measurement instrument.

4.2.2 Main Study

After the pilot study was completed, the main study was conducted. For the main study, participants were general online shoppers recruited through a market research firm and each participant had a chance to win 1 of the 5 monthly $1000 prizes that were awarded by the market research firm in exchange for his/her participation. To motivate participants to view the experiment as a serious task, they were informed prior to the experiment that 25% of them will get an additional award from $10 to $50 based on their performance (prior to the experiment, participants were informed that they would be asked to have justifications for their car selection decisions and their performance would be examined based on how persuasive their justifications were in supporting their decisions[1]).

A power analysis for a between-subject design determined that 180 subjects (45 subjects for each group) would assure a sufficient statistical power of 0.80 to detect a medium effect size (f = .25) (Cohen, 1988). In order to have a consistent number of subjects across all age groups, 90 subjects whose cognitive age is between 30 and 60 were also recruited. Thus, a total of 270 subjects were needed for this study. To account for possible spoiled surveys, a total of 300 participants were recruited.

4.3 Measurement Instrument

In order to ensure content validity, the study used previously validated instruments to measure constructs in the proposed research models. RA comprehensiveness was coded as a dummy variable (i.e., 0 for low level of RA comprehensiveness and 1 for high level of RA comprehensiveness). Scales were slightly adapted to reflect the context of this study. For example, the name of the specific system in question was changed to "recommendation agent" and the specific task was changed to "online shopping". Six dependent variables were examined in this study. There are well-established multi-item measures in the literature for perceived complexity (i.e., input complexity, output complexity, overall complexity), behavioural control, usefulness and

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[1] This study used a similar method to that used by Wang & Benbasat (2009) to examine how persuasive the participant's justifications were in supporting their shopping decisions. The author counted the number of supporting arguments provided by participants for selecting the car they did weighted by supporting strengths for each argument. Three levels of supporting argument strengths including: 0.5 for weak, 1 for normal, and 2 for strong were used.

intentions to use RAs. The measurement instruments, along with sources of the scales, are included in Appendix D and described briefly below:

- Behavioural intention was measured using a three item, 7-point Likert scale adapted from Wand and Benbasat (2009). In that paper, the items achieved a Cronbach's Alpha (α) reliability score of 0.98. The items were slightly modified to reflect the context of this study.
- Perceived usefulness was measured with a four item, 7-point Likert scale from (Hassanein & Head, 2007). In that paper, the items achieved a Cronbach's Alpha (α) reliability score of 0.86. The items were slightly modified to reflect the context of this study.
- Perceived behavioural control was measured with a three item, 7-point Likert scale from Hsieh, Rai, & Keil (2008). In that paper, the items achieved an internal consistency reliability score of 0.95. The items were slightly modified to reflect the context of this study.
- Perceived complexity (i.e., overall complexity, input complexity, output complexity) was measured with a four item, 7-point Likert scale from Thompson et al. (1991). In that paper, the items achieved an internal consistency reliability score of 0.6. The authors mentioned that the lower reliabilities for the scale could be because of the small number of items in the scales as the calculation of Cronbach's alpha is influenced by scale length. Chang et al. (2008) used the same scale and achieved an

internal consistency reliability score of 0.83. The items were slightly modified to reflect the context of this study.

- Age was measured using a cognitive age measure. The cognitive age scale was based on Barak and Schiffman (1981) where cognitive age is computed as the numerical average of the decade midpoints of the four components of feel, look, act, and interests, with higher numbers indicating having higher cognitive age (Wilkes, 1992).

4.3.1 Other Questions Included in the Study

In addition to the survey items related to the research models, other questions were included in this study. The survey of this study employed one open-ended question in order to gain further insights on the perceptions of participants regarding the use of online RAs. The question asked participants to provide justifications for their shopping decisions.

To conduct the manipulation check for RA comprehensiveness, after using an online RA (high or low in terms of comprehensiveness), each participant was asked to rate his/her perceptions of the comprehensiveness of the RA they used on a five-point Likert scale assessing the number of product attributes and the level of detail associated with each attribute in the input stage and the number of recommendations and the level of detail associated with these recommendations in the output stage.

The survey of this study also included questions related to seven control variables to explore their potential impacts on the relations in the research model. Several IS studies have found that education is positively related to favorable individual attitude towards using a new technology (Igbaria & Parasuraman, 1989; Harrison & Rainer Jr, 1992; Nadkarni & Gupta, 2007). Nadkarni & Gupta (2007) suggest that users with higher education are more likely to be tolerant of new technology complexity than users with lower education levels. Thus, an individual's education level is considered as a control variable in the research model of this study.

Participant's interest in purchasing a car is considered as another control variable as the RAs in this study are focused on helping customers to purchase a car and thus it was believed that an individual'' product interest could impact the different variables in the model. In addition, a participant's knowledge about cars in general is considered as another control variable in this study. This variable was selected as according to Arnold et al. (2006) and Wang & Benbasat (2009) the domain knowledge of the participants could impact on their perceptions regarding the use of the online RAs.

Kim & Son (2009) suggest that user experience (i.e., target system experience) and gender are important control variables in adoption phenomena. Thus, in this study, past online RA experience and gender are also used as control variables. Moreover, Web experience is also considered as one of the most important control variables in the context of online shopping experience (Szajna, 1996; Kim, Malhotra, & Narasimhan, 2005), and thus in the research model Internet usage is considered as a control variable.

According to Wood (1986) task complexity refers to the number of distinct acts that must be completed when performing a task. Prior research has found that high task complexity demands more cognitive resources and increases information processing requirements (Klemz & Gruca, 2003; Speier & Morris, 2003; Jiang & Benbasat, 2007). Thus, general complexity of the task of purchasing a new car is also considered as another control variable in the research model.

4.4 Model Validation

To validate the research model, structural equation modeling (SEM) techniques are used in this study as it allows for the simultaneous testing of both the measurement model and the structural model (the direction and strength of the relationship between the variables). More specifically, Partial Least Squares (PLS) was used as an SEM method as it has additional advantages over covariance-based methods (e.g., LISREL) as it maximizes the explained variance of endogenous variables (Gefen et al. 2000), and it does not make distributional assumptions regarding the data (Gefen et al. 2000; Xu et al. 2014).

The software that is used to validate the research model in this study was SmartPLS - Version 2.0 (Ringle, Wende, & Will, 2005) as it allows performing the analyses required for this study and results can be exported to different formats (e.g. Excel, HTML) (Temme, Kreis, & Hildebrandt, 2010). Further, this software has been used by numerous researchers in IS.

The assessment of the research models in PLS followed a two-step approach: the evaluation of (i) the measurement model, and (ii) the structural model (Chin, 2010).

Chapter 5 explains a detailed analysis of the research model. Next, a brief summary of the analyses performed is explained.

According to Barclay, Higgins, & Thompson (1995) and Chin (2010) individual measurement item reliability, construct reliability, and discriminant and convergent validity should be calculated for the assessments of measurement models. Table 4.2 below lists all the tests performed to evaluate the constructs (all constructs in the research model are reflected).

Table 4.2 Summary of Tests – Measurement Model

Analysis	Test	Note
Item reliability	**Item loading**	• Acceptance criterion: Value > 0.50 (Gefen, Straub, & Boudreau, 2000)
Construct reliability	**Cronbach's alpha**	• Cronbach's alpha is a measure of internal consistency of a construct (Cronbach, 1951) • Acceptance criterion: Value > 0.70 (Bernstein & Nunnally, 1994)
	Composite reliability	• Composite reliability is a measure of internal consistency reliability of a construct as compared with other constructs in the model (Werts, Linn, & Jöreskog, 1974) • Acceptance criterion: Value > 0.60 (Bagozzi & Yi, 1988)
Discriminant validity	**Average Variance Extracted (AVE)**	• Average Variance Extracted (AVE) is "the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error" (Fornell & Larcker, 1981, p. 45) • Acceptance criterion: The square root of the AVE of the variable must be larger than the correlation between that construct and any other construct in the model (Barclay et al., 1995)

Analysis	Test	Note
	Item cross-loading	• Loading on corresponding construct must be larger than loading on other constructs. • Acceptance criterion: The difference between the loadings should be at least 0.10 (Gefen & Straub, 2005; Chin, 2010)
Convergent validity	**Average Variance Extracted (AVE)**	• Average Variance Extracted (AVE) is "the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error" (Fornell & Larcker, 1981, p. 45) • Acceptance criterion: Value > 0.50 (Au, Ngai, & Cheng, 2008)

After evaluating the measurement model, the structural model was assessed to find out whether there was evidence to support the theoretical model proposed (Chin, 2010). Table 4.3 presents the analyses conducted with the structural model. Considering that all measures were collected at one point in time, it was also necessary to check for common method bias. In this study, two techniques were used to check for common method bias: (i) The Unmeasured Latent Marker Construct (ULMC) approach used by Liang et al. (2007); and the Harman's single-factor test, as per Podsakoff, MacKenzie, Lee, & Podsakoff (2003). Chapter 5 provides more details in this regard.

Table 4.3 Summary of Tests – Structural Model

Test	Calculation	Notes
R^2 for endogenous variables R^2: the proportion of variance in an endogenous variable explained by its antecedents (Rao, 2009)	Obtained from PLS software.	• R^2 should be high enough to achieve adequate explanatory power (Urbach & Ahlemann, 2010)

Test	Calculation	Notes
		• R^2 should be at least 0.10 (Falk & Miller, 1992)
PLS Path Estimates: Coefficients (β), Signs, and Significances	Obtained from PLS software.	The significance of coefficients was evaluated through a bootstrap approach (Chin, 2010)
Goodness of Fit (GoF) index: Absolute GoF can be used to assess the PLS model in terms of overall (both measurement and structural levels) prediction performance (Tenenhaus, Amato, & Esposito Vinzi, 2004; Vinzi, Trinchera, & Amato, 2010)	Calculated using PLS software output as the geometric mean of the average communality index and the average R^2. $GOF = \sqrt{\overline{Communality} \times \overline{R^2}}$	The suggested baseline values of GoF_{small} (.10), GoF_{medium} (.25), and GoF_{large} (.36) were used to evaluate fit of the model (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005; Wetzels, Odekerken-Schröder, & Van Oppen, 2009)
Effect sizes: used to examine whether an independent variable (IV) has substantive impact on a dependent variable (DV) (Chin, 2010).	PLS results are calculated once with the IV included in the model, and once with the IV excluded from the model. The effect size is calculated based on R^2 of the DV as formulated below: $f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$	The magnitude of the effect sizes of each path was evaluated following these values: f^2 small (.02), f^2 medium (.15), and f^2 large (.35) (Chin, 2010).

Finally, to test the moderating impact of cognitive age on the relation between RA comprehensiveness and RA input and output complexity, as well as RA usefulness perception as hypothesized in the research model, ANOVA analyses were conducted to understand whether any differences exist between older and younger adults' perceptions following a 2X2 factorial design (i.e., low cognitive age (between 20-30)/high cognitive age (above 60) X low RA comprehensiveness/high RA comprehensiveness) (Box, Hunter, Hunter, & others, 1978). The two ranges of cognitive age were chosen for this analysis because according to Tucker-Drob & Salthouse (2008), the cognitive abilities of individuals belonging to these two groups chronologically are markedly different with the younger group exhibiting significantly higher cognitive abilities compared to the older group. These differences are expected to still be present when comparing these groups on a cognitive age basis as the older group will still be cognitively much older than the younger group.

4.5 Post Hoc and Other Analyses

In addition to the main study data analyses, a number of post-hoc analyses were also conducted:

1. The participants chronological age and their cognitive age were classified into groups in order to better understand the relation between an individual's chronological age with their cognitive age.
2. ANOVA was conducted to analyze whether any differences exist between older and younger adults (based on both their cognitive and chronological ages) perceptions regarding RA input and output complexity when using RAs with low or high levels of comprehensiveness.

3. The effects of control variables that were captured in the study (i.e. product knowledge, task complexity, internet usage, education level, product interest, past RA experience, gender) were examined.
4. Finally, an assessment of an alternative model including non-hypothesized relationships was conducted to discover potential significant non-hypothesized relationships in the model.

4.6 Manipulation Check

In studies that involve manipulations (such as the RA comprehensiveness levels (low or high) used in this study), manipulation validation is required. According to Boudreau, Gefen, & Straub (2001) "manipulation checks are designed to ensure that subjects have, indeed, been manipulated as intended, a validity that can be empirically determined" (Boudreau, et al., 2001, p. 5). Therefore, a manipulation check for RA comprehensiveness was performed.

After using an online RA (high or low in terms of comprehensiveness), each participant was asked to indicate his/her perceptions regarding the number of product attributes and the level of detail associated with each attribute in the input stage of the RA operation on a five-point Likert scale (very low, low, neither low or high, high, very high). They were also asked to indicate their perceptions of the number of recommendations and the level of detail associated with these recommendations in the output stage of the RA operation on a similar scale. The two questions used for manipulation check were: (i) Please indicate your perceptions regarding the number of product attributes and the level of detail associated with each attribute in the stage where it elicited your preferences for the car attributes you are looking for. (ii) Please indicate your perceptions regarding the number of recommendations and the level of detail associated with these recommendations in the stage where recommendations were presented to you.

ANOVA was conducted to compare the scores provided by participants who used the low comprehensiveness RA to the scores provided by participants who used the high comprehensiveness RA (Xu, Benbasat, and Cenfetelli, 2014).

4.7 Summary

This chapter explained the research methodologies conducted in this study. Particularly, the experimental procedure as well as the details of the measurement instrument used was presented. Moreover, the procedures to validate the proposed theoretical research model, along with appropriate post hoc analyses and manipulation check to be carried out, were also described. The next chapter presents in detail the analyses performed in this study, as well as the results obtained.

Chapter 5: Data Analyses and Results

The previous chapter summarized the procedures used to collect and analyze data for this study. This chapter explains those procedures in detail. Section 5.1 explains briefly the process used for collecting data, while Section 5.2 describes the procedures used to screen this data. Section 5.3 summarizes the demographics of the participants in this study, followed by Section 5.4 which explains the manipulation check. Section 5.5 discusses the validation of the proposed research model, with emphasis on the measurement and structural models. Section 5.6 presents the post hoc analyses. The chapter ends with Section 5.7, which summarizes the chapter.

5.1 Data Collection

Participants in this study were general online shoppers from Canada and USA. Data were collected through a cross-sectional online survey hosted on FluidSurveys servers. A consent form (Appendix A) was shown to participants, and they were asked to electronically consent prior to the beginning of the survey (i.e., click on "I agree to participate" button). Only those participants that agreed to participate could access to the link (Appendix B) to use an online recommendation agent and then respond to the survey questions (Appendix C).

Participants for both the pilot and main studies were recruited through Research Now[2] (a market research firm) via e-mail from Canada and the U.S. The pilot study was

[2] Participants in Research Now's panel that take part in a survey accumulate points that can be redeemed for an award (Beedell, 2012).

conducted between September 11 and September 13, 2014 and 50 valid responses were obtained. After the pilot study, some changes (e.g., adding more product attributes for the RA with the high level of comprehensiveness) were made to the design of the online RAs. Thus, before starting the main study, a second pilot study was conducted to insure that no other changes need to be done to the RAs' design. The second pilot study was conducted between September 29 and October 2, 2014 and 48 valid responses were obtained. Since there were no other changes to the RAs design and the survey, the responses from the second pilot study were included in the analysis of the main study. Recruitment for participants in the main study started on October 6 and ended on October 11, 2014 and resulted in a total of 309 complete responses.

5.2 Data Screening

After collecting the data, they were screened to examine for valid responses, outliers and missing values. The data screening procedures were conducted using IBM SPSS Statistics, Version 22.

The first step in screening the data was to determine which of the responses collected were valid and eliminate the ones that were not. A "quality control" question was included in the middle of the survey that asked participants to provide a specific response to indicate they had read the questions carefully (see Appendix C). The responses of the participants that did not select the proper answer for this question were discarded. Moreover, answers were discarded if (i) participants took less than 45 seconds in using the RAs with a low level of comprehensiveness and 100 seconds in using the

RAs with a high level of comprehensiveness (ii) participants provided the same answers to most of the questions in the survey, or (iii) participants took less than 5 minutes in filling the survey. It was believed that those participants completed the survey mostly with the purpose of collecting incentives. As a result of those steps, 50 data cases were eliminated.

5.2.1 Outliers and Missing Values

Outliers are "cases with extreme or unusual values on a single variable (univariate) or on a combination of variables (multivariate)" (Meyers et al., 2006, p. 65). Composite scores were calculated for each of the constructs, and box plots were used to identify the outliers. In total, 27 unique cases were detected as outliers. As suggested by Meyers et al. (2006), since there was no known explanation for those outliers, they were removed from the data set. Table 5.1 shows the summary of the detected univariate outliers. Separate box plots for the individual constructs are shown in Appendix E.

Table 5.1 Univariate Outliers

Construct	Outlier Case ID	Number of Outliers	Number of new Outliers
Behavioural Intention	none	0	0
Usefulness	7, 16, 58, 60, 65	5	5
Behavioural Control	4, 18, 28, 39, 141, 249, 250, 251	8	8
Complexity	147, 184, 186, 214, 218, 226, 248, 250, 297	9	8
Input Complexity	4, 147, 163, 184, 226, 248, 249, 250, 265	9	2
Output	4, 58, 98, 164, 184, 186, 214,	13	4

Construct	Outlier Case ID	Number of Outliers	Number of new Outliers
Complexity	248, 249, 250, 253, 265, 273		
		Total	27

A Mahalanobis distance analysis was also conducted to detect multivariate outliers. This distance measures "the multivariate "distance" between each case and the group multivariate mean (known as centroid)" (Meyers et al., 2006, p. 67). Mahalanobis distance was calculated for each case and assessed with the chi-square distribution (alpha level = 0.001). According to Meyers et al. (2006) if a case reaches this threshold (i.e., its value is equal or larger than the distribution's critical value), it can be considered a multivariate outlier. After conducting this analysis, 7 new multivariate outliers was detected and removed from the data set. The outlier analyses left 273 usable cases. The next step in the data screening process was the identification of missing values. The usable cases did not have any missing values in the model's constructs.

5.3 Demographics

In addition to the questions for the variables included in the research model, some demographic information was also gathered from participants. Out of the 273 participants, 131 (48%) were female and 142 (52%) were male. The average age of the participants was 54.8 with the distribution as shown in Table 5.2. Minimum and maximum ages of participants in the sample were 20 and 88, respectively.

Table 5.2 Age Distribution of Participants

Age Group	Frequency	Percent
20-30	38	14%
30-60	98	36%
60+	137	50%

Some other questions regarding control variables (Internet usage, online RA experience, product knowledge, education level, product interest, and task complexity) were asked of participants, the results of which are shown in Table 5.3, 5.4, and 5.5.

Table 5.3 below indicates that about 32% of participants had a bachelor's degree, while 23% finished their high school, and 16% had a master's degree. Moreover, about 11% had a college diploma, and 3% had a PhD degree. In addition, 14% indicated that their education level is not included in any of the above categories.

Table 5.3 Frequencies of Demographic Variables

Variable	Category	Frequency	Percentage
Education	High School	63	23.0
	College diploma	30	10.9
	Bachelor's degree	88	32.1
	Master's degree	44	16.1
	Ph.D. degree	9	3.3
	Other	39	14.2

Additionally, participants were asked about their previous experiences with the Internet, and online RAs. As Table 5.4 shows, most participants (58%) indicated that they use the Internet between 1 to 5 hours a day. The majority of participants indicated they did not have high experience in using online RAs.

Table 5.4 Participants' Previous Experience Statistics

Variable	Category	Frequency	Percentage
Internet Usage	Less than 1 hour	12	4.4
	Between 1 to 5 hours	160	58.4
	More than 5 hours	101	36.9
Online RA Experience	Very High	8	2.9
	High	35	12.8
	Some	81	29.6
	Low	60	21.9
	Very Low	89	32.5

Participants were also asked about their knowledge and interest about cars, as well as their perceptions of the general complexity of the task of purchasing a new car. As can be seen in Table 5.5, most participants had at least some level of knowledge about cars in general. Moreover, most participants had some or high interests in purchasing a car. Finally, the majority of participants perceived that the task of purchasing a new car is complex in general.

Table 5.5 Participants' Car Knowledge, Interest, and Task Complexity Perception Statistics

Variable	Category	Frequency	Percentage
Product (car) Knowledge	Very High	23	8.4
	High	83	30.3
	Some	132	48.2
	Low	26	9.5
	Very Low	9	3.3
Product (car) Interest	Very High	45	16.4
	High	74	27.0
	Some	86	31.4
	Low	48	17.5
	Very Low	20	7.3
Task Complexity	Very High	32	11.7

	High	113	41.2
	Some	92	33.6
	Low	31	11.3
	Very Low	5	1.8

5.4 Manipulation Check

A manipulation check for RA comprehensiveness was performed. After using an online RA (high or low in terms of comprehensiveness), each participant was asked to indicate his/her perceptions regarding the number of product attributes and the level of detail associated with each attribute in the input stage of the RA operation on a five-point Likert scale. They were also asked to indicate their perceptions of the number of recommendations and the level of detail associated with these recommendations in the output stage of the RA operation on a similar scale.

For the input stage: participants who used the low comprehensiveness RA reported a mean of 2.68 with a standard deviation of 1.76 on the manipulation check question. On the other hand, participants who used the high comprehensiveness RA reported a mean of 3.51 and a standard deviation of 1.68 on the manipulation check question. This difference was significant (one-way ANOVA, $p < 0.001$) thus showing that the manipulation of RA input stage was successful. For the output stage: participants who used the low comprehensiveness RA reported a mean of 2.64 with a standard deviation of 1.77 on the manipulation check question. On the other hand, participants who used the high comprehensiveness RA reported a mean of 3.43 with a standard deviation of 1.74 on the manipulation check question. This difference was significant (one-way ANOVA, $p < 0.001$) thus showing that the manipulation of RA output stage was successful. In summary, the manipulation of RA comprehensiveness was successful for both the input and output stages of the RA operation.

5.5 Research Model Validation

SmartPLS - Version 2.0 is used to validate the research model (Ringle, Wende, & Will, 2005). This section presents the results of assessing the measurement model, common method bias, the structural model, goodness of fit of the model, effect sizes, and ANOVA results.

5.5.1 Measurement Model

The first step in validating the proposed research model using PLS is the measurement model evaluation. Thus, construct validity and reliability need to be assessed and confirmed before evaluating the validity of the proposed theoretical model. In this study, all the constructs in the research model are reflective in nature. This section presents the results of the measurement model evaluation for this study.

To evaluate the reflective constructs, the procedures for assessing the constructs when using the PLS approach of Götz, Liehr-Gobbers, & Krafft (2010) were followed. First, convergent and discriminant validity were evaluated to determine if any indicators needed to be removed because of the potential loading or cross-loading issues. Indicators need be assessed to ensure they load on their theoretically assigned latent construct more highly than any other latent construct (Gefen & Straub, 2005).

As Table 5.6 shows, all indicators loaded most highly on their own theoretically assigned construct, and at a minimum threshold of 0.50, as per Gefen, Straub, & Boudreau (2000). As cognitive age and RA comprehensiveness are single-item measures which results in a loading of 1.000, they were not included in the analysis. No cross-loading issues were identified between these two constructs and any other construct.

Gefen and Straub (2005) suggest that "loadings of the measurement items on their assigned latent variables should be an order of magnitude larger than any other loading" (p. 93) and the difference should be at least 0.10. Thus, this analysis took an iterative approach in assessing the cross-loadings and evaluating the differences between the indicator loading and the next highest loading to ensure that the difference was the minimum 0.10. In each iteration the indicator with the smallest difference (< 0.10) was removed. This process continued until the minimum difference in the values was all greater than 0.10. This analysis showed that two complexity output indicators should be removed. The reason of having cross-loadings between these output complexity indicators with the input and overall complexity constructs is likely due to the fact that they were all measured with the same scale from Thompson et al. (1991). The final set of indicators is provided in Table 5.7.

Table 5.6 Initial Loading and Cross Loading of Measures

	BC	**BI**	**COM**	**IC**	**OC**	**PU**
Behavioural Intention (BI1)	0.402	**0.965**	-0.222	-0.160	-0.135	0.778
Behavioural Intention (BI2)	0.408	**0.979**	-0.254	-0.185	-0.157	0.770
Behavioural Intention (BI3)	0.418	**0.976**	-0.259	-0.197	-0.169	0.767
Behavioural Control (BC1)	**0.854**	0.296	-0.430	-0.373	-0.364	0.254

Behavioural Control (BC2)	**0.914**	0.428	-0.478	-0.390	-0.399	0.432
Behavioural Control (BC3)	**0.854**	0.363	-0.361	-0.370	-0.370	0.402
Complexity (COM1)	-0.428	-0.321	**0.805**	0.662	0.684	-0.316
Complexity (COM2)	-0.436	-0.165	**0.926**	0.759	0.831	-0.190
Complexity (COM3)	-0.419	-0.223	**0.915**	0.718	0.807	-0.226
Complexity (COM4)	-0.449	-0.194	**0.916**	0.761	0.821	-0.225
Input Complexity (IC1)	-0.299	-0.171	0.619	**0.842**	0.645	-0.161
Input Complexity (IC2)	-0.424	-0.135	0.764	**0.926**	0.759	-0.171
Input Complexity (IC3)	-0.389	-0.215	0.747	**0.926**	0.751	-0.212
Input Complexity (IC4)	-0.435	-0.157	0.803	**0.930**	0.815	-0.188
Output Complexity (OC1)	-0.405	-0.168	0.783	0.829	**0.887**	-0.214
Output Complexity (OC2)	-0.400	-0.160	0.844	0.729	**0.938**	-0.189
Output Complexity (OC3)	-0.386	-0.123	0.820	0.732	**0.930**	-0.181
Output Complexity (OC4)	-0.395	-0.129	0.787	0.735	**0.909**	-0.186
Usefulness (PU1)	0.442	0.738	-0.278	-0.193	-0.229	**0.927**
Usefulness (PU2)	0.367	0.743	-0.246	-0.200	-0.190	**0.945**
Usefulness (PU3)	0.385	0.746	-0.230	-0.185	-0.170	**0.954**
Usefulness (PU4)	0.404	0.772	-0.255	-0.186	-0.203	**0.956**

Table 5.7 Final Loading and Cross Loading of Measures

	BC	**BI**	**COM**	**IC**	**OC**	**PU**
Behavioural Intention (BI1)	0.402	**0.965**	-0.220	-0.160	-0.119	0.778
Behavioural Intention (BI2)	0.408	**0.979**	-0.252	-0.185	-0.131	0.770
Behavioural Intention (BI3)	0.418	**0.976**	-0.257	-0.197	-0.139	0.767
Behavioural Control (BC1)	**0.854**	0.296	-0.430	-0.373	-0.358	0.254
Behavioural Control (BC2)	**0.914**	0.428	-0.477	-0.390	-0.371	0.432
Behavioural Control (BC3)	**0.854**	0.363	-0.361	-0.370	-0.357	0.402
Complexity (COM1)	-0.428	-0.321	**0.799**	0.662	0.617	-0.316
Complexity (COM2)	-0.436	-0.165	**0.929**	0.759	0.821	-0.190
Complexity (COM3)	-0.419	-0.223	**0.915**	0.718	0.780	-0.226
Complexity (COM4)	-0.449	-0.194	**0.918**	0.762	0.809	-0.225
Input Complexity (IC1)	-0.299	-0.171	0.617	**0.842**	0.615	-0.161
Input Complexity (IC2)	-0.424	-0.135	0.765	**0.926**	0.729	-0.171
Input Complexity (IC3)	-0.389	-0.215	0.746	**0.926**	0.694	-0.212
Input Complexity (IC4)	-0.435	-0.157	0.804	**0.930**	0.763	-0.188
Output Complexity (OC3)	-0.386	-0.123	0.820	0.733	**0.949**	-0.181
Output Complexity (OC4)	-0.395	-0.129	0.788	0.735	**0.940**	-0.186
Usefulness (PU1)	0.442	0.738	-0.277	-0.193	-0.220	**0.927**

Usefulness (PU2)	0.366	0.743	-0.244	-0.200	-0.171	**0.945**
Usefulness (PU3)	0.385	0.746	-0.228	-0.185	-0.159	**0.954**
Usefulness (PU4)	0.404	0.772	-0.253	-0.186	-0.183	**0.956**

Next, the reliability of the constructs is assessed, using Composite reliability and Cronbach's alpha, with the thresholds of 0.6 and 0.7, respectively (Bagozzi & Yi, 1988; Bernstein & Nunnally, 1994). As Table 5.8 below shows, reliability holds for all the constructs. As can be seen in Table 5.8 the reliability for behavioural intention and perceived usefulness is above 0.95. Straub et al (2004) indicate that when participants are subjected to similar items in the same scale, it is possible to have very high reliability values because of the ability of the participants to recall previous responses and that this could raise a common method bias concern. However, and as detailed later in Subsection 5.5.2 below, common method bias was not an issue in this study.

Table 5.8 Construct Reliability Assessment

Construct	Composite reliability	Cronbach's alpha	AVE
BC	0.907	0.847	0.765
BI	0.982	0.972	0.947
CoAge	1.000	1.000	1.000
Comp	0.939	0.913	0.795
INC	0.949	0.928	0.822
OTC	0.943	0.879	0.892
PU	0.971	0.961	0.894
RCom	1.000	1.000	1.000

CoAge: Cognitive Age; RCom: RA Comprehensiveness; BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

The convergent and discriminant validity of the constructs was also evaluated. Convergent validity was tested through the Average Variance Extracted (AVE), making sure it exceeded the variance due to measurement error for that construct (i.e. AVE > 0.5) (Au, Ngai, & Cheng, 2008). As shown in Table 5.8, this criterion is met by all constructs.

In Table 5.9, the diagonal elements show the square roots of the AVE of variables, and the off-diagonal numbers represent the correlation between variables. According to Barclay et al. (1995), to have adequate discriminant validity, the square root of the AVE of the variable must be larger than the correlation between that construct and any other construct. As shown in Table 5.9 below, all variable pairs met this requirement. Furthermore, as can be seen in Table 5.7 above, the loadings of a constructs' items should be larger than loading on other constructs. According to Gefen & Straub (2005) and Chin (2010), the minimum difference between an item loading on its own construct and its loading on any other construct should be at least 0.10, which further support to discriminant validity. This criteria is also met.

Table 5.9 Construct Correlation Matrix

	BC	**BI**	**CoAge**	**Comp**	**INC**	**OTC**	**PU**	**RCom**
BC	**0.87**							
BI	0.42	**0.97**						
CogAge	-0.21	-0.25	**1.00**					
Comp	-0.48	-0.25	0.43	**0.89**				
INC	-0.43	-0.18	0.30	0.81	**0.90**			
OTC	-0.41	-0.13	0.34	0.85	0.77	**0.94**		
PU	0.42	0.79	-0.24	-0.26	-0.20	-0.19	**0.94**	
RCom	0.08	0.17	-0.01	0.14	0.14	0.18	0.25	**1.00**

Values in the diagonal contain the square root of AVE by each construct

CoAge: Cognitive Age; RCom: RA Comprehensiveness; BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

5.5.2 Common Method Bias (CMB)

In this study, two techniques were used to examine the presence of Common Method Bias (CMB), namely Harman's one factor test, and unmeasured latent marker construct technique. To perform the Harman's one factor test (Podsakoff and Organ 1986), all the items of the research model are entered into a factor analysis. Then, the unrotated solution to the principal component analysis is conducted for all of the variables measured in this study. According to Podsakoff and Organ (1986), CMB exists if (i) items tend to load on a single general factor (i.e., only one single factor emerges from the factor analysis), or (ii) one of the variables contributes more than 50 percent of the total variance. As described below, results of this test are not suggestive of the presence of CMB in this study.

The unrotated solution to the Principal Component Analysis (PCA) suggested 3 factors with eigenvalues greater than 1. The first factor accounted for 45.78 percent of the variance and the 3 factors together accounted for 77 percent of the variance in data. The eigenvalue of the last factor was 1.392. Several items loaded on components other than the first extracted factor. As a result, it was concluded that the study items do not load on a single general factor (i). Next, as the first factor accounted for less than 50 percent of the variance (ii), it shows a lack of a considerable CMB.

An ULMC technique was also used to assess for the presence of CMB. This technique was used by Liang, Saraf, Hu, & Xue (2007) and adopted by other IS researchers. In this method, three steps are followed: First, each item of the research model is used to create a single-item construct. Then, the model's constructs are linked to those single-item constructs. Finally, a method construct with all the items is added to the research model and linked to each single-item construct.

Following Liang et al. (2007), as shown in Table 5.10, the coefficients of the paths from the substantive constructs and the method factor to each single-indicator construct (denoted as L1 and L2, respectively) were assessed. Moreover, the squared loadings of the substantive constructs were interpreted as the item variance caused by those constructs (i.e. $(L1)^2$), and the square loadings of the method factor were interpreted as the variance caused by the method factor (i.e. $(L2)^2$). Liang et al. (2007) recommend that "if the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances, we can conclude that common method bias is unlikely to be a serious concern" (Liang, Saraf, Hu, & Xue, 2007, p. 87). As can be seen in Table 5.10, only one item had significant method factor loadings ($p < 0.05$), and the substantive construct loadings that were all significant ($p < 0.001$). Considering that the average substantive variances (0.85) were considerably larger than the average method variances (0.004), the results suggest that CMB is not a concern in this study.

Table 5.10 ULMC Common Method Bias

		Substantive construct			**Method factor**		
Construct	**Item**	**Loading (L1)**	**Sig**	**$(L1)^2$**	**Loading (L2)**	**Sig**	**$(L2)^2$**
BC	BC1	0.918	p < 0.001	0.84	0.073	n.s.	0.00
	BC2	0.856	p < 0.001	0.73	-0.068	n.s.	0.00

	BC3	0.854	p < 0.001	0.72	0.002	n.s.	0.00
BI	BI1	0.975	p < 0.001	0.95	0.017	n.s.	0.00
	BI2	0.978	p < 0.001	0.95	-0.002	n.s.	0.00
	BI3	0.968	p < 0.001	0.93	-0.015	n.s.	0.00
Comp	Com1	0.625	p < 0.001	0.39	0.202	p < 0.05	0.04
	Com2	1.01	p < 0.001	1.02	-0.095	n.s.	0.00
	Com3	0.979	p < 0.001	0.95	-0.072	n.s.	0.00
	Com4	0.926	p < 0.001	0.85	-0.01	n.s.	0.00
INC	INC1	0.952	p < 0.001	0.90	-0.121	n.s.	0.01
	INC2	0.913	p < 0.001	0.83	0.008	n.s.	0.00
	INC3	0.914	p < 0.001	0.83	0.019	n.s.	0.00
	INC4	0.857	p < 0.001	0.73	0.081	n.s.	0.00
OTC	OTC3	0.943	p < 0.001	0.88	0.004	n.s.	0.00
	OTC4	0.946	p < 0.001	0.89	-0.004	n.s.	0.00
PU	PU1	0.896	p < 0.001	0.80	-0.046	n.s.	0.00
	PU2	0.956	p < 0.001	0.91	0.014	n.s.	0.00
	PU3	0.976	p < 0.001	0.95	0.032	n.s.	0.00
	PU4	0.954	p < 0.001	0.91	-0.001	n.s.	0.00
Average		**0.92**		**0.85**	**0.00**		**0.004**

Sig:Significance
BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

5.5.3 Structural Model

To assess the predictive power of the research model, the R^2 values of endogenous constructs were calculated. According to Gefen et al (2000), although there is no established cut-off value for this measure, large values are sought after. A threshold recommended by Falk & Miller (1992) is R^2 to be at least 0.10. As shown in Figure 5.1, R^2 for all endogenous variables reached this threshold. Moreover, the antecedents of behavioural intention explained 63% of the variance observed in the collected data for that construct.

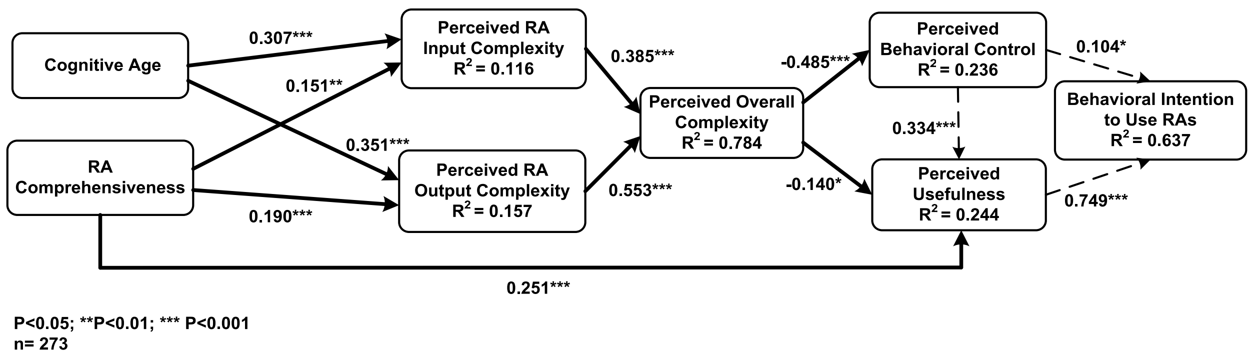

Figure 5.1 PLS Model Results

As can be seen in Table 5.11, all the hypothesized relationships were supported. A discussion on the results is provided in Chapter 6. It is worth mentioning that the relations on the right side of the model that were not hypothesized (as they have been already well established in the IS literature) were also examined. The results are shown in Table 5.12. As can be seen in this Table, they are also all significant.

Table 5.11 Validation of the Study Hypotheses

Hypothesis	Path	Path Coefficient	t-Statistic	Sig. Level	Validation Result
H1	RCom→INC	0.152	2.741	0.006	Supported
H2	RCom→OTC	0.190	3.495	0.001	Supported
H3	RCom→PU	0.251	4.829	0.000	Supported
H4	CoAge→INC	0.307	6.398	0.000	Supported
H5	CoAge→OTC	0.351	7.418	0.000	Supported
H9	INC→ Comp	0.385	5.750	0.000	Supported
H10	OTC→ Comp	0.553	8.109	0.000	Supported
H11	Comp→PU	-0.140	2.135	0.034	Supported
H12	Comp→BC	-0.485	9.274	0.000	Supported

CoAge: Cognitive Age; RCom: RA Comprehensiveness; BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

Table 5.12 Validation of the Relations Not Hypothesized

Path	Path Coefficient	t-Statistic	Sig. Level
BC→ BI	0.104	2.537	0.012
PU→ BI	0.749	21.686	0.000
BC→ PU	0.334	4.671	0.000

The impacts of perceived overall complexity on behavioural intention were assessed to understand whether they are fully or partially mediated through perceived behavioural control and/or perceived usefulness. To test for mediation, the four step procedure suggested by Baron & Kenny (1986) was followed. First, Figure 5.1 shows the impact of overall complexity (independent variable) on behavioural control and usefulness (potential mediators). The direct impact of overall complexity on behavioural intention (dependent variables) was tested. Results showed that the path from overall complexity to behavioural intention was significant ($\beta = -0.25$, $p < 0.001$). Then, behavioural control and usefulness were added to the equation with overall complexity to predict behavioural intention. Results showed that the impact of overall complexity on behavioural intention was no longer significant with a coefficient of -0.001 ($p > 0.05$). Therefore, behavioural intention and usefulness fully mediated the relationship between overall complexity and behavioural intention.

5.5.4 Goodness of Fit of the Model (GoF)

To evaluate the quality of the structural model, the Goodness of Fit (GoF) index was calculated. Akter, D'Ambra, & Ray (2011) defined GOF index as the "geometric mean of the average communality and average R^2 for all endogenous constructs" (Akter, D' Ambra, & Ray, 2011, p. 3). Unlike covariance-based SEM tools such as LISREL and AMOS, SmartPLS does not provide a GoF index. However, to assess the fit of the model, it is possible to calculate a GoF based on the results of SEM in SmartPLS. In this study, Wetzels et al.'s (2009) approach was used (Equation 5.1) for measuring GoF.

Equation 5.1 – Goodness of Fitness Formula (Wetzels et al., 2009)

$$GOF = \sqrt{\frac{\sum_n AVE_n}{n} \times \frac{\sum_m R_m^2}{m}}$$

n = number of total constructs
m = number of endogenous constructs

Based on the above formula, the GoF for the proposed model is 0.56, which is significantly higher than the suggested threshold of 0.36 (Wetzels et al., 2009). Thus, this result also supports the validity of the proposed research model and demonstrates that the collected data fits the proposed research model very well.

5.5.5 Effect Sizes

Effect size can be calculated to understand the impact of an independent variable on a dependent variable with the following guidelines: f^2 small (.02), f^2 medium (.15), and f^2 large (.35) (Cohen, 1988; Rosenthal, 1991). As recommended by Cohen (1988), the following formula was used to calculate the effect size based on the R^2 of a dependent variable once with the independent variable in the model and once without the independent variable in the model.

Equation 5.2 – f^2 Formula (Cohen 1998)

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

The results of the analysis of effect sizes are included in tables 5.13. The effect sizes are varied (8 small, 2 medium, and 2 large).

Table 5.13 Effect Sizes Analysis

Dependent Construct	Independent Construct	R^2		f^2	Effect Size
		Included	Excluded		
INC	CoAge	0.116	0.022	0.09	Small
	RCom		0.093	0.02	Small
OTC	CoAge	0.157	0.034	0.12	Small
	RCom		0.121	0.04	Small
Comp	INC	0.784	0.727	0.2	Medium
	OTC		0.664	0.35	Large
PU	Comp	0.244	0.229	0.02	Small
	BC		0.161	0.1	Small
	RCom		0.183	0.07	Small
BC	Comp	0.236	0.00	0.23	Medium
BI	PU	0.637	0.177	0.56	Large
	BC		0.629	0.02	Small

CoAge: Cognitive Age; RCom: RA Comprehensiveness; BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

5.5.6 Tests of Moderation Hypotheses

To test the moderating impact of cognitive age on the relation between RA comprehensiveness and RA input and output complexity, as well as RA usefulness perception as hypothesized in the research model of Figure 3.2, ANOVA analyses were conducted to understand whether any differences exist between older and younger adults' perceptions following a 2X2 factorial design (i.e., low cognitive age (between 20-30)/high cognitive age (above 60) X low comprehensiveness RA/high comprehensiveness RA) (Box, Hunter, & Hunter 1978).

A series of ANOVA tests were conducted which indicated the presence of interaction effects between cognitive age and level of comprehensiveness; followed by group contrast analyses between older and younger adults using Bonferroni tests (see Appendix F). This study involved two levels of RA comprehensiveness (i.e., low and high) for which the Bonferroni tests are considered suitable (Kirk 1982).

The results of the Bonferroni tests for younger and older adults are reported in Table 5.14. Hypotheses H6, H7 and H8 in the research model focus on the moderating effects of an individual's cognitive age on the relation between RA comprehensiveness and RA input and output complexity as well as RA usefulness perceptions. Thus, the contrasts were conducted under two groups (i.e., low and high RA comprehensiveness). In one group, participants interacted with the RA having a low level of comprehensiveness, whereas in the other group participants interacted with the RA having a high level of comprehensiveness. Referring to Table 5.14, as expected, cognitive age was found to moderate the relationships between RA comprehensiveness and input and output complexity such that the effect is stronger for older adults. Therefore, both H6 and H7 were supported. Surprisingly, however, cognitive age was also found to moderate the relationship between RA comprehensiveness and perceived RA usefulness such that the relation is *stronger for older adults*, contrary to what was hypothesized. Therefore H8 was not supported.

Table 5.14. Multiple Comparison Results: Younger Versus Older Adults (Bonferroni Test)

Group A	Group B	Younger Adults (20-30) Mean Difference (A-B)	Younger Adults (20-30) Sig	Older Adults (>60) Mean Difference (A-B)	Older Adults (>60) Sig	Hypothesis Supported
Perceived RA Input Complexity						
Low RA Comp	High RA Comp	-0.17	1.00	-0.62*	**0.019**	**H6 Supported**
Perceived RA Output Complexity						
Low RA Comp	High RA Comp	-0.08	1.00	-1.23*	**0.000**	**H7 Supported**
Perceived Usefulness						
Low RA Comp	High RA Comp	-0.18	1.00	-1.51*	**0.000**	**H8 Not Supported**

5.6 Post Hoc Analysis

5.6.1 Control Variables

As mentioned earlier in chapter 4, in addition to the items included in the research model, a series of control variables were collected in the questionnaire. Those variables were assessed to control for their potential impact on the endogenous constructs of the model. In total, 7 control variables were analyzed: education, product interest, RA experience, gender, Internet usage, task complexity, and product knowledge. In order to test the influences of these variables on the model, they were each added to the model one at a time, by linking the control variable to each endogenous variable in the model using SmartPLS.

To test the control variables' effect, the level of significance of each relationship of the control variable with other endogenous variables was examined. As shown in Table 5.15, 8 out of the 42 relationships were significant. As can be seen in this table, gender had a negative impact on perceived RA usefulness, indicating that female participants experienced more usefulness of the online RAs. Education had a negative impact on perceived usefulness, indicating that participants that had a lower level of education perceived the RAs to be more useful. RA experience had a negative impact on perceived behavioural control, indicating that participants that had higher experience with online RAs perceived more behavioural control over their task while using online RAs, compared to those that had lower RA experience. Internet usage had a positive impact on perceived behavioural intention to use online RAs, indicating that participants that used the Internet for more than 5 hours a day had more intention to use online RAs in their future online shopping experiences. Product knowledge had a negative impact on perceived behavioural control, indicating that participants that had higher product knowledge perceived more control over their task while using online RAs. Product interest had a positive impact on perceived RA complexity, indicating that participants that had less product interest perceived more RA overall complexity. In addition, product interest had a negative impact on perceived behavioual control, indicating that participants that had high product interest perceived more control over their task while using online RAs. Further, product interest had a negative impact on perceived behavioual intention to use RAs while shopping online, indicating that participants that had lower product interest perceived less intention to use online RAs while shopping for that product.

Table 5.15 Control Variable Analysis

Control Variable	Endogenous Construct	Path	Significance
Gender (1=female, 2=male)	***INC***	-0.004	n.s.
	OTC	0.015	n.s.
	Comp	-0.00	n.s.
	BC	-0.001	n.s.
	PU	**-0.206**	**$p < 0.001$**
	BI	-0.03	n.s.
Education (1= High School, 2= College diploma, 3= Bachelor's degree, 4= Master's degree, 5= Ph.D. degree)	***INC***	0.001	n.s.
	OTC	0.087	n.s.
	Comp	0.02	n.s.
	BC	-0.009	n.s.
	PU	**-0.141**	**$p < 0.01$**
	BI	0.01	n.s.
RA Experience (1=Very High, 2= High, 3=Some, 4=Low, 5=Very Low)	***INC***	-0.109	n.s.
	OTC	-0.09	n.s.
	Comp	0.03	n.s.
	BC	**-0.147**	**$p < 0.01$**
	PU	-0.06	n.s.
	BI	-0.07	n.s.
Internet Usage (1= Less than 1 hour, 2= Between 1 to 5 hours, 3= More than 5 hours)	***INC***	-0.005	n.s.
	OTC	-0.01	n.s.
	Comp	-0.036	n.s.
	BC	0.05	n.s.
	PU	-0.00	n.s.
	BI	**0.065**	**$p < 0.05$**
Product knowledge (1=Very High, 2= High, 3=Some, 4=Low, 5=Very Low)	***INC***	0.051	n.s.
	OTC	-0.005	n.s.
	Comp	0.036	n.s.
	BC	**-0.124**	**$p < 0.05$**
	PU	0.057	n.s.
	BI	-0.002	n.s.
Product Interest (1=Very High, 2= High, 3=Some, 4=Low, 5=Very	***INC***	0.04	n.s.
	OTC	0.006	n.s.

Control Variable	Endogenous Construct	Path	Significance
Low)	***Comp***	**0.087**	**$p < 0.01$**
	BC	**-0.112**	**$p < 0.05$**
	PU	-0.042	n.s.
	BI	**-0.128**	**$p < 0.01$**
Task Complexity (1=Very High, 2= High, 3=Some, 4=Low, 5=Very Low)	***INC***	0.004	n.s.
	OTC	-0.04	n.s.
	Comp	0.027	n.s.
	BC	-0.072	n.s.
	PU	-0.09	n.s.
	BI	-0.035	n.s.

BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

In addition, to further examine the predictive power of the control variables, their effect sizes could be measured to determine the statistical power of their relationships with endogenous variables (Hair, Black, Babin, Anderson, & Tatham, 2006) using Equation 5.2. Thus, the effect sizes of all of the above significant relations involving control variables were calculated. As can be seen in Table 5.16, the results showed that the effects of all the control variables were small. Thus, it could be concluded that the control variables did not change the conclusions derived from the hypotheses of this study.

Table 5.16 Effect Sizes Analysis for Control Variables

		R^2		f^2	Effect size
Control Variable	**Endogenous Construct**	**Included**	**Excluded**		
Gender	PU	0.286	0.243	0.05	Small
Education	PU	0.263	0.243	0.02	Small
RA Experience	BC	0.257	0.236	0.02	Small
Internet Usage	BI	0.642	0.637	0.01	Small
Product Knowledge	BC	0.251	0.236	0.02	Small
Product Interest	Comp	0.793	0.785	0.03	Small

	BC	0.248	0.236	0.01	Small
	BI	0.653	0.637	0.04	Small

BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; PU: Perceived Usefulness

5.6.2 Saturated Model Analysis

To explore possible non-hypothesized relationships among the variables of the research model, a saturated model was created by establishing all possible links among the variables in the originally proposed model of this study. Then, PLS path estimates and R^2 for the endogenous variables in the model were tested. Results of these examinations are shown in Table 5.17 and 5.18.

Table 5.17 shows PLS results for the non-hypothesized paths that were added to the research model. As can be seen in this table, 4 non-hypothesized paths had statistically significant path coefficients (path numbers: 1, 3, 6, and 13). Path 1 relates to the impact of an individual's cognitive age on their RA overall complexity perception. Although there are theoretical justifications for this path (i.e., as people become older they perceive more complexity in using new technologies (Hong et al. 2013)), in this study, the mediating role of RA input and output complexity is considered to understand how cognitive age impacts on the individual's overall perception of RA complexity. For the other significant paths (i.e., 3, 6, and 13) there was no theoretical justification. In order to investigate the possible influences of these paths on the explanatory power of the research model, changes in the R^2 of the model variables due to the addition of these non-hypothesized paths were compared across the proposed model and the saturated model.

Table 5.18 presents the R^2 values for the variables before and after adding the non-hypothesized paths. As can be seen in the table, the changes are significant (f^2>.02) for Comp, BC, and BI for which f^2 is 0.08, 0.03, and 0.04, respectively. As mentioned before, f^2 values of 0.02, 0.15, 0.35 refer to small, medium, and large effect sizes, respectively. Thus, the changes in R^2 of Comp, BC, and BI are considered small. Hence, it was concluded that the non-hypothesized paths did not have a significant impact on the explanatory power of the proposed research model.

Table 5.17 PLS Results for Non-Hypothesized Paths – Saturated Model Analysis

Path Number	Non-Hypothesized Paths	β	p	Validation
1	CoAge→Comp	0.148	0.00	Supported
2	CoAge→BC	0.005	0.92	Rejected
3	CoAge→PU	-0.130	0.02	Supported
4	CoAge→BI	-0.06	0.11	Rejected
5	RCom→Comp	-0.002	0.92	Rejected
6	RCom→BC	0.163	0.001	Supported
7	RCom→BI	-0.05	0.183	Rejected
8	INC→BC	-0.122	0.177	Rejected
9	INC→PU	0.028	0.74	Rejected
10	INC→BI	-0.025	0.71	Rejected
11	OTC→BC	-0.00	1	Rejected
12	OTC→PU	0.045	0.67	Rejected
13	OTC→BI	0.217	0.004	Supported
14	Comp→BI	-0.126	0.117	Rejected

β: PLS Path Coefficient; **p**: Significance Level ($p<.05$ significant)
CoAge: Cognitive Age; RCom: RA Comprehensiveness; BC: Behavioural Control; BI: Behavioural Intention; Comp: Complexity; INC: Input Complexity; OTC: Output Complexity; PU: Perceived Usefulness

Table 5.18 Changes in R^2 of the Study Variables – Saturated Model Analysis

Model	INC	OTC	Comp	BC	PU	BI
Original Model of this Study	0.116	0.157	0.784	0.236	0.244	0.637
Saturated Model	0.116*	0.157*	0.803	0.265	0.259	0.654
ΔR^2	.00	.00	.019	0.029	0.015	0.017
f^2	0	0	0.08	0.03	0.01	0.04

*As in the saturated model, there were no additional paths to add to INC and OTC, the R^2 did not change in these constructs.

5.6.3 Supplementary Analysis on Cognitive versus Chronological Age

Participant's chronological age and their cognitive age were classified into groups in order to better understand the relationship between an individual's chronological and cognitive ages. As can be seen in Table 5.19, 10 of the 11 individuals (90.9%) of the people whose chronological ages were between 80 to 89 years old perceived their age to be younger than their chronological age, while 67 individuals (81.7%) of people whose chronological ages were between 70 to 79 years old perceived their age to be younger than their chronological age. The percentage of individuals feeling that their age is younger than their chronological age goes down for the remaining age groups to 75%, 45.7%, 52.2% and 44.2% for the (60-69), (50-59), (40-49) and (30-39) chronological age groups respectively. Hence, as expected, as individuals become older, they tend to feel younger than their chronological age with most individuals classifying feeling they are 10 years younger than their actual age.

Table 5.19. Chronological Age Versus Cognitive Age

	Cognitive Age							
Chronological Age Group	**20-29**	**30-39**	**40-49**	**50-59**	**60-69**	**70-79**	**80-84**	**Total**
20-29	32	3						**35**
30-39	19	20	3	1				**43**
40-49	3	9	8	3				**23**
50-59	3	2	11	17	2			**35**
60-69			6	27	11			**44**
70-79			4	18	45	14	1	**82**
80-89				1	2	7	1	**11**
Total	**57**	**34**	**32**	**67**	**60**	**21**	**2**	**273**

As mentioned earlier, consumer research has shown cognitive age to be a better predictor of an individual's behaviours than chronological age (Sherman et al., 2001; Goulding & Shankar, 2004, Hong et al., 2013). Thus, in this study, the individual's cognitive age was used in the research model. An ANOVA analysis was conducted to assess whether different results would be obtained if chronological age is used instead of cognitive age in terms of the differences in an individual's input and output complexity perceptions when they use RAs with low or high levels of comprehensiveness. The results of this analysis as shown in Tables 5.20 and 5.21 below can be summarized as follows:

- There are no significant differences in the RA input complexity and RA output complexity perceptions between chronologically younger and older adults who used the low comprehensiveness RA. These results are contrary to the ANOVA results when we used an individual's cognitive age.

- There are no significant differences in RA input and output RA complexity perceptions between chronologically younger adults who used the RA with a low or high level of comprehensiveness. These results are consistent with the results obtained when using an individual's cognitive age.
- Chronologically older adults who used the low comprehensiveness RA perceived significantly lower output complexity compared to older adults who used high comprehensiveness RA. This is similar to the results obtained for cognitive age. On the other hand, these two groups showed no significant difference in their input complexity perceptions which is contrary to the results obtained for cognitive age.
- There are no significant differences in the input and output RA complexity perceptions between chronologically younger and older adults using the high comprehensiveness RA which is contrary to the results obtained for cognitive age.

Table 5.20. ANOVA Summary Table for Perceived RA Input Complexity

		Chronological Age		**Cognitive Age**	
		Mean Difference	Sig.	Mean Difference	Sig.
Low RC, YA	Low RC, OA	-0.31	1.000	-0.57*	**0.015**
	High RC, YA	-0.50	0.715	-0.17	1.000
Low RC, OA	High RC, OA	-0.42	0.072	-0.62*	**0.019**
High RC, YA	High RC, OA	-0.24	1.000	-1.02*	**0.000**

RC: RA Comprehensiveness; YA: Younger Adults (20-30); OA: Older Adults (>60)
*. The mean difference is significant at the 0.05 level.

Table 5.21. ANOVA Summary Table for Perceived RA Output Complexity

		Chronological Age		Cognitive Age	
		Mean Difference	Sig.	Mean Difference	Sig.
Low RC, YA	Low RC, OA	-0.34	1.000	-0.54*	**0.008**
	High RC, YA	-0.52	0.581	-0.08	1.000
Low RC, OA	High RC, OA	-0.62*	**0.001**	-1.23*	**0.000**
High RC, YA	High RC, OA	-0.44	0.457	-1.68*	**0.000**

As younger adults have higher cognitive abilities compared to older adults (Uechi, 2010), it is expected lower perceptions of complexity among younger adults while using online RAs. Thus, taken together, the results in this and the previous sections indicate that as an individual's cognitive age leads to results that are more consistent with aging theories, it is a better predictor of their beliefs regarding RA complexity than their chronological age.

5.7 Summary

This chapter presented details about the data collection and screening, as well as the summary of the demographic figures of the participants. Then, the detailed procedures and results of validating the proposed research model were described. Finally, post hoc analyses were presented. The implications of the results obtained will be discussed in the next chapter.

Chapter 6: Discussion and Conclusion

This chapter examines the results reported in Chapter 5 above in detail. Section 6.1 summarizes the findings for each one of the research questions of this dissertation. Section 6.2 outlines the contributions of this dissertation to theory and practice. Then, the limitations of this study are elaborated in Section 6.3, followed by Section 6.4 which provides directions for future research. Finally, Section 6.5 concludes this chapter and this dissertation.

6.1 Answers to Research Questions

6.1.1 Research Question 1

RQ1: *How does RA comprehensiveness impact antecedents of user intentions to use online RAs?*

Related Hypotheses:

H1: Higher levels of RA comprehensiveness lead to higher perceptions of RA input complexity

H2: Higher levels of RA comprehensiveness lead to higher perceptions of RA output complexity

H3: Higher levels of RA comprehensiveness lead to higher perceptions of RA usefulness

RA comprehensiveness was hypothesized as an antecedent of RA input complexity, RA output complexity, and RA usefulness. Based on the findings presented in the previous chapter, RA comprehensiveness significantly impacts RA input complexity. This relation had a statistically significant beta coefficient[3] of 0.151 (p-value < 0.01) exhibiting a small effect size ($f^2 = 0.02$). The direction and significance of the path coefficient supported hypothesis H1.

RA comprehensiveness was also hypothesized as an antecedent of RA output complexity. Based on the findings presented in the previous chapter, RA comprehensiveness was found to significantly impacts RA output complexity. This relation had a statistically significant beta coefficient of 0.190 (p-value < 0.001) exhibiting a small effect size ($f^2 = 0.04$). The direction and significance of the path coefficient supported hypothesis H2.

According to Cognitive Complexity theory (Kieras & Polson, 1985), and Cognitive Load theory (WM Van Gerven, 2000), it is logical to expect that consumers will experience higher complexity in using more comprehensive RAs. Asking users about a large number of product attributes in the input stage may increase their perceptions of RA input complexity. Likewise, providing too many product recommendations in the output stage may induce users to compare a large number of alternatives which may increase their perception of complexity.

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[3] PLS results are presented in Table 5.11

RA comprehensiveness was also hypothesized as an antecedent of RA usefulness. Based on the findings presented in the previous chapter, RA comprehensiveness significantly impacts perceived RA usefulness. This relation has a statistically significant beta coefficient of 0.251 (p-value < 0.001)[4] exhibiting a small effect size ($f^2 = 0.07$). The direction and significance of the path coefficients supported hypothesis H3.

Xiao & Benbasat (2007) argue that users perceive RAs to be useful when they perceive high utility of RAs. Thus, by providing detailed information in the input stage, the RA educates users about different product attributes. Likewise, by presenting a large number of recommendations and a high level of details associated with them in the output stage, the RA educates users about the particular product and the recommended alternatives, which contribute to the user's perception of the RA usefulness.

6.1.2 Research Question 2

RQ2: *How does cognitive age impact antecedents of user intentions to use online RAs?*

Related Hypotheses:

H4: Higher cognitive age leads to higher perceptions of input complexity while using an RA

[4] RA comprehensiveness also impacts indirectly on perceived usefulness through input, output, overall complexity and behavioral control perceptions. However, results show that the direct impact of RA comprehensiveness on perceived usefulness is much stronger (i.e., 0.251) than indirect impact (i.e., -0.049).

H5: Higher cognitive age leads to higher perceptions of output complexity while using an RA

Cognitive age was hypothesized as an antecedent of RA input complexity as well as RA output complexity. Based on the findings presented in the previous chapter, this relation has a statistically significant beta coefficient of 0.307 (p-value $<$ 0.001) exhibiting a small effect size[5] (f^2 = 0.09). The direction and significance of the path coefficients supported hypotheses H4.

The ANOVA results showed that there is a significant difference ($p < .05$) in the RA input complexity perceptions between individuals whose cognitive age was between 20 and 30 (considered as younger adults), and individuals whose cognitive age was above 60 (considered as older adults) where older adults perceived higher input complexity compared to younger adults, which again supports H4.

Cognitive age was also hypothesized as an antecedent of RA output complexity. Based on the findings presented in the previous chapter, this relation has a statistically significant beta coefficient of 0.351 (p-value $<$ 0.001) exhibiting a small effect size (f^2 = 0.12). The direction and significance of the path coefficients supported hypotheses H5.

In addition, the ANOVA results showed that there is a significant difference ($p < .05$) in the RA output complexity perceptions between individuals whose cognitive age was between 20 and 30 (considered as younger adults), and individuals whose cognitive

[5] Direct effect sizes are presented in Table 5.13

age was above 60 (considered as older adults) where Older adults perceived higher output complexity compared to younger adults, which again supports H5.

The impact of individual cognitive age on both RA input and output complexity perception is consistent with the resources, speed, and inhibition theories of aging (Cabeza, 2002) which argue that older adults with higher age will perceive higher levels of complexity.

6.1.3 Research Question 3

RQ3: *How do complexity and usefulness perceptions of users of RAs with different levels of comprehensiveness vary between younger and older adults?*

Related hypotheses:

H6: Cognitive age moderates the effect of RA comprehensiveness on perceived RA input complexity, such that the effect is stronger for older adults.

H7: Cognitive age moderates the effect of RA comprehensiveness on perceived RA output complexity, such that the effect is stronger for older adults.

H8: Cognitive age moderates the effect of RA comprehensiveness on perceived RA usefulness, such that the effect is stronger for younger adults.

To answer the third research question (RQ3), ANOVA tests were conducted to understand if the complexity perceptions of users of RAs with different levels of comprehensiveness varied between younger and older adults. The ANOVA results (Table

5.14) show that there is a significant difference ($p < .05$) in the RA input complexity, RA output complexity, and RA usefulness perceptions between younger and older adults who used the low or high level of RA comprehensiveness. Older adults who used RA with a higher or lower level of comprehensiveness perceived more complexity in the RA input stage, and output stage, than those younger adults that used RAs with a same level of comprehensiveness, supporting hypotheses H6 and H7. However, in terms of perceived RA usefulness, the results show that younger adults did not perceive the RA with the high level of comprehensiveness to be significantly more useful than the RA with the low level of comprehensiveness. Interestingly, results show that older adults perceived that the RA with the high level of comprehensiveness to be significantly more useful than the RA with the low level of comprehensiveness. Therefore, H8 was not supported. This could be due to the fact that older adults are generally more patient than younger adults (Roschk, Müller, & Gelbrich, 2013). Thus, older adults are more amenable to spending more time to take full advantage of the higher level of detail and support provided by the more comprehensive RA to realize its full utility for better decision-making.

6.1.4 Research Question 4

RQ4: *How do RA input and output complexity impact RA users' experience?*

Related hypotheses:

H9: Higher RA input complexity leads to higher perceptions of RA overall complexity

H10: Higher RA output complexity leads to higher perceptions of RA overall complexity

H11: Higher RA overall complexity leads to lower perceptions of RA usefulness.

H12: Higher RA overall complexity leads to lower perceptions of behavioural control in making online shopping decisions.

RA input complexity was hypothesized as an antecedent of RA overall complexity perception. Based on the findings presented in the previous chapter, this relation has a statistically significant beta coefficient of 0.385 (p-value < 0.001) exhibiting a medium effect size ($f^2 = 0.2$). The direction and significance of the path coefficients supported hypotheses H9.

RA output complexity was also hypothesized as an antecedent of RA overall complexity perception. Based on the findings presented in the previous chapter, this relation has a statistically significant beta coefficient of 0.553 (p-value < 0.001) exhibiting a large effect size ($f^2 = 0.35$). The direction and significance of the path coefficients supported hypotheses H10.

Together, RA input and output complexity explained 78% of RA overall complexity's variance. This could be due to the fact that individuals have the most interaction with RAs in the input and output stages (Ghasemaghaei et al. 2014). Thus, higher complexity perceptions in these stages significantly impacts an individual's overall complexity perception (H9 & H10) while using RAs in their online shopping decision-making. According to Cognitive Load Theory, when the amount of information processing (e.g., in the input and output stages of RAs) exceeds an individual's cognitive capacity, he/she would perceive information overload and thus complexity (Kahneman, 1973).

RA overall complexity was hypothesized as an antecedent of RA usefulness perception. Based on the findings presented in the previous chapter, RA overall complexity significantly impacts perceived RA usefulness. This relation has a statistically significant beta coefficient of -0.140 (p-value < 0.001) exhibiting a small effect size (f^2 = 0.02). The direction and significance of the path coefficients supported hypotheses H11. This result is consistent with TAM (Davis, 1989), as it indicates that perceived ease of use has a positive relation with perceived usefulness. Hence, the RA overall complexity perception has negative impacts on perceptions of usefulness.

RA overall complexity was hypothesized as an antecedent of behavioural control perception. Based on the findings presented in the previous chapter, RA overall complexity significantly impacts perceived behavioural control. This relation has a statistically significant beta coefficient of -0.485 (p-value < 0.001) exhibiting a medium effect size (f^2 = 0.23). The direction and significance of the path coefficients supported hypotheses H12. This result is consistent with the cognitive complexity theory (Kieras and Polson, 1985) that when users perceive difficulty in using new technologies, they would perceive it would be difficult for them to perform the associated behaviour (Dean, 2008).

6.2 Contributions

Findings from this dissertation provide significant contributions to both theory and practice, which are detailed below.

6.2.1 Contributions to Theory

The results of this study make important theoretical contributions. First, although older adults are the fastest growing segment of Internet users, there is a lack of understanding of special design consideration of online RAs for this segment of consumers. Extant RA studies (Swaminathan 2003; Benbasat & Wang 2005; Komiak & Benbasat 2006; Xu et al. 2014) studied the agent interface without investigating the role of consumer age. This knowledge gap is addressed by applying aging theories and TPB theory to explain the impact of user's age on their intention to use RAs while shopping online. In so doing the RA literature is advanced by considering the impact of a user's age in the design of the agent interface. Recent findings suggest cognitive age as a better age measure for understanding consumer behaviours towards new information technologies. Thus, as opposed to most IS studies on understanding the role of age in technology adoption, in this study an individual's cognitive age was used rather than simply using their chronological age to understand their intentions to use RAs. This study also responded to Tams et al.'s (2014) call for studies examining the emerging importance of studying age-related impacts on IS phenomena.

RA comprehensiveness is an important factor that affects a user's evaluation of RAs. The effects of different levels of RA comprehensiveness in terms of the number of required product attributes in the input stage and the number of recommendations and associated product attributes in the output stage on a user's RA complexity perceptions were investigated in both the input and output stages of the RA operation. While several recent RA studies investigated the RA design (Swaminathan 2003; Wang & Benbasat 2005) in the input stage, to the best of my knowledge, no other RA studies have investigated the RA design in both its input and output stages. This study contributes to this knowledge gap by analyzing how the different levels of RA comprehensiveness (low or high) influences a user's complexity perceptions in both the input and output stages of online RAs' operation. The results demonstrate that RA comprehensiveness has a significant impact on a user's RA complexity perceptions in both the input and output stages of the RA operation with this effect being more prominent for the output stage. Showing such differential impacts of RA comprehensiveness on RA input and output complexity perceptions is a significant contribution to the theoretical understanding of a user's interactions with RAs. This study further illustrates that the impact of RA comprehensiveness on both RA input and output complexity is moderated by an individual's cognitive age, such that it is stronger for older adults. Another novel contribution to theory is showing that user perception of overall RA complexity is more affected by user perception of the complexity of the output stage of the RA than her/his perception of the complexity of the RA in the input stage.

Interestingly, it is found that as RAs become more comprehensive, although as a consequence individuals perceive more RA complexity in both their input and output stages, they perceive more comprehensive RAs to be more useful. Thus, RA comprehensiveness has both positive and negative impacts on antecedents to a user's intention to use online RAs. Specifically, high levels of RA comprehensiveness positively impacts a user's intention to use online RAs through RA usefulness perception, while it negatively impacts a user's intention to use online RAs through complexity perceptions in both the input and output stages of the RA operation.

As expected, cognitive age was found to moderate the relationships between RA comprehensiveness and input/output complexity such that the effect is stronger for older adults. Surprisingly, however, cognitive age was also found to moderate the relationship between RA comprehensiveness and perceived RA usefulness such that the relation is stronger for older adults. This could be due to the fact that older adults are generally more patient than younger adults (Roschk, Müller, & Gelbrich 2013). For example, Aljukhadar and Senecal (2011) found that increasing the length of the online product search process made younger consumers complain about the time it took to complete the search more than older adults did. Hence, older adults are more amenable to spending more time[6] to take full advantage of the higher level of detail and support provided by the more comprehensive RA to realize its full utility for better decision-making. Another reason could be due to the fact that older adults may appreciate having more comprehensive

[6] Results from this study show that on average younger adults spent 143.6 seconds using the low comprehensiveness RA, while older adults spent 167.3 seconds using it. The results also show that on average younger adults spent 296.2 seconds using the high comprehensiveness RA, while older adults spent 407.3 seconds using it. Whereas there is not a significant difference between younger and older adults in terms of time spent using the low comprehensiveness RA, the significance level between younger and older adults on time spent using the high comprehensiveness RA is $p < 0.10$. Some IS researchers (e.g., Dimoka & Davis 2008; Dimoka, Hong, & Pavlou 2012; Hong & Pavlou 2010) refer to this level of significance as 'modest' or 'marginal' significance ($0.10 < p < 0.05$).

information because they don't need to search for it themselves and to have to subsequently file and retain the information until they make a decision. This alleviates trying to remember all the information relevant to their online shopping experience which would be an important advantage given their memory deficits.

The results of the effect of RA input and output complexity perceptions on the overall RA complexity perception provide unique insights. In particular, although both input and output complexity have a positive impact on the overall perceptions of RA complexity, RA output complexity has a more significant role in increasing the overall RA complexity perception with users. As theorized, this is because of the number of recommendations and associated product attributes in the output stage, which could cause information overload and increase the overall RA complexity perception more than the RA input stage where just the consumer's preferences are elicited through a number of product attributes solicited from the user one at a time. This study will help researchers to better underscore the importance of the user interface design that suits the cognitive abilities of different customer segments to increase an individual's intention to use online RAs while shopping online, and understand how RA comprehensiveness impacts the overall perceptions of RA complexity through both the RA input and output complexities, as well as RA usefulness.

6.2.2 Contributions to Practice

This study also has significant implications for practitioners. First, the results of the study suggest that an individual's cognitive age influences his/her intentions to use online RAs while shopping online. This study suggests that the concept of age is not as simple as it seems. Customers may perceive their age differently, and such self-perceived age (i.e., cognitive age) seems to play a critical role on an individual's intention to use online RAs. Hong et al. (2013) suggest that the typical market segmentation approaches based on an individual's chronological age do not correctly identify the needs of those customers with a cognitive age that does not match their chronological age, and has the risk of misclassifying target customer groups by ignoring potential dissimilarities of their cognitive age. Considering the individual's cognitive age as a basis for customer personalization and segmentation would help practitioners to better understand what consumers really need. This study has demonstrated this to also be the case with online RAs. Online vendors can use the results of this study to better customize the design of their RAs to suit different customer segments by age, and as a result, users will be more willing to use their online RAs while shopping online. Vendors could simply measure the consumer's cognitive age by asking consumers about their perceptions regarding their looks, feelings, actions, and interests. It should be emphasized that the nature of the cognitive age scale used in this study lends itself well to a quick and non-intrusive way of assessing cognitive age. Thus, consumers would be less reluctant to respond to this quick survey.

The results indicate that employing a high level of RA comprehensiveness in terms of the number of the required product attributes in the input stage and the number of recommendations and associated product attributes in the output stage leads to an increase in the user's perceptions of RA complexity in both the input and output stage of its operation. Further, as people become older, they perceive more complexity in the input and output stages of the RA operation. Thus, practitioners who desire older adults to perceive less overall complexity while using online RAs could design RAs with low level of comprehensiveness particularly in the output stage, as it has a more critical role in forming the individual's overall complexity perceptions. This highlights the danger of overwhelming older adults with too much information in terms of the number of recommendations and associated product attributes in the output stage of the RA operation.

More importantly, practitioners are also advised to consider that RA comprehensiveness has both positive and negative impacts on a user's intention to use online RAs. In particular, a high level of RA comprehensiveness increases a user's intention to use online RAs through RA usefulness perceptions, while it reduces a user's intention to use online RAs through higher complexity perceptions in both the input and output stages of the RA operation. In addition, the surprising finding that cognitive age moderates the relationship between RA comprehensiveness and perceived RA usefulness, such that the relationship is stronger for older adults, has important implications for the design and provision of RAs for different age groups. Given that younger users find the RAs of low and high comprehensiveness equally complex and equally useful, for the designers of e-commerce sites the issue of choosing the right level of RA comprehensiveness for younger adults is not the main concern. Instead, designers need to be more concerned about older users since for them there is a definite tradeoff between obtaining higher usefulness and the cost of additional complexity. Thus, designers should provide older users in particular with the means of *customizing* the comprehensiveness level of RAs based on their individual preferences so that they are in better control of choosing between the benefits of using a more comprehensive RA versus the cognitive cost they have to incur in using the RA to make a product selection decision. In summary, designers should consider that the design of the input and output stages of the online RA involves a delicate balance that is influenced by the cognitive age group that the customer belongs to.

6.3 Limitations

As with any research project, this dissertation study has some limitations, which are summarized in this section. The first limitation is that this study was conducted in a context in which the participants assessed an online RA in the early stage of their interaction with it. However, when participants become more familiar with the agent, the factors that impact their intention to use it may be different. For instance, it is possible that the perceptions of the complexity of an agent are reduced when users become more familiar with it, and as such, the effects of overall complexity perceptions on the antecedents of intention to use the RA may also be decreased. On the other hand, the effect of perceived usefulness on an individual's intention to use RAs may become stronger. This notion consists of the findings in the literature that as the individuals gain more experience, the impacts of perceived ease of use (opposite of perceived complexity) on intentions to use a new technology reduce, whereas the impacts of the perceived usefulness increase (Taylor & Todd, 1995).

Second, only attribute-based RAs are considered in this study, which limits the generalizability of the results to other types of RAs such as need-based agents (Ansari et al. 2000).

Third, perceived RA input and output complexity can be affected by factors other than the individual's cognitive age and RA comprehensiveness, such as the familiarity with the RA. Thus, caution should be taken in the interpretation of the magnitude of input and output complexity perception in this study.

Fourth, this study was conducted among Canadian and US online shoppers. Thus, caution should be taken in generalizing the research findings of this study to other cultures.

Fifth, this study took a positivist approach to address its research questions. The findings of this study could have been strengthened through triangulation by including more open-ended questions to better understand the perceptions of the study participants regarding their experiences with the experimental treatments and tasks.

Sixth, the present research considered cars as the product for the experiment which is a high involvement product. Although online RAs are mostly used for high involvement products, it would be interesting to explore if using RAs while shopping for low involvement products (e.g., pens, books) would lead to different results.

Seventh, this experimental study was conducted in an artificial setting where participants evaluated a fictitious RA while pretending to buy a car. Consumers who are engaged in using a real online RA while actually shopping for a car might have different perceptions from the participants in this study. However, the experimental RAs used in this study closely mimicked real RAs available from leading online RA providers and several techniques were used to increase the realism of the task (e.g., adding an open-ended question asking participants to provide justification for selecting a specific car recommended by the RA).

6.4 Future Research

Considering the findings and limitations of this study, there are several opportunities to conduct future research in this area. First, this study was conducted in a context in which the participants assessed an online RA in the early stage of their interaction with it. However, as discussed previously in this chapter, when participants become more familiar with the agent, the factors that impact their intention to use it may be different. Therefore, possible venues of future research are to further assess the importance of different factors on post-adoption perceptions and behaviours toward online RAs.

Second, as only the design of the attribute-based RAs are considered in this study, further research is required to determine the extent to which the findings of this study can be extended to other types of RAs. For example, future research could design need-based RAs that are different in the level of comprehensiveness in both input and output stages of the RA to determine whether the findings of this study can be extended to other types of RAs.

Third, as the R^2 for both RA input and output complexity is not very high, 0.116 and 0.157, respectively, there could be other factors other than an individual's cognitive age and RA comprehensiveness that impact on individuals' RA input and output perceptions. Hence, the impact of other factors on perceived RA input and output complexity warrants future research.

Fourth, as discussed, the study is conducted among Canadian and US online shoppers. Further research exploring this issue is hereby suggested to examine the impact of cognitive age and RA comprehensiveness on the antecedents of an individual's intention to use online RAs in other cultures in order to further generalize the research findings.

Fifth, a longitudinal study could be designed to understand the impact of an individual's cognitive age and RA comprehensiveness on the antecedents of an individual's intention to use RAs while shopping online at three points in time: pre-usage, initial usage, continued use. In such research, the influence of an individual's cognitive age and RA comprehensiveness at each point in time on perceptions and usage behaviour at later points can be investigated.

Sixth, recall from Subsection 5.6.1 of this dissertation that a number of control variables were found to be associated with some of the factors in the research model of this study. Although implications of the results for this study are discussed in this chapter, understanding of the nature of the associations was beyond the scope of this dissertation. Hence, further research is required to explain the results.

6.5 Conclusion

This study addressed an important gap in research in terms of understanding the role of cognitive age and RA comprehensiveness in influencing a user's perceived RA input and output stages complexities which impact on the antecedents of an individual's intention to use online RAs. This study extended previous RA research by proposing the impact of a user's cognitive age on their intention to use online RAs, a novel aspect not previously considered in RA research. The inclusion of individual cognitive age sheds light on how a user's self-perceived age impacts their intention to use online RAs. This study suggests that the concept of age is not as simple as it seems and an individual's chronological age does not correctly identify the needs of customers whose cognitive age is not the same as their chronological age. Thus, a user's cognitive age rather than chronological age can be used to evaluate alternative RA interface designs in the future and how those interfaces may vary by cognitive age group. In contrast to past research that focused on only the input stage of online RAs, this study empirically compared user perceptions regarding RAs of various comprehensiveness levels in both the input and output stages of their operation. In so doing, the results of this study showed that compared to the RA input complexity, RA output complexity has a more significant role in shaping a user's perceptions about the RA overall complexity. This study also identified a positive effect of the comprehensiveness level of the RA on a user's perceptions of the usefulness of the RA. Surprisingly, cognitive age was found to moderate the relationship between RA comprehensiveness and perceived RA usefulness such that the relation is stronger for older adults. The results provide online RA designers with important guidelines that should be considered when designing RAs for different consumer segments by age.

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Appendix A – Consent Form

LETTER OF INFORMATION / CONSENT

A Study of/about: Online Recommendation Agents

We are conducting this experiment as part of a PhD dissertation that aims to find out what factors contribute to individuals' intention to use online recommendation agents while shopping online products. This research will result in guidelines for the design of online recommendation agents.

You will be asked to use a recommendation agent to shop for a car. After using a recommendation agent for about 5-10 minutes, you will be asked to complete an online survey, which will require approximately 10 minutes. In the survey, you will be asked to respond to closed-ended questions about your experience while using an online recommendation agent to shop for a car. After completing the survey, you will be asked to respond to open-ended questions to gather more details about your experience with the online recommendation agent.

CONSENT

I understand the information provided for the study "Designing Online Recommendation Agents" as described herein. My questions have been answered to my satisfaction, and by selecting the "I agree to participate" button below, I agree to participate in this study. I understand that if I agree to participate in this study, I may withdraw from the study at any time.

Click here to see the consent form which has been reviewed by the McMaster University Research Ethics Board and received ethics clearance.

- "I agree to participate."
- "I do not agree to participate."

Appendix B – Directing Participants to Online RAs

While shopping for online products, recommendation agents elicit your preferences for product attributes, and make recommendations accordingly. With the help of these agents, you can evaluate your options and make better decisions while purchasing online products.

Please click on a following link to use an online recommendation agent which helps you to shop for a car from Toyota, and then answer the following questions regarding your experience with using that online recommendation agent. Here is the link:

http://www.my-car-shopping-assistant.ca/

Note: After using the online recommendation agent, please come back to this page and click on next to answer the survey questions.

Appendix C – Survey Questions

Cognitive Age Questions

Please specify which age group you FEEL you really belong to regardless of your chronological age (the date of birth age):

	20s	30s	40s	50s	60s	70s	80s	90s
I FEEL as though I am in my								
I LOOK as though I am in my								
I DO most things as though I were in my								
My INTERESTS are mostly those of a person in his/her								

Please indicate the degree to which you agree or disagree with the following statements regarding your experience with using the online recommendation agent to shop for a car. Please keep in mind that there are no right or wrong answers, so please answer the questions as honestly as possible.

Page 1 – Behavioural Intention, & Perceived Usefulness

	Strongly disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree
Assuming I had access to this recommendation agent while shopping online, I intend to use it.	○	○	○	○	○	○	○
Assuming I had access to this recommendation agent while shopping online, I predict that I would use it.	○ –	○ –	○ –	○ –	○ –	○ –	○ –
Assuming I had access to this recommendation							

	Strongly disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree
agent while shopping online, I plan to use it.							
This recommendation agent provides good quality information for my online shopping task.	○	○	○	○	○	○	○
This recommendation agent improves my performance in my online shopping task.	○	○	○	○	○	○	○
This recommendation agent increases my effectiveness for shopping online.	○	○	○	○	○	○	○
Overall, this recommendation agent is useful for online shopping.	○	○	○	○	○	○	○

Page 2 – Behavioural Control and Quality Control Question

	Strongly disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree
I have the resources, knowledge, and ability to use this recommendation agent.	○	○	○	○	○	○	○
I can use this recommendation agent.							

Using this recommendation agent is entirely within my control.	○	○	○	○	○	○	○
Some people do not read the questions carefully or consider their answers thoughtfully. To indicate that you have read and answered the questions carefully and thoughtfully, please select 'Agree'	○	○	○	○	○	○	○

Page 3 – Overall Complexity, Input Complexity, Output Complexity

	Strongly disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree
Using this recommendation agent takes too much time.	○	○	○	○	○	○	○
Working with this recommendation agent is so complicated; it is difficult to understand what is going on.	○	○	○	○	○	○	○
Using this recommendation agent involves too much time doing different operations.	○	○	○	○	○	○	○
It takes too long to learn how to use this recommendation agent to make it worth the effort.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree

Using this recommendation agent took too much time in the stage where it elicited my preferences for the car attributes I was looking for.	○	○	○	○	○	○	○
Working with this recommendation agent was so complicated in the stage where it elicited my preferences for the car attributes I was looking for; it was difficult to understand what is going on.	○	○	○	○	○	○	○
Using this recommendation agent involved too much time doing operations in the stage where it elicited my preferences for the car attributes I was looking for.	○	○	○	○	○	○	○
It took too long to learn how to use this recommendation agent to make it worth the effort in the stage where it elicited my preferences for the car attributes I was looking for.	○	○	○	○	○	○	○

	Strongly disagree	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	Strongly agree
Using this recommendation agent took too much time in the stage where recommendations were presented to me.	—	—	—	—	—	—	—

Working with this recommendation agent was so complicated in the stage where recommendations were presented to me; it was difficult to understand what is going on.	○	○	○	○	○	○	○
Using this recommendation agent involved too much time doing operations in the stage where recommendations were presented to me.	○	○	○	○	○	○	○
It took too long to learn how to use this recommendation agent to make it worth the effort in the stage where recommendations were presented to me.	○	○	○	○	○	○	○

Page 4 – Manipulation Check & Open-ended Questions

For the following question, please remember not to include names or other information that could identify you either directly or indirectly.

Please indicate your perceptions regarding the number of product attributes and the level of detail associated with each attribute in the stage where it elicited your preferences for the car attributes you are looking for?

○ Very low

○ Low

○ Neither low or high

○ High

○ Very High

Please indicate your perceptions regarding the number of recommendations and the level of detail associated with these recommendations in the stage where recommendations were presented to you?

Very low

○ Low

○ Neither low or high

○ High

○ Very High

Please briefly tell us how you reached a decision in selecting a specific recommended car while using the recommendation agent.

Page 5 – Demographics & Control Variables

Please answer the following questions that will provide us with some basic background information about you:

Which of the following describes your present gender identity?

○ Female

○ Male

○ Other

What is your age?

Which of the following best describes your knowledge about cars?

○ Very high

○ High

○ Some

○ Low

○ Very low

Which of the following best describes your perception regarding the general complexity of the task of purchasing a new car?

Very high

- High
- Some
- Low
- Very low

Which of the following describes the amount of time you spend in using the Internet per day?

- Less than 1 hour
- Between 1 to 5 hours
- More than 5 hours

What is your highest education level?

- High School
- College diploma
- Bachelor's degree
- Master's degree
- Ph.D. degree
- Other, please specify... | static | other

Which of the following describes the amount of interest you have in purchasing a car?

- Very high
- High
- Some
- Low
- Very low

Which of the following describes the amount of experience you have in using online recommendation agents?

- Very high
- High
- Some
- Low

- Very low

Have you ever been diagnosed to have mild cognitive impairment? (Mild cognitive impairment causes a slight but noticeable and measurable decline in cognitive abilities, including memory and thinking skills)

- Yes
- No
- Prefer not to answer

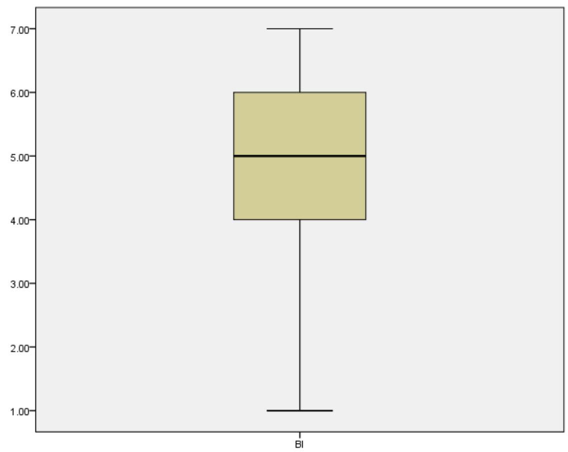
Appendix D – Measurement Instrument

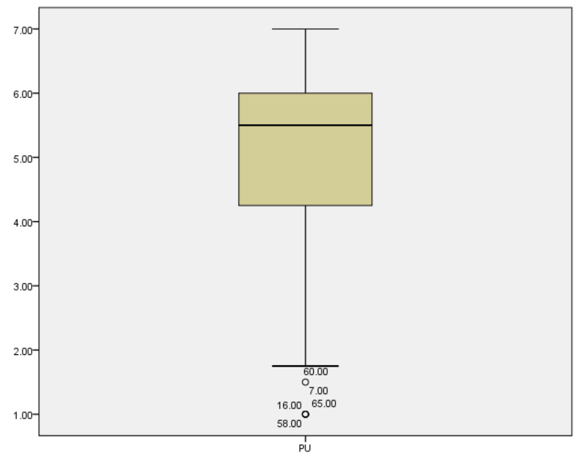
Construct Names	Item Descriptor	Item	Sources
Perceived Complexity	• Comp1	• Using this recommendation agent would take too much time.	Thompson et al. (1991)
	• Comp2	• Working with this recommendation agent seems so complicated; it would be difficult to understand what is going on.	
	• Comp3	• Using this recommendation agent involves too much time doing mechanical operations (e.g., data input).	
	• Comp4	• It would take too long to learn how to use this recommendation agent to make it worth the effort.	
Perceived Input Complexity	• INC1	• Using this recommendation agent took too much time in the stage where it elicited my preferences for the car attributes I was looking for.	Thompson et al. (1991)
	• INC2	• Working with this recommendation agent was so complicated in the stage where it elicited my preferences for the car attributes I was looking for; it was difficult to understand what is going on.	
	• INC3	• Using this	

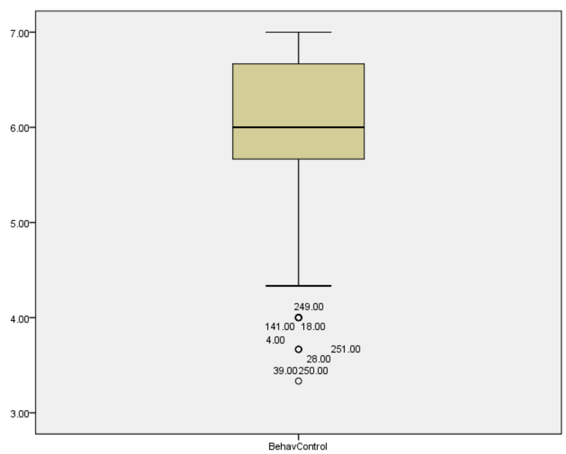
		recommendation agent involved too much time doing operations in the stage where it elicited my preferences for the car attributes I was looking for.	
	• INC4	• It took too long to learn how to use this recommendation agent to make it worth the effort in the stage where it elicited my preferences for the car attributes I was looking for.	
Perceived Output Complexity	• OTC1	• Using this recommendation agent took too much time in the stage where recommendations were presented to me.	Thompson et al. (1991)
	• OTC2	• Working with this recommendation agent was so complicated in the stage where recommendations were presented to me; it was difficult to understand what is going on.	
	• OTC3	• Using this recommendation agent involved too much time doing operations in the stage where recommendations were presented to me.	
	• OTC4	• It took too long to learn how to use this recommendation agent to make it worth the effort in the stage where recommendations were presented to me.	

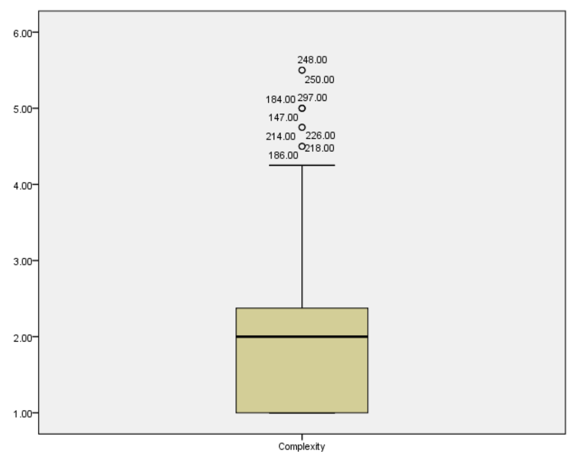
Perceived Behavioural Control	• BC1	• I have the resources, knowledge, and ability to use this recommendation agent.	Hsieh, Rai, & Keil (2008)
	• BC2	• I can use this recommendation agent.	
	• BC3	• Using this recommendation agent is entirely within my control.	
Perceived Usefulness	• PU1	• This recommendation agent provides good quality information for my online shopping task.	Hassanein & Head (2007)
	• PU2	• This recommendation agent improves my performance in my online shopping task.	
	• PU3	• This recommendation agent increases my effectiveness for shopping online.	
	• PU4	• Overall, this recommendation agent is useful for online shopping.	
Intention to Use an RA	• BI1	• Assuming I had access to this recommendation agent while shopping online, I intend to use it.	Wang & Benbasat (2009)
	• BI2	• Assuming I had access to this recommendation agent while shopping online, I predict that I would use it.	
	• BI3	• Assuming I had access to this recommendation agent while shopping online, I plan to use it.	

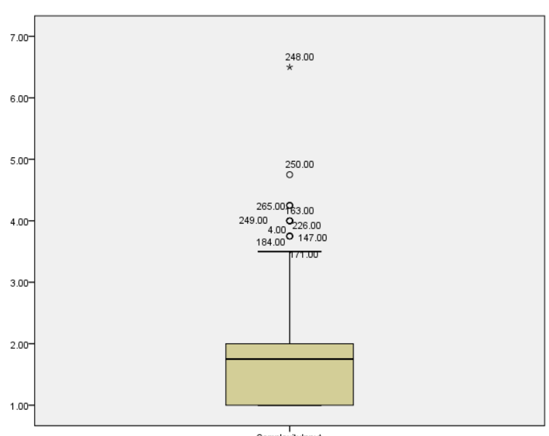
Appendix E – Composite/Indicator Box Plots

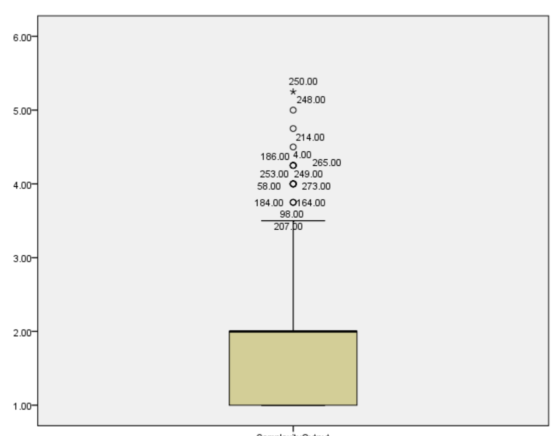












Appendix F –Group Comparisons with Bonferroni

Tables F1, F2, and F3 as well as Figures F1, F2, and F3 show the ANOVA results for perceived RA input complexity, RA output complexity, and RA usefulness for older and younger adults (i.e., younger age (20-30), older age (>60)) with RAs with different levels of comprehensiveness (i.e., low or high). These two ranges of cognitive age were chosen for this analysis since according to Tucker-Drob & Salthouse (2008), the cognitive abilities of individuals belonging to these two groups chronologically are markedly different with the younger group exhibiting significantly higher cognitive abilities compared to the older group. These differences are expected to still be present when comparing these groups on a cognitive age basis as the older group will still be cognitively much older than the younger group.

Tables F1 and F2 show that RA comprehensiveness and an individual's cognitive age significantly impact perceived RA input and output complexity. In addition, these tables show that the interaction between RA comprehensives and cognitive age on perceived RA input and output complexity is also significant. In general, Tables F1, and F2 and Figures F1, and F2 show that as people become cognitively older, they perceive lower or higher RA input and output complexity when they use lower or higher RA comprehensiveness, respectively, compared to the cognitively younger adults.

Table F1. ANOVA Summary Table for Perceived Input Complexity

Independent Variable	Sum of Squares	df	Mean Square	F	Sig.
RA Comp	6.344	1	6.344	10.697	0.001
Cognitive Age	19.766	1	19.766	33.328	0.00
RA Comp* Cognitive Age	2.269	1	2.269	3.826	0.05

RA Comp: RA comprehensiveness type

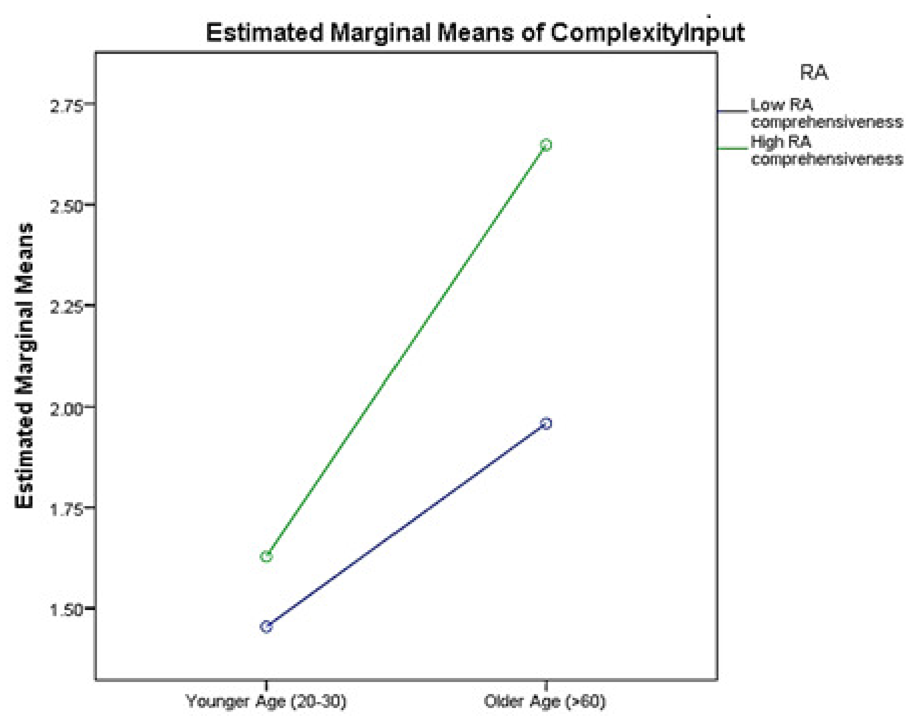


Figure F1. Interaction Effect between Cognitive Age and RA Level of Comprehensiveness on Perceived Input Complexity

Table F2. ANOVA Summary Table for Perceived Output Complexity

Independent Variable	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
RA Comp	16.253	1	16.253	34.488	.000
Cognitive Age	39.782	1	39.782	84.416	.000
RA Comp* Cognitive Age	12.439	1	12.439	26.395	.000

RA Comp: RA comprehensiveness type

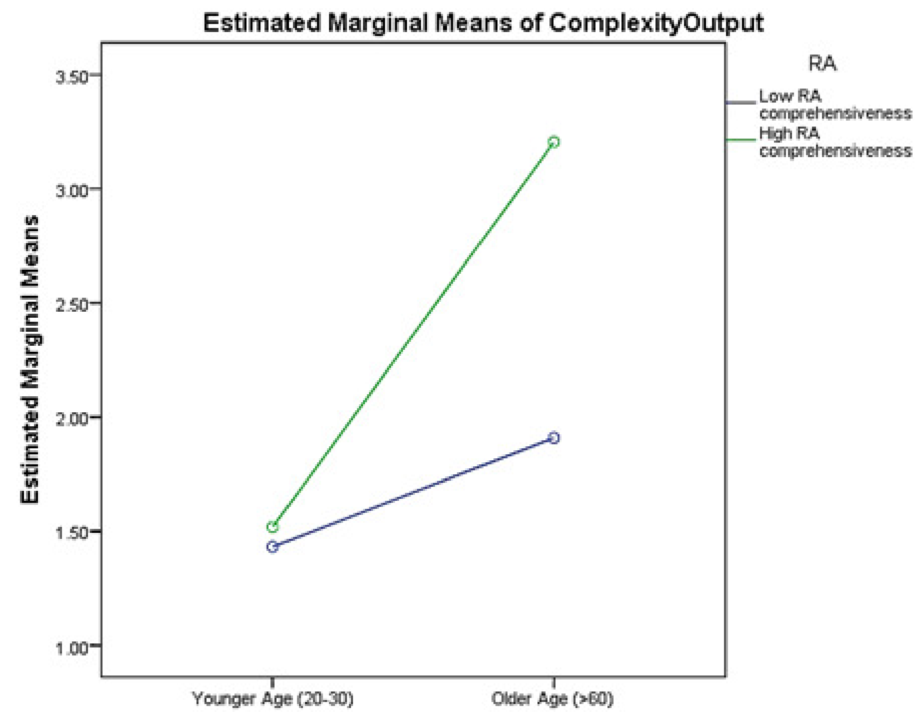


Figure F2. Interaction Effect between Cognitive Age and RA Level of Comprehensiveness on Perceived Output Complexity

Table F3 shows that RA comprehensiveness and an individual's cognitive age significantly impact perceived RA usefulness. In addition, this Table shows that the interaction between RA comprehensiveness and cognitive age on perceived RA usefulness is also significant. Surprisingly, Table F3 and Figure F3 show that as the RA becomes more comprehensive, compared to the younger adults, older adults perceive the RA to be more useful than the RA with the lower level of comprehensiveness.

Table F3. ANOVA Summary Table for Perceived Usefulness

Independent Variable	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
RA Comp	29.075	1	29.075	20.685	.000
Cognitive Age	33.595	1	33.595	23.901	.000
RA Comp* Cognitive Age	18.585	1	18.585	13.222	.000

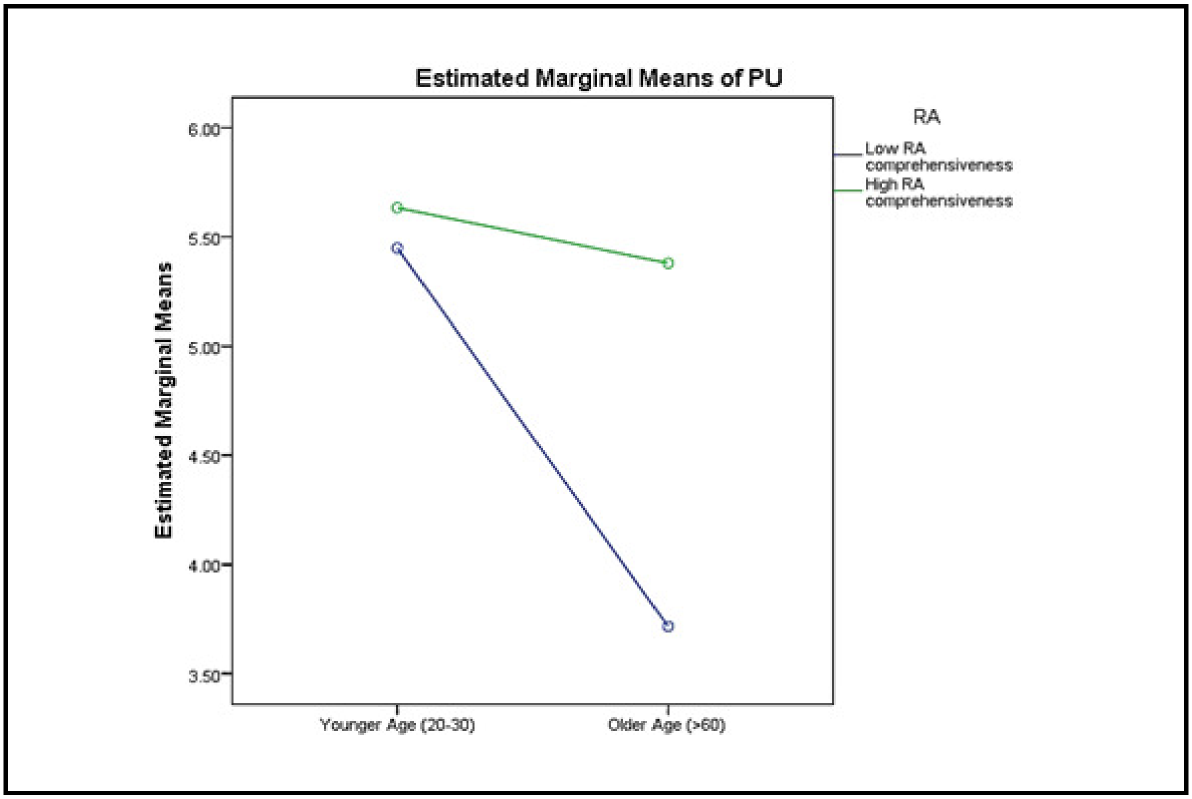


Figure F3. Interaction Effect between Cognitive Age and RA Level of Comprehensiveness on Perceived Usefulness