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PhD Dissertation

THE IMPACT OF AGE AND COGNITIVE STYLE ON E-COMMERCE DECISION-MAKING: A MULTI-METHOD APPROACH

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Table of Contents

List of Definitions

List of Figures

List of Tables

THE IMPACT OF AGE AND COGNITIVE STYLE ON E-COMMERCE DECISION-MAKING: A MULTI-METHOD APPROACH

Lay Abstract

This study explores how people of different ages and decision-making styles process information and make choices when shopping online. Using eye-tracking technology, the research introduces a new measure, Visual Perceptual Comprehensiveness (VPC), to understand how thoroughly people look at product information.

Younger adults were found to scan more broadly and carefully than older adults. Surprisingly, people who usually take more time to make decisions (maximizers) looked at less information than those who decide more quickly (satisficers).

While people who looked at more information spent more time deciding, this did not always lead to better or more satisfying choices. The type of task and the presence of decision-making "traps" like flashy images or item order also affected behavior. These insights can help improve online shopping experiences to better match how different people think and decide.

THE IMPACT OF AGE AND COGNITIVE STYLE ON E-COMMERCE DECISION-MAKING: A MULTI-METHOD APPROACH

Abstract

This dissertation explores how age and cognitive style influence decision-making in e-commerce, with a focus on visual information processing. Cognitive style is an individual-difference decision factor that describes an individual's general tendency to either make quick gut-feel decisions (Satisficer) on one extreme or be very meticulous in gathering evidence before making a well-informed decision (Maximizer) on the other extreme. A novel eye-tracking-based construct, Visual Perceptual Comprehensiveness (VPC), was developed and validated to measure the breadth and deliberation of visual attention of participants who completed a series of online shopping tasks under different bias conditions (i.e., vividness, order, control). VPC was developed to investigate individual decision-making processes in an attempt to understand how and why individuals may fall prey to cognitive biases, which are systematic errors in judgement and decision-making.

The study draws on the Attention Drift Diffusion Model (aDDM), Dual Process Theory, and Cognitive Bias Theory. A pilot study of 17 participants validated the study design, followed by a main study of 54 participants to test the hypotheses. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and multigroup analysis (PLS-MGA), using two bootstrapped data augmentation approaches.

Findings show that older adults exhibited significantly lower VPC as hypothesized, while maximizers demonstrated lower VPC than satisficers, contrary to expectations. Cognitive style moderated the age–VPC relationship, mitigating age-related declines in visual processing. VPC strongly predicted decision effort, suggesting that broader and more deliberate visual attention is associated with longer decision times. However, VPC showed weak or inconsistent relationships with decision quality and perceived outcomes, implying that increased visual attention does not necessarily translate into better or more *satisfying decisions. Task type significantly moderated several effects, revealing that the presence and nature of cognitive bias (e.g., vividness or order) influences how individual differences affect decision-making.*

This research introduces a new construct to the NeuroIS literature, emphasizes age and cognitive style as critical individual differences, and offers practical implications for designing more inclusive and bias-resilient digital decision environments.

Keywords: *aging, older adults, cognitive style, cognitive bias, order bias, vividness bias, eye tracking, visual perceptual comprehensiveness, decision quality, decision effort, effort-accuracy framework, dual-process theory*

1 Introduction

This study aims to explore how the individual difference factors of age, cognitive style, and their interaction impact both perceived and actual cognitive effort and decision quality in e-commerce.

First, the background and context of the research are discussed. This is followed by a brief discussion of the motivation for the research and the gaps in the literature. Finally, the objectives of the research are outlined along with a discussion of the advantages of utilizing NeuroIS theories and methods.

1.1 Research Background

In a world driven by rapid technological innovation and continuous digital transformation, the importance of online shopping (e-commerce) to retail consumers is ever-growing. **E-commerce** refers to the use of Information Systems (IS) to access information about and purchase goods and services from businesses or consumers (Statista 2023a). The e-commerce industry has been booming across the world, with online sales revenues expected to reach $6.4 trillion by the end of 2025, compared to $5.6 trillion in 2023 (Statista 2025a). The percentage of e-commerce sales of total retail sales globally is also expected to increase from 16% in 2023 to an estimated 19.1% by the end of 2025 (Statista 2025b). North America is the second-largest business-to-consumer (B2C) e-commerce market, following Asia (Statista 2023b), with sales growing from $640 billion in 2017 to $1.1 trillion in 2022 (Statista 2017a, 2022a).

Consumers are increasingly shifting to e-commerce at the expense of traditional retail channels. That phenomenon only accelerated with the advent of the SARS-CoV-2 pandemic and the consequent COVID-19 worldwide lockdowns. The global e-commerce share of total retail increased from 12% in 2019 to 17.1% in 2022 and is expected to increase to 19.1% by the end of 2025 (Statista 2025b). Online sales accounted for 24% of total North American retail sales in 2022, a significant increase from the pre COVID-19 17% figure in 2019 (Statista 2022b). Canada follows a similar trend, with online sales comprising 15% of total retail sales in 2022 compared to 12% in 2019, peaking at 25% during the height of the pandemic lockdowns (Statista 2022c). These statistics also vary by retail sector. At 21%, the Canadian "Electronics and Appliances" sector is leading in terms of e-commerce sales as a percentage of total sales, followed by "Sporting goods, hobby…" at 15.6% (Statista 2022d).

Consumer products are increasingly becoming more complex with innovations, digital or otherwise, complicating e-commerce decisions for consumers (Rayna and Striukova 2021). Consumers view e-commerce not only as an additional channel for purchasing goods and services, but also as a convenient decision-making platform with unique customizable decision support features (Mieles 2019; Nielsen 2016; Zong et al. 2021). Further, some manufacturers and retailers sell some, or all, of their products and services exclusively through online channels, making e-commerce a necessity for accessing these offerings. Consumers are increasingly turning to digitized shopping platforms for decision-making, especially multi-brand marketplace aggregators such as Amazon (Statista 2024a), because e-commerce platforms facilitate easier searching, organizing, and processing of huge amounts of information on products and services, allowing consumers to make better-informed decisions (Statistics Canada 2021), both online and offline (Forbes Insights 2016; Mieles 2019; Nielsen 2016). A recent study by Statista reported that only 34% of consumers research product information in stores, and that consumers typically utilize multiple online touchpoints in their shopping journey, including e-commerce, before making a decision (Statista 2023c). Forty five percent of retail consumers in the U.S indicate that they conduct online research first before making any major purchase decisions (Statista 2023d). About 28% of all global online purchases took place in a physical retail store (Statista 2025b).

Of all product categories, the top two product categories that consumers prefer to research online rather than offline are consumer electronics (e.g., TVs) and household appliances (e.g., stoves, refrigerators, washing machines) at 66% and 47%, respectively (Statista 2019). E-commerce sales constituted 21% of total electronics and appliances retail sales in 2020 (Statista 2022d). Revenues from consumer electronics and household appliance are expected to comprise 8.9% ($310 million) and 6.6% ($230 million) of total e-commerce revenues by the end of 2025 (Statista 2025b), excluding food as it experienced an outlier rapid rate of growth due to the advent of food delivery apps (e.g., Uber Eats, Skip The Dishes).

Unfortunately, not all consumers benefit equally from e-commerce as a convenient platform for researching product information and decision-making. Older adults, those who are 60 years or older (United Nations 2002; United Nations Department of Economic and Social Affairs 2007, 2015a; World Health Organization 2022), are one of those major consumer groups that face challenges in e-commerce contexts

(Llorente-Barroso et al. 2024). They are the fastest-growing population segment both globally and in North America (Statistics Canada 2019; United Nations Department of Economic and Social Affairs 2014, 2015a; World Health Organization 2022). Additionally, they are the fastest-growing segment of Internet users (Anderson and Perrin 2017; Statista 2023d) and largest user group in North America (Statista 2017b, 2023d).

Older adults are generally more affluent and, therefore, more lucrative for vendors as a consumer segment. The average net worth of households led by older adults is approximately 470% more than those led by younger adults according to the most conservative estimates (Norris 2019; Spring Financial Inc. 2023; Statistics Canada 2017). In 2023, the median net worth of Canadians 65 years and older was 464% more than that of Canadians under the age of 35 (Statistics Canada 2024). Older adults are interested in online shopping (Nielsen 2013; Smith and Anderson 2016; Wang et al. 2024), and many features of e-commerce (e.g., convenience, increased reach, lack of physical barriers, personalized accessible interfaces) can be particularly useful to older consumers and aid them in making better decisions (El Shamy et al. 2024; El Shamy and Hassanein 2015). For example, home delivery and convenience are the two most prominent consumer drivers for using e-commerce over other channels (Statista 2004, 2024b), which align very well with the needs of older adults especially those who face physical mobility barriers (Saric et al. 2024; El Shamy et al. 2024).

Nonetheless, due to the natural process of aging older adults suffer from a decline in several physiological abilities such as hearing, sensorimotor skills, and Useful Field of View (UFOV) (Czaja et al. 2006; National Institute on Aging and National Library of Medicine 2002; Prieto et al. 1996; Romano Bergstrom et al. 2013). Additionally, older adults suffer from a decline in fluid cognitive abilities such as selective attention and working memory capacity (Czaja et al. 2006; Plude and Doussard-Roosevelt 1989; Roberts and Allen 2016; Salthouse and Babcock 1991; Tams, Grover, et al. 2014). These declines prevent them from reaping the full benefits of information technologies and can be taxing to the quality of their e-commerce decisions compared to younger age groups (Rydzewska et al. 2024; Tams, Grover, et al. 2014). What further exacerbates the issue is that the majority of older adults report that many websites aren't designed to meet their needs, as e-commerce interfaces are typically designed and tested for younger adults (Nielsen Norman Group 2023).

To summarize, digital innovation is transforming consumer products, making them more and more complicated for consumers. The abundance of choice and information also exacerbate the complexity of retail channels including e-commerce platforms. Consumers are not just utilizing e-commerce as a convenient method of shopping, they are also using it as a decision-making support system that aggregates and summarizes information as well as reduces the complexity of purchasing decisions, whether offline or online. Unfortunately, some disadvantaged consumers groups cannot equally benefit from all the affordances and benefits of e-commerce. Older adults, one of those groups, are the largest growing e-commerce user groups, who can particularly benefit from e-commerce to live independently and gracefully in place avoiding physical mobility challenges (El Shamy et al. 2024). From a merchant perspective, older adults are also the most lucrative consumer segment. However, older adults face cognitive challenges in making decisions in complex e-commerce contexts. This behooves us to examine and address those challenges to help older consumers make better online decisions.

1.2 Research Motivation

E-commerce decision-making is generally a complex process for all consumers, regardless of age. Online consumers have access to virtually unlimited choices and information that exceeds anyone's cognitive capacity (Aljukhadar et al. 2012; Gudigantala et al. 2010; Wan et al. 2009; Wang and Doong 2010). For example, searching for a stove, TV, refrigerator, and washing machine on Google Shopping yields 430, 112, 512, and 471 results, respectively[1]. Each of these products vary on numerous common and unique attributes. These multi-alternative, multi-attribute decision contexts can be extremely cognitively taxing for any individual. In such cognitively overwhelming conditions, decision-makers typically resort to suboptimal decision-making strategies, including "satisficing" (Gigerenzer et al. 2014; Kahneman 2011;

[1] Search in June 2024 using Google Shopping via Google Chrome Incognito Mode to avoid personalized results.

Simon 1956) or utilizing simplifying heuristics (Bazerman and Moore 2009; Gigerenzer et al. 2014; Kahneman 2011; Tversky and Kahneman 1974) to optimize cognitive resources.

Satisficing, a portmanteau of “satisfactory” and “sufficing,” implies a decision maker’s willingness to settle for a choice that is good enough yet suboptimal (Bazerman and Moore 2009; Simon 1978). **Heuristics** are decision shortcuts and rules of thumb (Gigerenzer et al. 2014; Kahneman 2011; Tversky and Kahneman 1974) that allow individuals to make decisions more efficiently. To conserve cognitive effort, decision-makers trade accuracy for reduced cognitive effort at different individual quality tolerance thresholds (Chu and Spires 2000; Johnson and Payne 1985; Kahneman 2011; Payne 1982). In doing so, they render themselves susceptible to a host of harmful cognitive biases (Bazerman and Moore 2009; Davern et al. 2012; Fleischmann et al. 2014; Kahneman 2011; Tversky and Kahneman 1974).

Cognitive Biases are predictable, systematic, and directional deviations from rational and optimal decisions (Kahneman 2011; Tversky and Kahneman 1974) affecting laymen and expert decision-makers alike (Kahneman 2011; Montibeller and von Winterfeldt 2015; Tversky and Kahneman 1974). The age-related declines in cognitive abilities render older adults particularly vulnerable to the negative influences of cognitive biases (Coolin et al. 2015; Martinelli et al. 2022; Peters et al. 2007; Rydzewska et al. 2024). There is evidence that cognitive biases impact the quality of decisions in the context of e-commerce (Cheng and Wu 2010; Fleischmann et al. 2014; Wu 2011; Wu et al. 2008; Xu and Kim 2008).

Decision-makers may approach different decision-making contexts using different decision strategies (Hamilton et al. 2016; Johnson and Payne 1985). However, they tend to have a dominant approach to collecting and evaluating information before making decisions (Appelt et al. 2011; Karimi et al. 2015; Sproles and Kendall 1986; Thunholm 2004). On one extreme, some decision-makers predominantly exert a lot of cognitive effort to deliberate on decisions thoroughly. They pay meticulous attention to, and carefully consider, all or most of the available decision alternatives and their attributes. On the other extreme, some decision-makers prefer preserving cognitive effort and completely rely on gut feel, intuition, and heuristics to make a decision relatively quickly.

The degree to which individuals predominantly approach their decisions by either relying on heuristics or deliberation as a decision-making strategy corresponds to their **Cognitive Style** (Barkhi 2002; Carlson

1985; Schwartz et al. 2002; Sproles and Kendall 1986). Cognitive style impacts individuals' information-seeking behaviour during e-commerce tasks by influencing the breadth and depth of information gathered and cognitively evaluated (Karimi et al. 2015; Misuraca and Fasolo 2018). A satisficer will make quick decisions based on minimal information and gutfeel, while a maximizer will consider the most amount of information possible before making an informed decision. This effect can be further exacerbated by the diminishing fluid cognitive abilities that are associated with aging (Bruine de Bruin et al. 2007; Hsieh et al. 2020; Pachur et al. 2017; Peters et al. 2007; Queen et al. 2012; Rydzewska et al. 2024).

Research has shown that individual decision-making is influenced by three main factors. First, there are individual difference factors such as age, gender, and cognitive style. Second, there are decision context factors such as social context, cognitive load, and time pressure. Finally, there are factors related to the features of the decision itself such as the order, vividness, and framing of choices (Appelt et al. 2011; Hamilton et al. 2016; Johnson and Payne 1985).

Unfortunately, the role of some individual difference factors such as socioeconomic status or cognitive ability in decision making have not received sufficient attention in the literature (Appelt et al. 2011; Hamilton et al. 2016; Hsieh et al. 2020; Silk et al. 2021). Specifically, the roles of age, cognitive style, and their interaction have not been rigorously investigated in IS. There have been recent calls to scrutinize the roles of age (Saric et al. 2024; Tams, Grover, et al. 2014) and cognitive style (Karimi et al. 2015; Misuraca and Fasolo 2018; Rydzewska et al. 2024; Silk et al. 2021) in IS phenomena including understanding online consumers' decision-making behaviour. Additionally, some of these calls have specified the need to delve deeper into understanding these phenomena using neurophysiological methods such as eye-tracking (Rydzewska et al. 2024).

1.3 Research Objectives

This research attempts to address the above gap by examining how individuals' age and cognitive style in e-commerce contexts impact both objective and perceived decision-making processes and outcomes. Specifically, this research examines how these factors impact perceived and actual decision quality and effort. With age as the main focus, this research will investigate decision-making differences between Young Adults (18-39) and Young Older Adults (60-74) who shall be henceforth simply referred to as Older Adults. (see ***Section 2.5.2*** *for justification for the selected age ranges*). The first research objective can be stated as:

RO1. To understand how the individual difference factors of age and cognitive style, and their interaction, impact both objective and perceived decision quality and cognitive effort in the context of e-commerce decisions.

These two individual difference factors are expected to influence individuals' susceptibility to cognitive biases that manifest in e-commerce decisions. In his seminal paper, Arnott (2006) argues that cognitive bias theory can be utilized as a foundation for explaining differences in the performance of IS users. He argues that **Decision Support Systems (DSS)** can rarely be developed to address cognitive biases with complete *a priori* knowledge because it is difficult to anticipate the challenges the target decision-maker faces in particular decision contexts. DSS must evolve from a clear understanding of the decision task. This can be achieved by adopting design science, design thinking, and agile design methods which heavily involve the end-user in the design process (Alvarez et al. 2019; Arnott 2006; Arnott and Pervan 2008). The author provides evidence that when a DSS is developed with a clear understanding of the nature of cognitive biases, it becomes more effective in reducing or eliminating their harmful effects, which is referred to as **Debiasing**. Arnott (2006) outlines a design science approach and extends a set of guidelines for the study of Cognitive Biases in DSS, which are adapted for this study and outlined in ***Table 1***.

Table 1: Design Science research method guidelines adapted from Arnott (2006)

Research Process	Application in this Research
1. Problem Recognition	How to improve decision-making for e-commerce users of different age groups and cognitive styles
2. Suggestion	Use Cognitive Bias theory as a foundation for DSS development for future research by understanding how biases manifest
3. Artefact Development	Develop DSS in future research with an understanding of user behaviour and bias susceptibility in e-commerce decisions
4. Evaluation	Test the DSS in future research with the intended users and evaluate its feasibility and effectiveness
5. Reflection	Reflect on the outcomes and identify refinements

Following these seminal guidelines, this research study attempts to examine the nature of two decision biases that are particularly prevalent in e-commerce and relevant to Age and Cognitive Style, namely **(i) Order Bias** and **(ii) Vividness Bias** (Arnott 2006; Browne and Parsons 2012; Fleischmann et al. 2014; Xiao and Benbasat 2007). These two cognitive biases emanate from the **Availability Heuristic** *(discussed in **Section 2.2.3**)* and are decision feature factors. They are elicited by the way information is presented. They pertain to the interplay between selective attention, memory, cognitive effort, and information presentation (Arnott 2006; Fleischmann et al. 2014; Orquin and Loose 2013; Saric et al. 2024). Consequently, they are considered particularly relevant to age and cognitive style in e-commerce decision-making. These concepts are defined and discussed in depth in ***Section 2.2***.

Following Arnott's framework (2006) for debiasing using DSS, outlined in ***Table 2***, this program of research is divided into two stages. The first stage, which constitutes this study, seeks to confirm the existence and magnitude of these biases in e-commerce decisions. However, a major methodological challenge when studying these latent cognitive biases (i.e., Steps 2 and 4 in ***Table 1***) is identifying their triggers and examining how they manifest in-depth (Fleischmann et al. 2014). This is because these cognitive biases are difficult, or impossible, to self-report by research participants as they may manifest subconsciously. The nature of these biases and their triggers are very difficult to detect and quantify using qualitative or traditional quantitative methods alone (Riedl and Léger 2016). This challenge, and how it was tackled in this study, are discussed in-depth in ***Section 1.4*** below.

Table 2: Studying Biases and De-Biasing with DSS, framework adapted from Arnott (2006)

Step	Application in this Research	Corresponding Stage of this Research Proposal
1. Bias Impact	Identify the existence, impact, and magnitude of the potential bias	**Stage 1** (This Study)
2. Bias Nature	Identify the nature of the bias	
3. Debiasing	Evaluate alternative means for reducing or eliminating the bias	**Stage 2** (Future Research)
4. Feedback	Reassure decision-maker that the presence of biases is not a criticism of their cognitive abilities. Reflect on the outcomes of debiasing	

After understanding the nature of these biases in this study, the findings will inform the development of appropriate debiasing strategies in future research (i.e., Stage 2 in ***Table 2***). These strategies could then be incorporated into common e-commerce decision aids [e.g., Recommendation Agents(RAs)], and their effectiveness in improving the quality of individuals' e-commerce decisions can be re-evaluated, quantified, and refined once again in the follow-up research study (i.e., Steps 3 through 5 in ***Table 1***.)

Cognitive biases are inherent and subtle cognitive prejudices that occur subconsciously, likely without the awareness of the decision-maker (Dimoka et al. 2011; Kahneman 2011). The elusive nature of cognitive biases makes them obscure and hidden deep in the decision-maker's mind. This makes it difficult for researchers to observe and measure these latent phenomena objectively (Dimoka et al. 2011, 2012; Riedl and Léger 2016). It is challenging to understand how they manifest and impact a decision process, and ultimately devise effective debiasing strategies (Arnott 2006; Bazerman and Moore 2009; Gilovich et al. 2002; Kahneman 2011; Montibeller and von Winterfeldt 2015). This challenge can be tackled using Neurophysiological Information Systems (NeuroIS) theories and methods.

NeuroIS is a subfield of IS that utilizes theories and methodologies from numerous reference disciplines, including cognitive neuroscience, decision neuroscience, and cognitive psychology (vom Brocke and Liang 2014; Dimoka et al. 2011, 2012; Riedl and Léger 2016). NeuroIS allows researchers to directly investigate latent phenomena, such as cognitive biases, that are sometimes difficult or impossible to study using traditional behavioural methods alone (Dimoka et al. 2012; Riedl and Léger 2016). Combining NeuroIS with traditional behavioural methods is recommended in the design of Information Technology (IT) artefacts (Vance et al. 2018), such as DSS, which is the ultimate objective of this research.

This study utilizes eye tracking, a NeuroIS method, as a complementary gateway to tap into, older and younger adult, participants' visual behaviour, attention, encoding, and cognitive decision processes. Fixation, gaze, and saccade data are collected as participants interact with, process, and evaluate product multi-alternative multi-attribute information to make e-commerce decisions. Fixations, gaze, and saccadic movement data helped explain how users sought and processed information and whether they were subject to harmful cognitive biases. The study objectives were achieved by adopting the design science approach recommended by Arnott (2006) as well as theoretical perspectives of Cognitive Biases (Arnott 2006; Gilovich et al. 2002; Kahneman et al. 1982; Tversky and Kahneman 1974), the Effort/Accuracy Framework (Johnson and Payne 1985; Payne et al. 1993; Todd and Benbasat 1992), Dual-Process Theory (Kahneman 2011; Mirhoseini et al. 2023; Da Silva 2023; Stanovich and West 2000), attentional Drift-Diffusion Model (aDDM) (Krajbich et al. 2012; Milosavljevic et al. 2012; Orquin and Loose 2013), Feature Integration Theory of attention (Treisman 1986; Treisman and Gelade 1980), and the theory of Reading and Comprehension (Duchowski 2007; Just and Carpenter 1980; Kuo et al. 2009).

Understanding how different groups of decision-makers assess and process information differently in a decision task is extremely valuable in explaining how the aforementioned cognitive biases are triggered and how they manifest. It will have implications for designing an appropriate Debiasing Decision Support System (DDSS) in the future (Arnott 2006).

In this research, state-of-the-art non-invasive eye-tracking technology was utilized to tap into the decision-maker's mental processes (Duchowski 2007; Glaholt and Reingold 2011; Kahneman 2011; Novák et al. 2023; Wang et al. 2014; Yen and Chiang 2021) and provide more objective and holistic insights (Dimoka et al. 2012; Duchowski 2007; Kahneman 2011; Wang et al. 2014) into the mechanisms of falling prey to harmful decision biases. Using eye tracking as a complementary method in this study is in line with the guidelines set by vom Brock and Lian (2014) as well as other notable IS scholars (Dimoka et al. 2012; Riedl and Léger 2016; Tams, Hill, et al. 2014).

The second research objectives can thus be stated as:

RO2. To objectively investigate how susceptibility to harmful cognitive biases in e-commerce decisions vary by age and its interaction with cognitive style, due to differences in information-seeking behaviour, and assess how this susceptibility might impact objective and subjective decision quality and cognitive effort

This study introduces a new composite eye-tracking construct, Visual Perceptual Comprehensiveness (VPC) as an objective measure of susceptibility to cognitive biases in e-commerce in an effort to explain how the individual differences of age and cognitive style influence the objective and perceived decision outcomes of effort and accuracy. This is discussed in more depth in ***Section 2.7.3*** *below*. The third and final research objective can be stated as:

RO3. To validate Visual Perceptual Comprehensiveness (VPC) as an objective measure of consumer susceptibility to cognitive biases in e-commerce decisions, and assess whether it can explain how and why age, cognitive style, and their interactions impact both objective and perceived decision quality and effort.

The value of the novel VPC construct likely extends beyond this nomological network to explain relationships between other constructs in e-commerce decisions. This is beyond the scope of this study for feasibility purposes. Future research can examine and validate the construct in a broader nomological network or with other relevant constructs.

1.4 Thesis Organization

The remainder of this thesis is organized as follows. ***Chapter 2*** provides a detailed review of decision-making in e-commerce and outlines the theoretical foundations of the proposed research culminating in a conceptual framework. ***Chapter 3*** advances the research model and hypotheses that are tested in this research building on the conceptual framework developed in the earlier section. ***Chapter 4*** describes the mix of methods that were utilized to test the research hypotheses, namely behavioural quantitative and eye tracking (NeuroIS) methods. ***Chapter 5*** outlines the analysis and discussion of the results. Lastly, ***Chapter 6*** outlines the contributions of this study both to theory and to practice and provides an acknowledgement of the limitations of this study, as well as implications for future research.

2 Literature Review & Conceptual Framework

The main purpose of this study is to understand how the individual difference factors of age, cognitive style, and their interaction impact both perceived and actual cognitive effort and decision quality in the context of electronic commerce (e-commerce) decisions. This understanding could then be leveraged in future research to inform the development and improvement of IT artefacts, namely a Decision Support System (DSS) such as a Recommendation Agent (RA) (Benbasat and Zmud 2003; Gregor 2006; Vance et al. 2018). The objective is to open the black box of cognition and unravel how decision processes and biases transpire as functions of age and cognitive style and how this ultimately impacts perceived and objective decision quality and effort. The IT artefact in this research is the DSS that presents product information to consumers and supports them in evaluating products to ultimately make a purchase decision (Arnott 2006; Xiao and Benbasat 2007).

To strengthen the rigour of this work, the IS literature is examined in addition to other reference disciplines as recommended when conducting NeuroIS research (vom Brocke and Liang 2014; Riedl and Léger 2016). These fields include cognitive psychology, gerontology, gerontechnology, information sciences, and decision neuroscience (Kwon 2016; Peek et al. 2016). In this chapter, the immediate nomological network for the IT artefact of focus (Benbasat and Zmud 2003) is examined, and the relevant theories are discussed.

First, an overview of e-commerce environments is provided. This is followed by a review of the general theories of judgement, decision-making, and biases. Next, decision support and cognitive biases specific to e-commerce are examined. This examination focuses on cognitive decision-making strategies influenced by age and cognitive style. Further, theories of cognitive style and age are discussed, and their influence in the context of e-commerce is outlined. Subsequently, the Human Visual System (HVS) is examined, and the relevant theories of attention allocation in decision-making tasks are discussed. Finally, a brief review of the theoretical base is provided, and a conceptual framework outlining the key theoretical constructs from the literature is outlined.

2.1 E-Commerce

2.1.1 Overview

E-commerce is a digital platform that enables businesses and consumers to conduct transactions through IT systems (e.g., personal computers, smartphones) connected via the Internet (IBISWorld 2017; Statista 2024b). With the advent of the Internet in the late 1990s and the ubiquity of connected personal and mobile IT devices (e.g., personal computers, laptops, tablets, smartphones) in the past two decades, e-commerce has gained much traction and popularity, having major implications for consumer behaviour and lifestyles as well as for business competition and economic growth (Burgess 2009; IBISWorld 2017; McKinsey 2013; Porter 2001; Statista 2024b). The e-commerce industry surpassed $1 trillion in global sales for the first time in 2012 (eMarketer 2013). For reference, 2022 e-commerce sales in the second largest e-commerce market, North America, alone was $1.1 trillion (Statista 2022a) and is $1.44 trillion in both Americas in 2024 (Statista 2025a).

E-commerce can be classified into several categories including Business to Consumer (B2C), Business to Business (B2B), Consumer to Consumer (C2C), Direct to Consumer (D2C), and others. The focus of this study is on individual consumer decision-making, the relevant platforms examined are B2C, C2C, and D2C. In B2C platforms (e.g., Walmart, Amazon), C2C platforms (e.g., Alibaba, eBay, Amazon, Kijiji), and D2C platforms (e.g., Nike, Air Canada) organizations and entrepreneurs list some, or all, of their products and services on a web portal and may include some, or all, of the following information: product attributes, services scope, delivery information, pricing, customer reviews, ratings and appraisals, images, videos, and interactive multimedia interfaces (Branca et al. 2023; Cyr et al. 2009; McKinsey 2013; Smith and Anderson 2016; Statista 2024b; Xiao and Benbasat 2007, 2014). This allows consumers to search products and services matching their preferences online, evaluate and compare attributes, and make a purchase decision (Xiao and Benbasat 2007).

From a consumer perspective, e-commerce platforms are extremely empowering as they democratize access to information and introduce consumers to a myriad of alternatives and substitutes beyond traditional physical and temporal boundaries (IBISWorld 2017; McKinsey 2013; Smith and Anderson 2016; Xiao and Benbasat 2007). Consumers have instant access to real time information on product attributes, reviews, pricing, stock availability, and much more (IBISWorld 2017; McKinsey 2013; Smith and Anderson 2016; Xiao and Benbasat 2007). With great convenience, consumers can purchase almost anything from the comfort of their homes, or on the run using their mobile IT device, and have it delivered to their device or doorstep (IBISWorld 2017; McKinsey 2013; Nielsen 2016; Smith and Anderson 2016). This is extremely beneficial for individuals, predominantly older adults, who face physical and mobility barriers (El Shamy et al. 2024). As a result, e-commerce platforms disrupted consumer shopping behaviour by driving most consumers to research products online (Statista 2025a).

2.1.2 The Complexity of the E-Commerce Environment

Despite the aforementioned advantages that e-commerce environments afford consumers, the online shopping experience is associated with a variety of challenges. Consumers have access to a plethora of vendor and product choices as well as product information and consumer reviews (Statista 2025a). For example, searching[2] the keyword "headphone" returns a list of 15,071 choices on Amazon.ca and 808,765 on eBay.ca, with at least a dozen attributes that can be used to evaluate each choice (e.g., brand, price, sales, weight, connection type, design, sound pressure level, battery life, shipping time).

This overabundance of choice and complex decision environment creates an interesting paradox. On the one hand, marketing and consumer behaviour research grounded in Economic Utility Theory (Golob et al. 1973), as well as IS research, has consistently found that consumers tend to gravitate to contexts with a variety of alternatives and prefer more complex RAs (Ghasemaghaei et al. 2019; Iyengar and Lepper 2000; Murray and Häubl 2008; Thompson et al. 2005) with more information, factors, and summarization options. On the other hand, the amount of information in this context is overwhelming to all consumers and may cause stress, frustration, confusion, and dissatisfaction (Iyengar and Lepper 2000; Mitchell and Papavassiliou 1999; Murray and Häubl 2008; Thompson et al. 2005; Xiao and Benbasat 2011). When facing decisions of such a complex nature, with abundant information and options, individuals tend to adapt their decision strategies to conserve cognitive effort and maximize utility (Bettman et al. 1990; Johnson and

[2] Search in June 2024 using Google Chrome Incognito Mode to avoid personalized results.

Payne 1985; Kahneman 2011; Kahneman et al. 1982; Simon 1955, 1956). This is discussed in more depth in the following section.

2.2 Judgement and Decision Making

2.2.1 Classical Theories of Decision Making

By the mid 20th century, individual decision-making was widely explained by normative theories of rational judgement (Weber and Coskunoglu 1990). Classical economic theories such as Game Theory (Von Neumann and Morgenstern 1945) and Expected Utility Theory (Friedman and Savage 1948), and their so-called “marginally revolutionized” neoclassical counterparts, including Subjective Expected Utility Theory (Luce 1988), propose elegant mathematical models that compute how individuals ought to make “rational decisions” (Bell et al. 1988; Machina 1987; Simon 1978; Weber and Coskunoglu 1990).

This paradigm has more or less been grounded in three main tenets. First, individuals are rational decision-makers who have, or seek, complete information related to a decision utilizing the most optimal decision strategy (Gigerenzer et al. 2014; Simon 1955, 1978; Weber and Coskunoglu 1990). Second, individuals integrate information and assign values to preferences, risks, and probabilities to evaluate choices and maximize decision outcomes (Friedman and Savage 1948; Kahneman et al. 1982; Simon 1978; Weber and Coskunoglu 1990). Finally, individual decisions are consistent across time and their evaluation of alternatives is independent from their decision procedure or preference elicitation (Johnson and Payne 1985; Kahneman 2011; Kahneman and Tversky 1979; Simon 1955; Weber and Coskunoglu 1990).

2.2.2 The Bounds of Rationality

Normative decision theories have been widely criticized for their fictitious suppositions regarding human cognitive abilities (Gigerenzer et al. 2014; Simon 1990), symmetry of knowledge and information (Gigerenzer et al. 2014), as well as mounting empirical evidence on decision behaviours violating the classical paradigm axioms (Bell et al. 1988; Kahneman and Tversky 1979; Machina 1987; Weber and Coskunoglu 1990).

In his seminal paper, Herbert Simon (1955) argued for an alternative descriptive view of decision-making, a paradigm that acknowledges the psychological bounds and limitations of human cognitive abilities. Simon reasoned that an organism’s understanding of a decision environment is bound by its limited physical and cognitive abilities. That is, organisms do not have the luxury of infinite time to make omniscient judgements, the physical ability to move around their environment indefinitely and gather evidence without restrictions, or the cognitive capacity to store, integrate, and process all relevant information (Simon 1955, 1956). As such, biological organisms, including humans, conserve physical and mental energy by resorting to satisficing (Simon 1956).

Another influential article by Kahneman and Tversky (1979), building on the work of the French economist Maurice Allais (1953; Edwards 1954), provided evidence that individuals evaluate risky decisions based on losses and gains from a reference point rather than total expected utility. The Nobel Prize winning Prospect Theory that they developed, provides an alternative model of decision behaviour under risk that classical theories of economic utility fail to explain (Kahneman 2011; Kahneman and Tversky 1979), including risk-seeking behaviour in gain prospects and risk aversion in contexts with loss potential, and overweighting of certain outcomes relative to probable outcomes. Additionally, they demonstrate decision-makers' preference reversal based on problem perception and framing (Grether and Plott 1979; Kahneman and Tversky 1979; Tversky and Kahneman 1981).

Other notable work conflicting with utility theory axioms includes Cognitive Dissonance Theory (Festinger 1962; Russo et al. 1996), which postulates that individuals may hold two or more conflicting beliefs simultaneously. To relieve the discomfort of having inconsistent thoughts, individuals will act irrationally by distorting information, either intentionally or subconsciously, in favour of a decision they made or are about to make (Russo et al. 1996; Vetter et al. 2010).

2.2.3 Decision Heuristics & Biases

Grounded in Simon's notion of bounded rationality (1955), Tversky and Kahneman identified several cognitive shortcuts, or heuristics, that decision-makers utilize when confronted with a highly demanding and complex decision (Kahneman et al. 1982; Tversky and Kahneman 1974). Both Simon and Kahneman argue that heuristics are biologically hardwired in our cognitive functions, the product of an evolutionary advantage that is necessary for survival: to perceive, process, and react promptly to environment stimuli (Kahneman 2011; Simon 1956, 1997). This has been empirically demonstrated in various fields including NeuroIS [e.g., technostress (Riedl 2013), surprise (Calic et al. 2020)]. In today's hectic world of digital transformation and information overabundance, heuristics are generally beneficial, arguably even necessary, as they enable decision-makers to simplify complex problems and act quickly with cognitive frugality to realize adequate decision outcomes in a myriad of contexts (Bazerman and Moore 2009; Gigerenzer et al. 2014; Kahneman 2011; Kahneman et al. 1982; Karimi et al. 2015; Rydzewska et al. 2024).

Unfortunately, these heuristics lead to systematic errors in judgements, and there is mounting evidence associating specific harmful cognitive biases to the use of some heuristics (Bazerman and Moore 2009; Gilovich et al. 2002; Kahneman 2011). Moreover, individuals may not necessarily be consciously aware that they're adopting a heuristic when making a decision, which inhibits their ability to be diligent and to avoid falling prey to these biases (Gilovich et al. 2002; Kahneman 2011; Kahneman et al. 1982; Oregon Research Institute 1973). In the context of individual decision-making, three main heuristics are identified: Availability, Representativeness, and Confirmation (Bazerman and Moore 2009; Kahneman 2011; Kahneman et al. 1982). These heuristics and their relevant biases (summarized in ***Table 3***) are briefly discussed below. Biases relevant to e-commerce are discussed in more depth in ***Section 2.3.2***).

Availability Heuristic: Individuals assess probabilities, frequencies, causes, or outcomes based on the degree to which relevant information is readily available in memory. Events that are first encountered, recent, vivid, specific, or easily imagined will be more readily available in memory than events that are not (Bazerman and Moore 2009). Given the cognitive limitations of the human brain, this heuristic can lead to several harmful cognitive biases related to memory and selective attention, including Order Bias, Vividness Bias[3], and Imaginability Bias[4] (Arnott 2006; Fleischmann et al. 2014; Kahneman 2011; Kahneman et al. 1982; Tversky and Kahneman 1974). For example, a manager may evaluate the performance of her subordinates by recalling salient situations, since they are more readily available in memory compared to their performance in mundane day-to-day activities, which might bias her judgment and lead to inaccurate performance appraisals and compensations (Bazerman and Moore 2009).

[3] **Order** and **Vividness** biases are the focus of this proposed research. They are discussed in ***Section 2.3.2***

[4] Other biases that aren't the focus of this proposed research but mentioned in the discussion are defined and summarized in ***Appendix 8.1***

Representativeness Heuristic: Individuals use approximations to make initial judgments by placing objects, people, or contexts into categories or stereotypes (Bazerman and Moore 2009). This can be useful to nudge a decision-maker towards evaluating the most relevant attributes or information, but it can also be problematic. This heuristic may lead a decision-maker to fall prey to several harmful cognitive biases including Base Rate Bias, Sample Size Bias, Misconception of Chance Bias, and the Conjunction Fallacy (Bazerman and Moore 2009; Kahneman 2011; Kahneman et al. 1982). For example, a manager may decide against hiring a potential good salesman because he seemed to be an introvert in his interview, since the manager believes that only extroverts make good salesmen (Bazerman and Moore 2009).

Confirmation Heuristic: Individuals tend to seek confirmatory rather than disconfirmatory evidence to support their decisions. Without disconfirmatory evidence, the decision-maker can make inaccurate assessments and fall prey to biases including Confirmation Bias, Anchoring, Overconfidence, and Hindsight Bias (Bazerman and Moore 2009; Champman and Johnson 1994; Gilovich et al. 2002; Kahneman et al. 1982). For example, when individuals believe that video games lead to increased violent behaviour, they tend to consider incidents in which the perpetrators of violent crimes were video gamers. However, a comprehensive evidence-based approach requires individuals to include four groups for a meaningful comparison: violent gamers, non-violent gamers, violent non-gamers, and non-violent non-gamers. By considering only one group, violent gamers, individuals are only seeking confirmatory evidence.

Table 3: Common Decision Heuristics and their relevant Cognitive Biases (Bazerman and Moore 2009; Gigerenzer et al. 2014; Kahneman 2011; Kahneman et al. 1982; Tversky and Kahneman 1974)

Heuristic	Description	Resulting Cognitive Biases
Availability	Individuals approach decisions armed with information that is most readily available in memory.	Order (Primacy, Recency), Vividness, Imaginability
Representativeness	Individuals make initial judgements by stereotypically grouping seemingly similar objects in predefined categories.	Base Rate, Sample Size, Misconception of Chance, Conjunction
Confirmation	Individuals make initial judgements and mostly seek confirmatory rather than disconformity evidence.	Confirmation, Anchoring, Overconfidence, Hindsight

2.2.4 Dual-Process Theories of Cognition

Stanovich and West (2000) introduced the terms System 1 and System 2 to refer to two distinct cognitive processes that take place in the mind of a decision-maker. **System 1** is automatic, subconscious, and very hasty in making intuitive, gut-feeling, and skill-based judgements (Kahneman 2011; Stanovich and West 2000). **System 2** is much slower and more deliberative and analytical in its processing by utilizing rules, information, and knowledge (Kahneman 2011; Stanovich and West 2000). Dual-Process Systems are summarized in ***Table 4***.

Table 4: Dual-Process Theory Cognitive Systems, adopted from Stanovich and West (2000)

System	Description
System 1	Automatic, tacit, intuitive, and relatively fast cognitive processes that are relatively undemanding of cognitive capacity and are more susceptible to bottom-up influences.
System 2	Controlled, analytic, deliberative, rational, rule-based, and relatively slower top-down cognitive processes that are relatively demanding of cognitive capacity.

One major distinction between the two systems is the significant amount of mental effort required by attention and cognitive processing for System 2 (Gao et al. 2012; Hammond et al. 1987; Johnson and Payne 1985; Kahneman 2011; Stanovich and West 2000). Individuals must "pay attention" in the form of expending mental effort to selectively perceive important sensory inputs and information, inhibit irrelevant perceptual inputs, and utilize deliberative analytical rule-based processes that are associated with System 2 (Kahneman 2011; Stanovich and West 2000). Thus, our minds generally operate in the effortless and unconscious System 1 mode, processing information from the world to interact with it appropriately and quickly. System 2, the "lazy controller" (Kahneman 2011), is continuously active at a fraction of its true capacity for the purposes of regulating the whims and desires of System 1 (Kahneman 2011). System 2 is only fully invoked when necessary, for example when a decision-maker faces a complex or unfamiliar context (Kahneman 2011). This mechanism helps regulate and maximize the utility of limited cognitive resources and reduces strain, cognitive fatigue, and improves decision-making efficiency. When an individual is busy making a deliberative decision in a situation with high cognitive load, the System 2 self-control mechanisms that regulate System 1 are loosened. Consequently, decisions are more likely influenced with System 1 intuitive heuristic-based decision-making, thus the individual may fall prey to making superficial judgements. This could result in decreased decision quality, low performance in tasks, inappropriate behaviours, or even renders the individual unaware to significant changes in the surrounding environment (Kahneman 2011). Thus, while System 2 processes are less susceptible to decision biases compared to System 1 processes, they are not fully immune to biases since they cannot be fully in control (Kahneman 2011).

2.2.5 The Effort/Accuracy Framework

Payne et al. (1985; 1993) introduced this framework to explain the interplay between the normative and descriptive cognitive decision processes. The main premise of this framework is that a decision-maker selects a judgement strategy based on the social context and the problem composition, and that this selection varies between decision-makers due to individual differences (Payne et al. 1993). The framework is grounded in five main tenets.

First, when facing a problem, an individual will have an “evoked set” of task-relevant decision strategies and heuristics that they acquired naturally through exposure, experience, or education. Second, each of these strategies has advantages, mainly in terms of decision outcome accuracy, as well as disadvantages, mainly in terms of decision process effort. These strategies are subjectively assessed by the individual and influenced by their cognitive abilities. Third, task environment characteristics influence the suitability and relative advantages and disadvantages of each strategy. Fourth, the decision-maker will “decide how to decide” by selecting a strategy that they anticipate being most fitting for the task by performing a cost-benefit trade-off analysis. Finally, these assumptions follow a top-down view; that is, the decision-maker will choose a decision strategy a priori based on perceptions and previous experiences with similar tasks. The nature of the data and evidence encountered may force a bottom-up change in the choice of a decision strategy and influence the decision process (Orquin et al. 2012; Orquin and Loose 2013; Payne et al. 1993). Under this framework, the primary drivers of a decision strategy choice is the individual’s desire to make an accurate decision competing with the individual’s desire to make the least amount of effort while doing so (Payne et al. 1993). These two primary drivers are discussed below.

Decision Effort: Cognitive *Decision Effort* is defined as the sum of cognitive resources (e.g., working memory, processing, attention) utilized by an individual to complete a decision task (Johnson and Payne 1985; Russo and Dosher 1983). On the one extreme, a decision-maker may take a lot of time and attempt to selectively consider all relevant information provided in a decision task and apply rule-based effortful deliberation and analysis, predominantly utilizing System 2 cognitive processes. This is performed to determine *Weighted-Additive (WADD) (refer to* ***Appendix 8.2****)* individual preferences' choice scores for the alternatives based on their attributes (Kahneman 1973, 2011; Payne et al. 1993). For most decision tasks, this is not feasible due to information asymmetry, time constraints, and mainly individuals' limited cognitive resources such as short-term memory and selective attention (Ebert 2001; Linden et al. 2003; Payne et al. 1993). On the other extreme, a decision-maker may quickly select an alternative at random, *Random Choice (RC),* with minimal cognitive effort exerted, with the maximum risk of a poor decision outcome (Johnson and Payne 1985; Payne et al. 1993).

Realistically, decision-makers utilize decision strategies that fall between these two extremes, utilizing a mix of intuitive System 1 heuristics and deliberative System 2 processes. These strategies (listed in ***Appendix 8.2***) include the *Equal Weighted Additive (EQW)* heuristic, the *Most Likely* or the *Lexicographic (LEX)* heuristic, the *Satisficing (SAT)* heuristic, and the *Elimination-by-aspects (EBA)* rule (Johnson and Payne 1985; Payne et al. 1993; Tversky 1972).

Each of these strategies involves a series of measurable Elementary Information Processes (EIPs) (summarized in ***Appendix 8.3***), grounded in the theory of Reading and Comprehension (Duchowski 2007; Just and Carpenter 1976, 1993), which are primitive operations involving reading, qualitative and quantitative evaluation, logical comparisons, and mental arithmetic (Bettman et al. 1990; Johnson and Payne 1985; Payne et al. 1993). These EIPs have been modified and utilized in the context of DSS (Chu and Spires 2000; Todd and Benbasat 1994a). Since each of these heuristics differs on the amount and type of information considered (e.g., compensatory WADD vs. non-compensatory EBA, as explained in ***Appendix 8.2***), the number of EIPs involved varies between strategies (Johnson and Payne 1985; Payne et al. 1993). The sum of these EIPs can be indicative of the cognitive effort involved under these different strategies (Johnson and Payne 1985; Newell and Simon 1972; Payne et al. 1993; Shugan 1980).

There are also subjective measures of effort in the literature such as *Perceived Decision Effort*, which is the subjective assessment of the decision-maker on the amount of effort they spent in making a specific decision. (El Shamy and Hassanein 2015, 2018; Sproles and Kendall 1986; Xu et al. 2014).

Decision Accuracy: The second major driver of decision strategy choice is decision quality. *Decision Quality* is defined and measured in numerous different ways in the extant literature (Lilien et al. 2004).

The first category includes objective *Decision Quality* measures based on normative utility models, in which decision quality is defined as how close the chosen alternative's score is to the one optimal alternative in a set (Lilien et al. 2004; Payne et al. 1993; Tan et al. 2010). In these measures, a nondominated alternative exists in the decision choice set that is superior to all other, dominated, alternatives either on all attributes or on a compensatory WADD utility score (Häubl and Trifts 2000; Lilien et al. 2004; Payne et al. 1993; Tan et al. 2010). Another measure of objective decision quality is whether or not the decision-maker switches to another alternative if given the chance to do so, as this is an indicator of poor initial decision quality (Häubl and Trifts 2000).

The second category includes subjective decision quality measures based on subjective utility or descriptive models (Häubl and Trifts 2000; Lilien et al. 2004; Tan et al. 2010). These include measures of the decision-maker' *Perceived Decision Quality* that are indicators of the degree of confidence in the decision (Häubl and Trifts 2000; Tan et al. 2010).

2.3 E-Commerce Decisions and DSS

2.3.1 Decision Support in E-Commerce

DSS naturally emerged and evolved in digital e-commerce platforms due to the overwhelming complexity and abundance of information within such environments. Vendors typically augment their e-commerce websites with typical DSS artefacts such as search tools, filter tools, product category taxonomies, Recommendation Agents (RAs), Comparison Matrices (CMs), consumer reviews, and price change alerts, among others (Xiao and Benbasat 2007, 2011, 2014).

RAs may solicit consumer preferences, implement attributes' cut-off thresholds, limit the number of alternatives presented to the user, or perform a combination thereof (Ghasemaghaei et al. 2019; Häubl and Trifts 2000; Xiao and Benbasat 2007). **CM**s furnish the set, or a selected subset, of the available alternatives on one axis and attribute information on another to facilitate easier comparison and evaluation (Häubl and Trifts 2000). These tools are essential to consumer decision-making, and vendors who implement effective support tools gain a competitive edge (Wang and Benbasat 2009; Xiao and Benbasat 2014).

Consumers have become so dependent on these standard tools to such extent that if particular vendors fail to provide them, either deliberately or due to poor platform design, third-party websites will capitalize on the opportunity and fill the gap. For example, Amazon doesn't provide CMs or a price history archive; hence, websites such as CamelCamelCamel.com and Google Shopping fill those gaps. Google Shopping facilitates comparisons across multiple vendors, including Amazon. Furthermore, there's an overabundance of consumer reviews, including vendor-generated fake reviews, and going through them all can be a tedious task; websites such as TheReviewIndex.com utilize Artificial Intelligence (AI) and machine learning for sentiment analysis to simplify the review evaluation process for consumers.

Research on decision-making and decision support in e-commerce has a long and rich history, starting as early as the 1990s (Xiao and Benbasat 2007). Research in this area has been overwhelmingly dominated (Davern et al. 2012; Xiao and Benbasat 2007) by the theory of Bounded Rationality (Simon 1955) and the Effort/Accuracy Framework (Johnson and Payne 1985; Payne et al. 1993; Todd and Benbasat 1994a). These paradigms acknowledge individuals' cognitive limitations and their behavioural tendencies to conserve cognitive effort during decision-making, by being "cognitive misers" (Häubl and Trifts 2000; Wang and Benbasat 2009).

In this respect, research grounded in the theory of Cognitive Fit focused on the technology artefact of decision support (Davern et al. 2012), fine-tuning it to fit the cognitive demands of the task and the cognitive capacity of the user (Davern et al. 2012; Hong et al. 2005; Tan et al. 2010). The objective is to improve decision-makers' performance in terms of efficiency (e.g., time, effort) and effectiveness (e.g., decision quality). The Effort/Accuracy Framework implies that decision-makers are concerned not only about their Decision Quality; but also about their Decision Effort (Todd and Benbasat 1992). Another implication from Cognitive Fit theory (Vessey and Galletta 1991) is that a better fit between the task, technology, and user results in the conservation of decision effort and cognitive resources that can then be reallocated towards enhancing accuracy (Chu and Spires 2000; Davern et al. 2012; Orquin and Loose 2013). For example, Hong et al. (2005) have found that different information presentation formats (i.e., lists, matrices), which are task and technology factors, result in choice alternatives competing for user attentional resources in different ways. They concluded that list presentation formats better fit browsing tasks, while matrices better fit searching tasks. Task, technology, and user fit enhanced users' task performance under different conditions. Similar results were found by Häubl and Trifts (2000).

In the Marketing domain, research consistently suggests that consumers tend to follow a typical pattern of behaviour after identifying a need for a specific product. Consumers begin by initially screening available alternatives, heavily utilizing heuristics and intuition, to build a “consideration set” that includes only those alternatives that are to be carefully evaluated (Häubl and Trifts 2000; Tan et al. 2010). Consumers then deliberately evaluate alternatives in the consideration set to make a decision (Häubl and Trifts 2000).

Findings suggest that different DSS, or diverse support strategies of DSS, introduce different amounts and types of information to the decision-maker that impact their cognitive load (Tan et al. 2010; Todd and Benbasat 1991, 1992, 1994b, 1994a; Wang and Benbasat 2009). Building on the Resource-Matching and Cognitive Load theories, Tan et al. (2010) provide evidence that decision-makers in e-commerce tend to perform better when the cognitive resources demanded in a task match the decision-makers’ available cognitive resources (Tan et al. 2010). However, performance deteriorates when there is an imbalance in either direction (Tan et al. 2010). The authors argue that in a context where a DSS imposes a high cognitive load, decision-makers will either satisfice and stop further searching for additional information or will utilize System 1-based simplifying heuristics that could render them susceptible to harmful biases (Tan et al. 2010). Hence, they echo similar calls to investigate the utility of designing DSS that could assist in debiasing such harmful cognitive biases in this context (Arnott 2006; Fleischmann et al. 2014; Lilien et al. 2004; Tan et al. 2010). Surprisingly, IS studies have demonstrated that individuals might prefer a more complex DSS, which requires more cognitive effort to use, than a simple one due to the increased perceived usefulness associated with higher complexity (Ghasemaghaei et al. 2019).

Traditional DSS in e-commerce are predominantly characterized by multi-attribute non-compensatory features, and are almost always limited to elimination-based strategies (e.g., LEX, EBA, MCD; see

Appendix 8.2) (Tan et al. 2010; Wang and Benbasat 2009). A review of DSS provided in the topmost visited shopping websites is provided in ***Appendix 8.5***.

2.3.2 Cognitive Biases in E-Commerce

While cognitive biases have been found to impact decisions in IS contexts, including e-commerce (Rydzewska et al. 2024; Wu and F.-F. Cheng 2011), there has been a dearth of research empirically investigating the phenomenon (Martinelli et al. 2022; Rydzewska et al. 2024). **Cognitive Biases** are inherent and systematic prejudices that influence decision-makers' behaviours and reduce the quality of their decisions (Arnott 2006; Bazerman and Moore 2009; Fleischmann et al. 2014; Gigerenzer et al. 2014; Kahneman 2011; Tversky and Kahneman 1974). They can manifest in different decision and cognitive processes and have been classified in the literature in different ways (Arnott and Pervan 2008; Fleischmann et al. 2014).

Some of these classifications include "perceptual" (Fleischmann et al. 2014) or "presentation" (Arnott 2006) biases that emanate from the Availability Heuristic (Bazerman and Moore 2009; Kahneman 2011). These relate to the information presentation format, which influences the attentional process of the decision-maker [e.g., inducing bottom-up cognitive processes instead of top-down deliberate processes (Orquin and Loose 2013)]. Arnott (2006) argues that this class includes the most important biases from a decision-making perspective because the mode of evidence presentation can significantly bias how decision-makers perceive, process, and utilize it.

Utilizing the Availability Heuristic, decision-makers first weigh events and information based on the ease with which they come to mind and are readily available in working memory, predominantly utilized by System 1-based intuition processes, until interrupted by System 2 (Kahneman 2011). Decision-makers then focus on the content using System 2-based deliberative processes (Kahneman 2011). While a decision-making task involves a downstream attentional control (System 2) by the decision-maker to find and process relevant task information, the order and vividness of presented information can force bottom-up, stimulus-driven attention capture and working memory encoding, interfering with top-down goal-driven attention control (Orquin and Loose 2013).

Order Bias: An order bias is the tendency of decision-makers to gravitate towards, and assign more value to, information presented earlier (e.g., top left) in a set. This is the result of the decline in attention resources and the gradual saturation of working memory (Arnott 2006; Fleischmann et al. 2014; Kahneman and Tversky 1984; El Shamy and Hassanein 2015; Yates and Curley 1986). The Order Bias is also referred to as the Sequential Bias (Fleischmann et al. 2014; Piramuthu et al. 2012) or the Primacy Effect (Fleischmann et al. 2014; Suh et al. 2013; Yates and Curley 1986). This is the opposite of the Recency Effect, where decision-makers gravitate towards the latest information they perceive and process because it's readily and conveniently available in working memory (Lourties et al. 2018).

Evidence of the order bias, and its different effects, has been reported in e-commerce, impacting consumers' formulation of vendor appraisal based on the order in which other users' ratings of a vendor is presented (Xu and Kim 2008). In NeuroIS, both the primacy and recency effects have been shown to impact different decision outcome antecedents differently. Primacy has been shown to have significantly more impact on arousal [i.e., cognitive load (Carmen et al. 2020)], while recency has been shown to have significantly more impact on emotional valence (Carmen et al. 2020; Lourties et al. 2018). In this study, I focus on the cognitive rather than the emotional component of decision making, hence this study will solely focus on the primacy effect, hereafter referred to as the order bias.

The attentional Drift Diffusion model (aDDM) posits that as decision-makers gaze and shift their attention (e.g., fixations, saccades) between alternatives, they accumulate evidence in their favour, and generally a "bias exists in favour of alternatives fixated on first because they have accumulated more evidence" (Orquin and Loose 2013). Additionally, cognitive psychology research utilizing eye-tracking methodologies has consistently shown that individuals tend to look more toward the top and left sides of the screen when browsing (Duchowski 2007; Orquin and Loose 2013; Pan et al. 2004), particularly in North America, where the major official spoken languages are English, French, and Spanish, which all follow the same left-to-right, top-to-bottom orthography.

Vividness Bias: A vividness bias is the tendency of decision-makers to gravitate towards salient and visually stimulating alternatives because they attract more attention and are easier to recall (Arnott 2006; Fleischmann et al. 2014; Orquin and Loose 2013; El Shamy and Hassanein 2015). Theories of image saliency and computational models of visual attention are widely established in cognitive psychology (Itti and Koch 2001; Orquin and Loose 2013; Scott and Vargas 2007). A salient stimulus in an environment will "pop out" of the visual scene automatically and effortlessly, attracting individuals' attention. On the other hand, shifting attention to less salient rival stimuli requires voluntary top-down effort (Itti and Koch 2001). Measures of saliency (e.g., contrast, colour against background, animation) are used extensively in advertising and e-commerce (Cyr et al. 2009; Djamasbi et al. 2010; Lim and Benbasat 2000; Milosavljevic et al. 2012). The richness of a vivid alternative or attributes stimulates and drives visual attention in its favour, making it more likely to be available in memory and thus weighted higher relative to others, and increasing working memory load has been found to increase this effect (Orquin and Loose 2013).

A summary of the definitions of these decision biases and their effects is presented in ***Table 5*** below. Since this study focuses on cognition and not on emotional valence, Vividness bias and Primacy Effect of the Order Bias (henceforth referred to as the Order Bias) are the central focus of this study.

Table 5: Cognitive Biases under investigation in this study (Arnott 2006; Bazerman and Moore 2009; Fleischmann et al. 2014; Kahneman et al. 1982)

Cognitive Bias	Definition
Order Bias	**Primacy Effect:** Gravitating towards the primal alternative or attribute in a given set as a result of declining attention
	Recency Effect: Gravitating towards the latest perceived information because it's conveniently readily available in working memory
Vividness Bias	Gravitating towards visually salient alternatives and attributes with relative ease compared to other less vivid stimuli

2.4 DSS and Debiasing

Debiasing is defined as the process of reducing or eliminating one or more harmful biases in a given decision task by introducing interventions (Arnott 2006; Bhandari et al. 2008; Fleischmann et al. 2014; Gilovich et al. 2002; Kahneman 2011; Kahneman et al. 1982). The nature of interventions varies between training and educating decision-makers using training sessions, video, or interactive tools; challenging their past or current decisions; requiring them to justify their decision outcomes; among others (Bhandari and Hassanein 2010; Kahneman 2011; Kahneman et al. 1982; Mirhoseini et al. 2023). DSS have been utilized to successfully debias various cognitive biases in individual decision-making contexts (Bhandari et al. 2008, 2009), and specifically in e-commerce contexts (Cheng and Wu 2010; Lin et al. 2005; Wu and F.-F. Cheng 2011; Wu and F. F. Cheng 2011).

Successful debiasing is dependent on utilizing the appropriate debiasing strategy (Arnott 2006; Bhandari and Hassanein 2010) or DSS features and capabilities (Wang and Benbasat 2009). Researchers argue that generic DSS tools, such as RAs and CMs, may not be successful in debiasing decision-makers and may even induce their own host of harmful cognitive biases. This is because they are developed without accounting for the nature of context-relevant cognitive biases and how exactly they manifest in the context, (Arnott 2006; Fleischmann et al. 2014; Wang and Benbasat 2009). Thus, understanding the nature, relevance, and magnitude of specific biases in a given context is a critical preliminary step toward developing appropriate debiasing strategies and incorporating them into appropriate DSS tools (Arnott 2006; Bhandari and Hassanein 2010). For example, Mirhoseini et al. (2023) examined two competing theories in the fake news domain. They provided empirical evidence that supports the Classical Reasoning Theory and rejects the theory of Motivated Reasoning. Based on the findings, they developed an intervention that targets users' overconfidence bias, improving the accuracy of their disinformation evaluation decisions by 14%.

Arnott (2006) extends a framework for understanding and debiasing cognitive biases that is adopted in this study (illustrated earlier in ***Table 2***). Bhandari and Hassanein (2010) extend taxonomies of cognitive biases and debiasing strategies (summarized in ***Table 6***), and suggest that different debiasing strategies are more or less appropriate and effective in debiasing biases of different natures. They provide evidence that introspective debiasing strategies, those that challenge decision-makers’ current assumptions and beliefs, are most effective in debiasing decision biases of a cognitive nature (Bhandari and Hassanein 2010) , while biases of the affective or conative nature are better addressed with prospective and retrospective debiasing strategies, respectively (Bhandari and Hassanein 2010).

Table 6: Taxonomy of Biases and appropriate Debiasing Strategies
Adopted from (Bhandari and Hassanein 2010)

Bias Categories	Bias Characteristics	Appropriate Debiasing Strategy	DSS Requirements
Cognitive (e.g., Order, Vividness, Framing)	Information-processing and perceptual biases, caused by the order, salience, patterns, and amount of information received.	**Introspective** (challenge the assumptions and belief systems of decision-makers by furnishing relevant information and/or simplifying relevant information)	Furnish information to support both sides of a decision. Portray information in different formats and salience levels. Present relevant information in a concise manner.
Affective (e.g., Disposition, House-Money)	Involve strong emotional elements such as fear, regret, and greed. Triggered by the arrival of new information.	**Prospective** (examine the impact of current decisions on the future goal of decision-makers and warn of possible consequences of such decisions)	Provide simulation capability to help investors visualise and understand the impact of current decisions on their long-term investment goals.
Conative (e.g., Overconfidence, Status-quo)	Persistent in nature. May exert their influences even in the absence of any new information.	**Retrospective** (question past decisions and behaviours with the objective of detecting persistent patterns of bias)	Provide capabilities for personality assessment and analysis, case-based reasoning, and pattern recognition.

2.5 Individual Differences in E-Commerce Decisions

Individual decision-making is influenced by three main factors. First, decision situation and context, including the type of decision, social context, and time pressure (Appelt et al. 2011; Payne et al. 1993). The second factor, decision features, includes the saliency and order of choice options as well as other factors such as framing (Appelt et al. 2011; Kahneman et al. 2011; Payne et al. 1993; Tversky and Kahneman 1981; Wu and F.-F. Cheng 2011; Yates and Curley 1986). Finally, decisions are influenced by an extensive variety of individual differences including age, cognitive style, gender, and product knowledge (Payne et al. 1993; Tan et al. 2010; Xiao and Benbasat 2007, 2014). Researchers seem to agree that more focus on the role of such individual differences is needed (Appelt et al. 2011; Hamilton et al. 2016; Rydzewska et al. 2024).

This study closely examines the roles of two individual difference factors (i.e., Age, Cognitive Style) and their interaction for two main reasons. First, these two factors have not been sufficiently examined in the IS literature. Recent publications are calling for further scrutiny of the impacts of Age (Rydzewska et al. 2024; Saric et al. 2024; Tams, Grover, et al. 2014) and Cognitive Style (Karimi et al. 2015; Lourties et al. 2018; Misuraca and Fasolo 2018; Silk et al. 2021) in IS research, including understanding online consumers' decision behaviour. Second, as discussed, these two factors are very closely related to the Availability Heuristic and the interaction between information presentation, fluid abilities (e.g., selective attention, working memory), and the Effort/Accuracy interplay as discussed below.

2.5.1 Cognitive Style

Cognitive Styles are habituated approaches to decision-making that individuals predominantly utilize when making decisions in particular contexts (Allinson and Hayes 1996; Sproles and Kendall 1986; Thunholm 2004). The number of cognitive styles varies between studies, ranging from two (Allinson and Hayes 1996; Karimi et al. 2015; Misuraca and Fasolo 2018; Schwartz et al. 2002), to three (Wickliffe 2004), and up to eight (Sproles and Kendall 1986). The majority of individuals tend to operate with one stable and predominant cognitive style, with only a small proportion able to operate with different styles depending on context (Aggarwal et al. 2022). Some studies even argue that these Cognitive Styles might not be two ends on the same continuum but separate independent constructs (Hamilton et al. 2016), an argument akin to the renowned trust vs. distrust finding in NeuroIS research (Dimoka 2010). Other studies, however, provide strong evidence of a trade-off and a negative correlation between satisficing and maximizing strategies (Chang and Wu 2012; Karimi et al. 2015). This confusion and disagreement are perhaps why this theory attracted some criticism (Benbasat and Taylor 1978; Davern et al. 2012; Hamilton et al. 2016; Huber 1983; Misuraca and Fasolo 2018). However, numerous studies (Aggarwal et al. 2022; Allinson and Hayes 1996; Barkhi 2002; Belk et al. 2012; Karimi et al. 2015; Kutschera 2002; Schwartz et al. 2002; Wan and Nakayama 2023) have empirically advanced the theory's validity and demonstrated useful theoretical and pragmatic implications, including in e-commerce (Barta et al. 2023). The critique is mainly focused on reaching an agreement among the research community on the concept definitions and terminology and a consensus and consistency in using measurement scales (Hamilton et al. 2016; Misuraca and Fasolo 2018).

Most studies conceptualize Cognitive Styles as two extremes on a "Satisficer – Maximizer" continuum, building on Simon's (1955) seminal theory of Bounded Rationality and satisficing (Davern et al. 2012; Iyengar et al. 2006; Karimi et al. 2015; Love 2009; Schwartz et al. 2002). **Maximizers** are perfectionists who engage in evidence-based decision-making and carefully and effortfully consider all available information as much as possible. This investment in time and cognitive effort is to carefully assess the set of alternatives and reach an ideal, or near-ideal, decision (Karimi et al. 2015; Schwartz et al. 2002). Thus, maximizers tend to favour higher accuracy at the expense of higher effort. **Satisficers**, on the other hand, are more concerned with the efficiency of their decision-making process and reduce the associated cognitive cost by heavily utilizing decision heuristics (Gilovich et al. 2002; Karimi et al. 2015; Schwartz et al. 2002). Satisficers favour the conservation of cognitive effort at the expense of lower accuracy and decision quality. Utilizing a mix of psychometric measures and process tracing techniques, Karimi et al. (2015) found that satisficers tend to spend less time when making online decisions. They consider fewer alternatives and attributes compared to maximizers. While satisficing by utilizing heuristics can be extremely beneficial (Bazerman and Moore 2009; Gigerenzer et al. 2014; Kahneman 2011) in certain contexts (e.g., situations with tight time constraints, life or death), it is generally a suboptimal strategy (Bazerman and Moore 2009; De Bruyn et al. 2008; Kahneman 2011; Karimi et al. 2015; Simon 1955; Tan et al. 2010) that makes the individual more susceptible to harmful cognitive biases (Bazerman and Moore 2009; Kahneman 2011; Tversky and Kahneman 1974). Satisficing heuristics can affect post-decision outcomes such as negative feelings [e.g., guilt, regret (Barta et al. 2023; Inbar et al. 2011; Schwartz et al. 2002)].

2.5.2 Age

The global population is aging at an unprecedented rate (Statista 2023e; Statistics Canada 2019; United Nations Department of Economic and Social Affairs 2015b). This is particularly evident in developed countries with low fertility rates that are accompanied by low mortality rates as a result of medical innovations and advancements in vaccines and health technologies (Statistics Canada 2014; United Nations Department of Economic and Social Affairs 2012, 2014, 2015b). Socioeconomic norms in those societies have been substantially transformed, motivating dual family careers, older adult independence, aging gracefully in place, and the support of fewer children. This is resulting in an increase in the proportion of older adults who are autonomous and make their own decisions, as there are fewer caretakers for older adults. This also means that the percentage of older adults, especially independent older adults, as a consumer segment, will likely continue to grow (World Health Organization 2022).

Older adults are the population segment most susceptible to mobility barriers (El Shamy et al. 2024). Additionally, they are the most at-risk population segment during pandemics (e.g., COVID-19) or flu seasons, and limiting their mobility in such situations to avoid infectious diseases may be their best strategy, as shopping online vs. in-person can literally be a life-or-death decision (El Shamy et al. 2024). Further, older adults are more affluent than their younger counterparts by orders of magnitude. All this means that the e-commerce industry should be prepared for that steady shift in demographics and should cater to an increasing number of older and more lucrative consumers (Statista 2023d). Furthermore, rapid technological innovations are transforming and digitizing the very nature of almost everything we do in our lives. These trends have substantial implications as societies transform and adapt their policies and service provisions to accommodate the needs of populations with increasing proportions of older people (United Nations Departmen of Economic and Social Affairs 2022; United Nations Department of Economic and Social Affairs 2014). As a result, research in the past few decades has increasingly focused on the role of age in the adoption and use of technology, including Information and Communication Technology (ICT), with research in IS and gerontology fields, among others, converging and giving birth to the nascent field of Gerontechnology (Bouma et al. 2007; Kwon 2016). However, aging research is generally more focused on the field of healthcare.

Age has been studied in IS research and has been found to influence the determinants of technology adoption and use (Morris et al. 2005; Morris and Venkatesh 2000; Venkatesh et al. 2003, 2012). For example, Morris and Venkatesh (2000) found that subjective norms and perceived behavioural control influenced older workers' intention to use a financial system in the workplace, while this effect was not as salient for younger workers. Older adults were found to make more errors and have longer response times in computer-based tasks (Czaja and Sharit 1993). Czaja et al. (2006) found that older adults have a more negative attitude towards computers and the Internet (i.e., lower computer self-efficacy, higher computer anxiety) than younger adults and have lower adoption in terms of use and breadth of use.

There are multiple conceptualizations of aging (Baltes and Baltes 1993; Hong et al. 2013; Kwon 2016; Peek et al. 2016; Tams, Grover, et al. 2014) and how age should be categorized. Generally, there is a distinction between normal, optimal, and pathological (i.e., sick) aging. In this view, a distinction must be made between normal aging processes and a manifest of illness (Baltes and Baltes 1993; Cleveland and Lim 2007; Tams 2017), for example, loss of memory due to normal aging versus suffering Alzheimer's disease or dementia. Under this view, normal aging can be enhanced to optimal levels by understanding the natural aging process impacts and optimizing ecological conditions accordingly (Baltes and Baltes 1993; Kwon 2016).

Chronological age, is a simple concept of aging, counting the number of years from birth (Baltes and Baltes 1993; Hong et al. 2013; Kwon 2016; Tams, Grover, et al. 2014). This is the conceptualization of age adopted for this research given its simplicity and pragmatic availability of information about consumer age for e-commerce retailers. Notwithstanding the straightforward nature of chronological age, there is a lack of consensus on what constitutes young and old (Nichols et al. 2003). For example, the United Nations considers individuals aged 60 years+ as "older adults" while the Government of Canada uses 65 years+ as the threshold for "older adults" (Statistics Canada 2014, 2019; United Nations Department of Economic and Social Affairs 2015b). Even researchers report conflicting age categories within and across disciplines (Kwon 2016; Neugarten 1974; Nichols et al. 2003; Schaie 1993). Many notable scholars argue for consistency in age categorization and recommend demarcations based on findings from the aging, gerontology, and psychology bodies of literature; these recommendations are summarized in ***Table 7***. The justification for the age groups of focus is for feasibility purposes to reduce study complexity, as the middle-aged group does not vary significantly from the the young adults group, while there are recruitment and eye-health related physiological concerns and with eye tracking particularly for the old-old group, this justification is outlined in more depth in ***Section 4.1.1*** .

Table 7: Literature-recommended chronological age groups that are adopted in this study (Cleveland and Lim 2007; Morrell et al. 2000; Sharit et al. 2008; Tams, Grover, et al. 2014)

Age Group	Chronological Age	Reference in this Study
Young Adults*	18-39	Younger Adults
Middle-Aged Adults	40-59	*Not included*
Young-Old Adults*	60-74	Older Adults
Old-Old Adults	75+	*Not included*

**The Young Adults and the Young-Old Adults age groups are the focus of this proposed study. Unless otherwise indicated, the term "Older Adults" refers to the Young-Old Adults age group, and the two terms are used to refer to this group throughout the dissertation interchangeably*

Another conceptual view of age is subjective, with Cognitive Age being an attitude and state of mind for each individual (Hong et al. 2013; Tams, Grover, et al. 2014). Hong et al. (2013) found that the impact of some antecedents to adopt an IT artefact (i.e., perceived usefulness, perceived enjoyment, subjective norm) varied between chronologically old but cognitively young individuals compared to those whose chronological and cognitive ages matched. Given the variance in convergent validity of different age conceptualizations on IS constructs, it is generally accepted that age is a composite construct, and that different conceptual definitions of age could be considered in research (Ghasemaghaei et al. 2014; Kwon 2016; Schaie 1993; Tams, Grover, et al. 2014).

Despite the importance of the role of age in IS research and the increasing number of publications investigating older adults' use of technology (McIntosh et al. 2021; Wagner et al. 2010), Tams et al. (Saric et al. 2024; 2014) argue that not much is known about its theoretical "touch points" with IS phenomena, and they set out a research agenda calling for further scrutiny of aging in IS research. These researchers highlight a need for explaining "how and why" age impacts IS phenomena rather than simply assessing "whether" it does.

It is well documented in the gerontology, cognitive, and neuropsychology literatures that the natural process of aging (i.e., healthy aging) is associated with physiological changes in cell and brain structures. These include reduction in cerebral volume (Coffey et al. 2001), reduction in gray and white matter (Farokhian et al. 2018; Ge et al. 2002; Resnick et al. 2003), and gene damage (Lu et al. 2004). As a result, aging is concomitant with a natural decline in various fluid cognitive abilities, such as selective attention and working memory capacity (Coffey et al. 2001; Czaja et al. 2006; Finucane et al. 2002; Gazzaley et al. 2005; Ghisletta et al. 2012) (cognitive abilities are summarized and defined in ***Appendix 8.4***). **Selective**

Attention is the discriminatory attendance to particular perceptual sensory inputs and the disregarding and inhibition of others (Orquin and Loose 2013; Tams 2017). **Working Memory** is a limited resource capacity of the brain where information required for accomplishing an active task is temporarily stored (Tams 2017). These two faculties are imperative to individuals' decision-making (Moye and Marson 2009; Orquin and Loose 2013; Pachur et al. 2017; Sharit et al. 2008), and impairments in these areas can impact individuals' information-seeking behaviour (Pachur et al. 2017; Plude and Doussard-Roosevelt 1989), bias their decision process, and diminish the quality of their decisions (Czaja and Sharit 1993; Peters et al. 2007), including e-commerce purchasing decisions. The neurophysiological substrates underlying selective attention and evidence processing are examined next.

2.6 Attention, Effort, and the Human Visual System

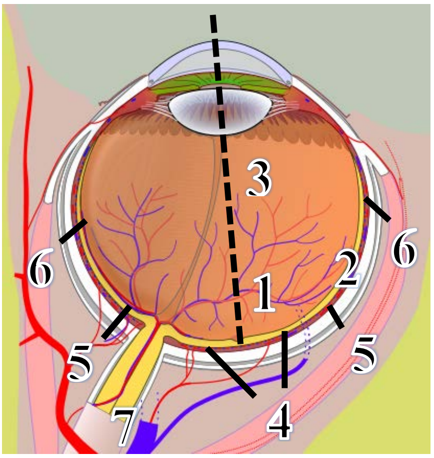
In e-commerce, information is predominantly delivered visually to consumers through a display in the form of text, images, or other rich media (e.g., video, interactive visuals). Thus, studying consumers' eye-gaze behaviour can provide valuable real-time insights by examining their attention allocation. NeuroIS methods, such as eye tracking, allows us to study how they individuals consume different information and understand how they arrive at decisions, while with pupillometry we can assess how their cognitive load changes throughout a decision task, with high spatial and temporal precision. To delve deeper and tap into the inherent cognitive processes of decision-makers in e-commerce, it is important to initially review the roles of attention and effort from a neurophysiological perspective by examining the Human Visual System (HVS). Eye movements are classified and discussed next. This is followed by discussing what drives these eye movements and how that relates to e-commerce biases.

2.6.1 Visual Attention and Perception

Our eyes are constantly capturing massive amounts of visual stimuli and sensory information. This information is dismantled and transmitted through the optic nerve to the brain's occipital lobe in raw form (i.e., neural impulses) for processing. The cognitive faculty of attention is responsible for reassembling and organizing this information to make sense of it and to filter out noise for further processing. In the words of the renowned psychologist William James (1981), "When the things are apprehended by the senses, the number of them that can be attended to at once is small, *'Pluribus intentus, minor est ad singula sensus'*" -

the Latin translation is “Many filtered into few for perception” (Duchowski 2007). What isn’t filtered out becomes the focus of consciousness and takes possession of cognition in clear and vivid form (James 1981). Thus, **Attention** is usually defined as selectivity in perception (Orquin and Loose 2013).

The neurophysiological substrate of the HVS introduces limitations on the amount of information that can be perceived from the field of view at any given moment. Specifically, the distribution of specific receptor cells (i.e., cones) on the retina is highly focused in the fovea, limiting the perception of fine details (i.e., foveal vision) to only a miniscule proportion of visual field of view (see ***Figure 1***). For example, a computer user is able to only perceive fine details of about 3% of a 21” computer display at a 60cm distance at any given moment (Duchowski 2007). Foveal vision constitutes an estimated 25% of the visual cortex processing (Riedl and Léger 2016). Cone cell concentration on the retina drops exponentially as the distance from the fovea increases. Information in the Useful Field of View (UFoV) is perceived with a little less acuity. Still, it could be utilized for glancing at information without needing head or eye movement. The rest of the field of view (i.e., peripheral vision) is perceived with much less acuity, and only limited features of stimuli (e.g., sharp edges, sudden movement) can be interpreted. This is an evolutionary advantage useful for hunting prey and fleeing predators. Thus, to clearly perceive information from a field of view, an “attentional feedback loop” exists that: (i) disengages attention, (ii) shifts attention and repositions the fovea, by moving the eyes, to an area of interest (i.e., saccadic eye movement), (iii) reengages attention (i.e., eye fixations) (Duchowski 2007).



1. Fovea
2. Retina
3. Visual Axis
4. Foveal Vision Edges (5°)
5. UFoV Edges (30°)
6. Peripheral Vision Edges (100° – 110°)
7. Optic Nerve

Figure 1: Diagram of the Eye and Different Vision Angles adapted from (Duchowski 2007)

2.6.2 Positional and Non-Positional Eye Movement

Eye movements can be classified into positional and non-positional categories. Positional movements are predominantly concerned with visual attention and repositioning the fovea on areas of interest in the field of view. Non-positional eye movements are concerned with physiological adaptation to the environment or stimuli (Duchowski 2007). One relevant non-positional movement (i.e., pupil dilation) and two relevant positional eye movements (i.e., saccades, fixations) are examined below.

Pupil Dilation and constriction are physiological responses of the Autonomous Nervous System (ANS) that allow the organism to adapt to environmental conditions (e.g., illumination, stressful event). Specifically, pupil dilation is one of the involuntary sympathetic "fight-or-flight" responses of the ANS that prepare the body for stressful situations (Riedl and Léger 2016). As a result, pupils dilate during difficult reading or decision tasks and reflect the mental processing and cognitive load during performance (Just and Carpenter 1993; Kahneman 1973, 2011; Piquado et al. 2010). For example, Kahneman (2011) reports that pupils immediately constrict upon unloading information from working memory in cognitive load tasks.

Saccades are extremely high velocity and short duration movement of the eyes. The purpose of this movement is to reposition the eye to bring a region of interest into foveal vision. Saccades last between 10ms and 100ms and their arc ranges from 5° - 50°. For the entire duration of saccades, the executor is effectively rendered blind and no working memory encoding occurs (Orquin and Loose 2013; Riedl and Léger 2016). Saccades are triggered both reflexively and deliberatively, and reflect a desire or need to change the focus of attention (Duchowski 2007; Stern et al. 2001).

Fixations are miniscule eye movements that relatively stabilize eye gaze over a stationary object of interest. Contrary to common belief, fixations are not lack of eye movement but a series of rapid minute movements (i.e., micro-saccades, tremor, drift). Due to the motion sensitivity of photoreceptor cells, movement of the eye on a target is necessary for cell stimulation and visual sensation. For example, if an image were to be artificially stabilized to perception by pegging its movement to micro-saccadic eye movement and keeping it locked on the retina, perception of the image would become blank and fade away. Fixations last between 150ms and 600ms and the average range of their arcs is 1°. Fixations constitute around 90% of total viewing time in tasks, during which information perceived from attentional processes is encoded into working memory (Orquin and Loose 2013). Fixations are also triggered both reflexively and deliberatively, and reflect a desire to maintain the focus of attention on a specific stimulus (Duchowski 2007; Stern et al. 2001).

The Theory of Reading and Comprehension provides evidence of fixation scan-paths reflecting the temporal sequence of sweeping textual information in reading tasks and demonstrates that the immediacy of information encoding to working memory and processing is reflected by longer fixation durations for conceptually difficult information. According to Just and Carpenter, "the eye-mind assumption posits that there is no appreciable lag between what is being fixated and what is being processed" (1980, p. 331). Research has confirmed the view that information during evidence gathering is selectively perceived, processed, and encoded to working memory during fixations (Orquin and Loose 2013).

A critical consideration to acknowledge is that foveal vision and fixations reflect overt attention. It is still possible to divert one's attention to stimuli that are present within the periphery but beyond foveal vision, which is defined as covert attention. For example, because peripheral vision is more sensitive to specific stimuli (e.g., twilight conditions, low luminance, low contrast), astronomers and stargazers are able to decouple attention from foveal vision to locate dim celestials in their periphery (Duchowski 2007). Similarly, the location of the next fixation during a decision-making task is partly pre-determined by relying on covert attention (Deubel and Schneidert 1996). However, covert attention is insufficient for information gathering and encoding, and foveation is necessary for complete perception (Orquin and Loose 2013).

The notion that attention can partly be influenced by the features of the stimuli (i.e., bottom-up stimulus-driven attention) in the visual field and also partly driven by volitional attentional control (i.e., top-down goal-driven attention) is important to examine, particularly when attempting to understand decision-making behaviour and susceptibility to perceptual cognitive biases (Duchowski 2007; Orquin and Loose 2013; Theeuwes 2010).

2.6.3 Top-Down and Bottom-Up Drivers of Attention

There has been much debate in decision-making models regarding whether attention is a passive mode of evidence acquisition or an active mode of evidence seeking (Schneider et al. 2012; Theeuwes 2010). However, decades of neurophysiological and eye tracking research provided insights that attention allocation during decision-making is the outcome of the interaction between top-down (i.e., endogenous attention) and bottom-up (i.e., exogenous attention) influences (Glaholt et al. 2010; Orquin and Loose 2013; Theeuwes 2010).

Top-Down Attentional Control refers to volitional and deliberative allocation of attention towards task-relevant stimuli in a visual field (Duchowski 2007; Orquin and Loose 2013; Theeuwes 2010). Goal-driven attention control has been consistently confirmed in using eye-tracking methods. Participants given different tasks on the same stimuli (e.g., infer social class vs. estimate ages from the same image) exhibit different scan-path patterns (Duchowski 2007; Glaholt et al. 2010; Glöckner et al. 2012). Another body of literature provides support that evidence-seeking patterns in natural tasks (e.g., driving) vary with expertise (Gegenfurtner et al. 2011). In goal-driven tasks, such as e-commerce decisions, decision-makers exert a System 2-based top-down control of their selective attention, steering their visual focus to the stimuli that are most relevant to their task demands (Orquin and Loose 2013). Gaze scan-paths have been shown to exhibit particular patterns when applying different decision heuristics [e.g., LEX, EQW, WADD (Orquin and Loose 2013; Renkewitz and Jahn 2012)].

Bottom-Up Attentional Control refers to the System 1-based involuntary, automatic, effortless, and passive gravitation towards salient stimuli in the visual field (Duchowski 2007; Orquin and Loose 2013; Theeuwes 2010). The Feature Integration Theory of attention (Treisman 1986; Treisman and Gelade 1980) illustrates the "pop-out" effect, in which salient visual stimuli can be pre-attentively located, which subsequently attracts foveal vision. The theory posits that an initial parallel scan of the visual field produces a retinal map of elementary feature boundaries (e.g., contrast, orientation, edges, colour differences but not what the colours are), which then require foveation to perceive what those features are (Duchowski 2007). Another significant bottom-up influence is the position of stimuli (Orquin and Loose 2013). Several eye tracking studies have demonstrated that alternatives on the top of a list and on the left of a grid receive more attention, while alternatives located at the end of both axes receive less attention and are less likely to be chosen (Huang and Kuo 2011; Navalpakkam et al. 2012; Orquin and Loose 2013). This is typically explained in terms of saturation of working memory through evidence accumulation during the performance of the task (Orquin and Loose 2013).

2.6.4 The Aging Human Visual System

There are several ways in which aging affects the HVS. On average, individuals after the age of 50 become at risk of contracting several eye diseases, including glaucoma, cataracts, diabetic retinopathy, and macular degeneration (Friedman et al. 2004; Haegerstrom-Portnoy et al. 1999; National Eye Institute 2018). These diseases lead to significant declines in visual acuity and may lead to blindness in extreme cases. While the proportion of individuals who suffer from these diseases consistently increases with age, reaching almost 2% by age 75, it surges dramatically to around 14% for the Old-Old (75+) age group (National Eye Institute 2018).

With regards to healthy aging, increased age is associated with slight decreases in pupil diameter and reductions in UFoV (Edwards et al. 2006; Sekuler et al. 2000; Stern et al. 2001). Natural aging is also associated with presbyopia, which is characterized by the reduced elasticity of the eye lens that results in low visual acuity for close objects, and can be easily treated with standard corrective eye glasses (Roberts and Allen 2016). Evidence seems to consistently indicate that visual acuity is very well maintained across age groups until the Old-Old (75+) age group, when it starts to deteriorate sharply. This includes several dimensions of visual acuity such as contrast sensitivity, luminance sensitivity, glare recovery, colour vision, among others (Haegerstrom-Portnoy et al. 1999). As a result, age-related variations in eye movement behaviour, up-to the age of 75 on average, are generally explained in terms of diminishing cognitive abilities rather than physiological deficiencies (Bergstrom et al. 2014; Roberts and Allen 2016; Romano Bergstrom et al. 2013). Specifically, variation in task performance for older adults is attributed to declines in top-down processes of attention control rather than bottom-up stimuli-driven influences (Gazzaley et al. 2005; Madden 2007; Zhuravleva et al. 2014).

Eye tracking and pupillometry methods are extremely beneficial in making task performance comparisons between older and younger age groups in a variety of contexts, including computer-mediated decision-making tasks (Bergstrom et al. 2014; Piquado et al. 2010; Romano Bergstrom et al. 2013). For example, older adults were found to fixate more towards the centre of the screen and less on the peripheral edges, putting them at a disadvantage compared to younger adults with regards to finding navigation elements of websites' user interfaces (Bergstrom et al. 2014). This insight would have been difficult to exhume without the use of eye-tracking methods, and the results can inform the design of alternative, and more older adult-friendly, website layout designs (Bergstrom et al. 2014).

2.6.5 Implications for E-Commerce Decision-Making

Several implications regarding the HVS role in decision-making could be extended to the realm of e-commerce. Evidence gathering is influenced by both top-down volitional and effortful control as well as bottom-up stimulus-driven cues (Orquin and Loose 2013). Additionally, relying on System 1 intuitive decision processes can render individuals more susceptible to such stimuli-driven influences (Croskerry 2009). Advertisers exploit these bottom-up influences that induce vividness and order biases for product placement in different contexts, including e-commerce (Duchowski 2007; Orquin and Loose 2013).

To induce the vividness bias, advertisers design their content in such a way, or overlay salient tags on their listings, to make them more vivid relative to their surroundings and "popout" by manipulating contrast, brightness, and colour. For example, Canadian Tire and Amazon promote listings by overlaying bright colourful tags over product pictures with attention grabbing text (e.g., Best Seller, Featured, Tested for Life in Canada). Similarly, Kijiji allows sellers to promote their ads, for a fee, by making them more salient and claims that these tactics double the viewership of the ads (Kijiji 2018a). Users can flag their ads with bright red banners and can also highlight their ads by using a blue background instead of the website's standard white. Examples of vividness bias inducing tactics in e-commerce are provided in ***Appendix 8.6***.

With regards to the order bias, advertisers strive to position their content at the top of result lists through free means such as Search Engine Optimization (SEO) tactics, paid and sponsored placements, or a combination thereof (Clifton 2010). Google is infamous for utilizing this as a business model for its world leading search engine (e.g., google.ca, shopping.google.com). Search results are populated, sorted, and presented to users by utilizing algorithms (e.g., PageRank) that calculate a numerical value representing each result's weighted importance and relevance to a search query (Google 2018; Pan et al. 2007). However, relevant sponsored content and ads, which can have lower numerical importance scores, can override the results' order and occupy the top spots. Google sells up to four top spots per result page through its AdWords services (Google 2018). Similarly, Kijiji sells the top spots in C2C listings and claims that the top position receives ten times as much views as other ads (Kijiji 2018b). Kijiji sellers can purchase the top spot and bump up their listings on a recurring basis. Examples of order bias inducing tactics are in ***Appendix 8.6***.

Salient and primal alternatives are more likely to attract attention, which biases users' evidence acquisition in their favour, and makes them more likely to be ultimately chosen (van der Laan et al. 2015; Milosavljevic et al. 2012; Orquin et al. 2012; Orquin and Loose 2013; Schneider et al. 2012). These alternatives might not necessarily have the highest utility for different e-commerce consumers, which could be detrimental to their decision quality and decision satisfaction. Consumers who tend to rely more on decision heuristics and System 1 intuitive processes, such as older adults and satisficers, could be particularly vulnerable to these effects.

2.7 Summary and Conceptual Framework

2.7.1 Theoretical Overview

Decision-making is influenced by three main factors: decision features, decision context, and individual differences. Age and cognitive Style are important individual difference factors that influence how decision-maker in e-commerce contexts approach decisions, how they exert effort to screen and evaluate alternatives, and the accuracy of their decisions outcomes. Specifically, these factors influence decision-makers' trade-off between utilizing System 1 intuitive and heuristic processes, and System 2 analytical and deliberative processes. While System 2 processes are not immune to decision biases, System 1 processes tend to make decision-makers more susceptible and vulnerable to harmful cognitive biases emanating from decision heuristics and bottom-up visual cues.

Decisions in e-commerce are characterized as multi-alternative multi-attribute complex and cognitively demanding decisions. Facing an abundance of information and a myriad of choices, decision-makers may resort to suboptimal heuristic-based decision strategies, rendering them more vulnerable to cognitive biases and bottom-up stimuli. Cognitive biases emanating from the Availability Heuristic can be particularly relevant in the context of e-commerce, where consumers make decisions solely based on product information that is presented in various forms on the screen, with minimal direct interaction with the products. As a result, understanding how decision-makers differ in allocating their attention to consume evidence and process product information is an important first step in developing appropriate debiasing strategies to incorporate into DSS in future research.

2.7.2 The Value of Eye Tracking

Given that heuristics and cognitive biases are subtle and latent cognitive processes and prejudices that likely occur subconsciously, decision-makers may not be aware of their reliance on these heuristics or susceptibility to these biases (Gilovich et al. 2002; Kahneman 2011; Kahneman et al. 1982; Oregon Research Institute 1973). Additionally, they may fail to recall their decision process in detail retrospectively. Further, individuals might not accurately reflect their own bias susceptibility due to social desirability bias (Dimoka et al. 2012) or bias blind spot (Pronin et al. 2002), which influence individuals' assessment and self-reporting of their own susceptibility. This makes it difficult for researchers to study the mechanisms through which such biases affect decision-making.

NeuroIS measures, such as eye tracking, have been generally encouraged specifically for constructs that are amenable to subtle or unconscious cognitive or physiological processes (e.g., attention, stress, anxiety) (Dimoka et al. 2012; Riedl et al. 2014; Riedl and Léger 2016). This notion of eye-mind enables researchers to trace and make objective inferences about the latent mental processes of users through eye tracking methodologies (Dimoka et al. 2012; Duchowski 2007; Orquin and Loose 2013; Riedl and Léger 2016). Thus, eye tracking can be particularly useful in tracing the cognitive processes of users in real-time (Glaholt and Reingold 2011), without the need for the user to stop and think aloud, which might interrupt the natural process of their decision-making. Additionally, objective eye gaze behaviour is much less prone to self-presentation biases that might influence the user during recall, and is immune to failure to recall (Dimoka et al. 2012).

Figure 2 illustrates the stages of consumer action and the interplay between memory and selective attention in the form of an external information search for decision-making (Duchowski 2007). In this study, I tap into the perceptual black box of human cognition using eye tracking, and examine the evolution of a decision-makers' overt attention during information acquisition, as well as their eye gaze scan-paths and dwelling behaviour in real-time (Duchowski 2007). This information can provide valuable insights on how individuals fall prey to harmful decision biases, which is a major contribution to our understanding of the impact of age and cognitive style on this process. This will ultimately inform the development of appropriate debiasing strategies to incorporate in DSS in future research.

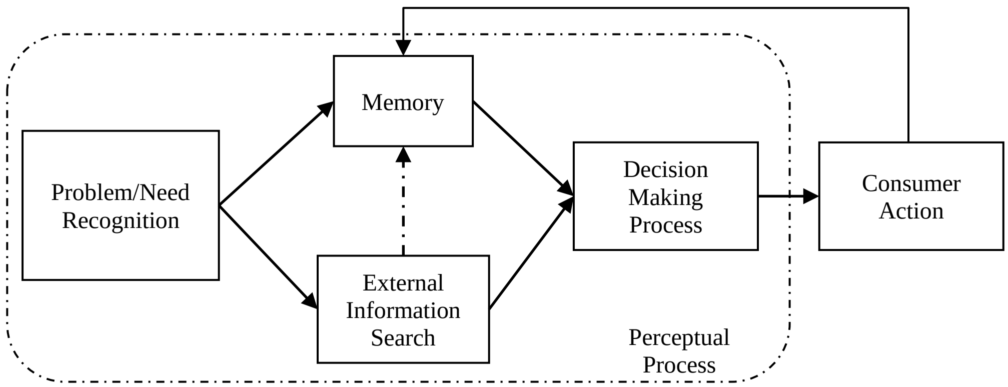


Figure 2: Model of Consumer Action
Adopted from (Duchowski 2007)

Utilizing state of the art eye tracking equipment measuring eye gaze at high frequencies in this study, a deep insights into users' decision-making processes was gained, including visual perceptual behaviours and selective attention allocation, with high temporal and spatial precision. This provides a more holistic understanding of decision process effectiveness, efficiency, and cognitive bias susceptibility (Dimoka et al. 2011; Glaholt and Reingold 2011; Riedl et al. 2014; Riedl and Léger 2016; Tams, Hill, et al. 2014). Findings based on this approach will assist the development of appropriate debiasing strategies to inform the design of effective DDSS (Vance et al. 2018).

2.7.3 Conceptual Framework

Building on this theoretical foundation, a conceptual framework for e-commerce decisions is constructed in ***Figure 3*** that is in line with the taxonomies proposed by Lilien et al. (2004) and Tan et al. (2010), and extended to include the typologies of factors affecting decision-making performance (i.e., decision context, individual differences, decision features) (Appelt et al. 2011). Within this framework, various e-commerce decision contexts are examined through combining a mix of individual differences (i.e., Age, Cognitive Style) and decision features (i.e., Cognitive Biases). The performance of the different groups of e-commerce decision-makers will be assessed in different contexts in terms of the decision process and decision outcomes criteria. For each criterion, both objective and subjective assessments will be considered (Lilien et al. 2004; Tan et al. 2010). However, it is not feasible to include all these variables in one research study. Thus, subjective indicators of the decision process (i.e., Perceived System Quality) were excluded from this study.

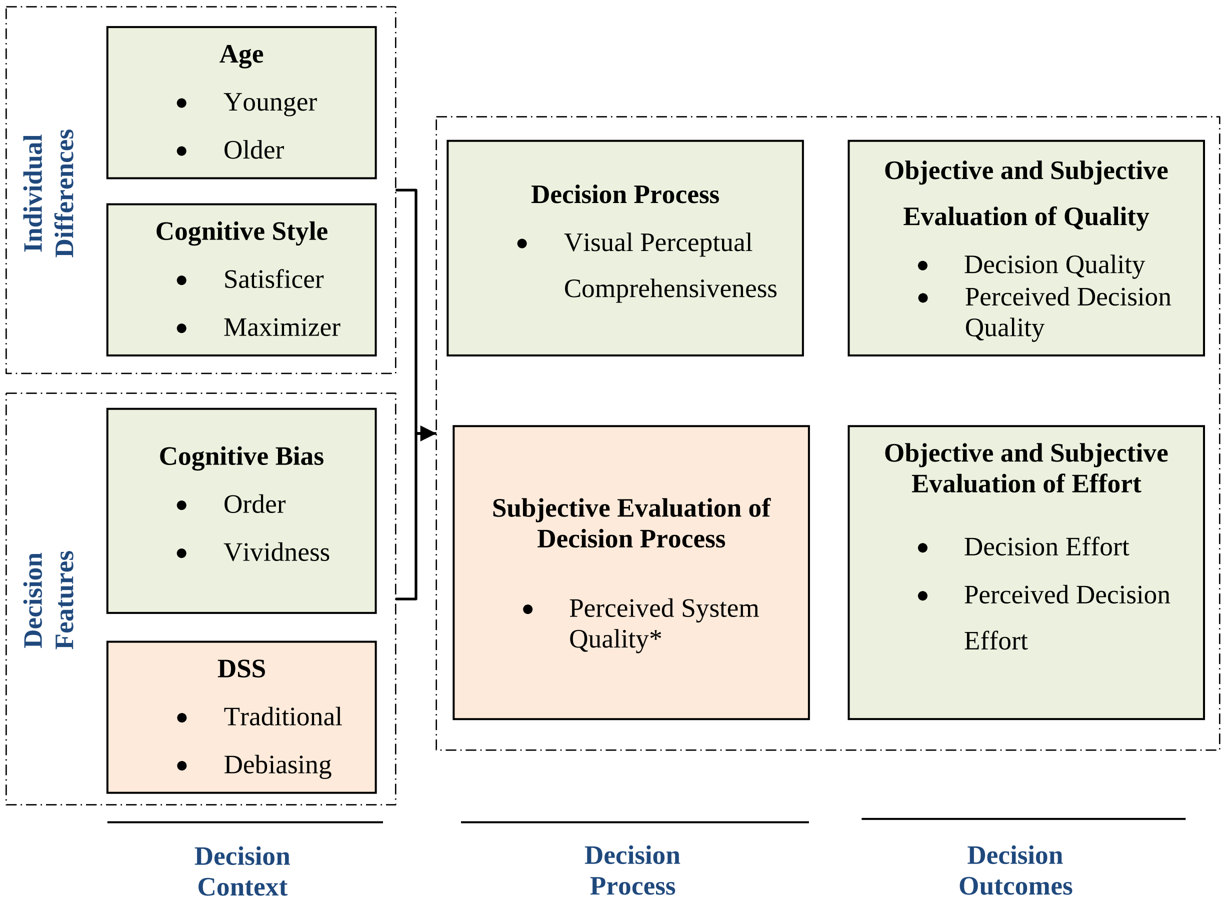


Figure 3: Conceptual Framework for e-commerce decisions, adapted from (Lilien et al. 2004; Tan et al. 2010)
** To reduce the complexity of the research design, DSS, Perceived System Quality, and other relevant variables were excluded from this study*

Visual Perceptual Comprehensiveness (VPC) is proposed as an objective, and meaningful, assessment of cognitive decision making, and relative effort allocation, as well as an indirect metric of cognitive bias susceptibility. As discussed in ***Section 2.2.5*** earlier, previous research has, either directly or indirectly, utilized a variety of objective measures of effort. These include decision time (Tan et al. 2010), number of detailed information queries (Häubl and Trifts 2000; Karimi et al. 2015; Xiao and Benbasat 2007), consideration set size (Häubl and Trifts 2000), and EIPs (Chu and Spires 2000; Todd and Benbasat 1994a). While these measures are extremely useful, some of them suffer from some limitations. For example, decision time could be partially spent attending to product-irrelevant information (Tan et al. 2010). Additionally, queried information may not necessarily be fully attended to for comparison across alternatives. For example, previous research has accounted for the quality of queried information or the quality of the consideration set (Häubl and Trifts 2000; Xiao and Benbasat 2007). Unfortunately, there is no guarantee that users attend to the information deliberatively or self-report their consideration with accuracy. Understanding how decision time was spent and which information was selected for attention allocation, and why, would provide significant insights on decision-making behaviour in e-commerce. This is possible with eye tracking.

For this study, **VPC** is defined as the symmetry of total mental workload and attention allocation exerted by individuals to perceive, encode, process, and evaluate product-relevant information to accomplish a set of goals in a given task. Measurement of VPC is discussed later in ***Section 4.4.1***. Analogous to Elementary Information Processes (EIPs) (Bettman et al. 1990; Payne et al. 1993), VPC is proposed as a metric of cognitive effort exerted in a decision-making task and its distribution over product-relevant information and is a reflection of cognitive bias in teach task. However, the two concepts differ on the following assumptions.

EIPs rely on decomposing a problem into a rational sequence of operations and using process tracing methods to objectively calculate the "optimum number" of EIPs for each decision strategy (Payne et al. 1993). Thus, cognitive effort calculated as a total of EIPs follows a normative model (Todd and Benbasat 1994a). Payne et al. (1993) argue that this model is not a realistic simulation of a complex decision-making process because it assumes that the decision-maker is aware of all the possible decision strategies, that their calculations are not erroneous, and that their memory is both unbound and infallible (Payne et al. 1993).

On the other hand, VPC is conceptualized within the paradigms of Cognitive Load Theory and Effort/Accuracy Framework from a descriptive perspective, as a conceptualization of relative cognitive effort that acknowledges individual cognitive bounds and differences. For example, older adults suffer from a reduced working memory capacity that may cause them to repeat some processes (e.g., re-read information) and utilize fixations as an external memory space (Schmutz et al. 2010). In this case, EIPs would vary between older and younger adults for reasons other than the applied decision strategy. VPC, on the other hand, is an assessment of the symmetry in the allocation of attention to perceive different information, which more accurately reflects the breadth and depth of information acquisition (Huang and

Kuo 2011). VPC is grounded in the theories of Reading and Comprehension and aDDM which provide support that there is a strong relationship between overt attention, covert attention, working memory, and perception (Just and Carpenter 1980; Orquin and Loose 2013). VPC can be used to understand bias susceptibility by examining the symmetry, or skewness, of attention allocation on different alternatives during information acquisition and the quality of the decision outcome.

3 Theoretical Model and Hypotheses

3.1 Research Model

Building on the conceptual framework that was presented in ***Section 2.7.3***, the research model illustrated in ***Figure 4*** was developed to assess the relationships between the identified relevant constructs, validate VPC in a nomological network (Cronbach and Meehl 1955; Tams, Hill, et al. 2014), and achieve the research objectives of the study. To guide the development of the research model, this study was anchored in three core research objectives: (1) to develop and validate a measure of visual information processing during decision-making, (2) to examine the influence of individual differences on this visual processing, and (3) to explore how such processing relates to decision outcomes. These objectives directly informed the selection of constructs in the conceptual framework. Visual Perceptual Comprehensiveness (VPC) was introduced as a novel construct to address the first objective. Age and cognitive style were included to capture individual differences central to the second objective. Finally, the inclusion of both objective (e.g., decision quality, decision effort) and subjective (e.g., perceived decision quality and effort) outcomes aligned with the third objective, enabling a comprehensive assessment of VPC's impact on decision-making. This logical progression from objectives to constructs ensured a coherent and theory-informed research model.

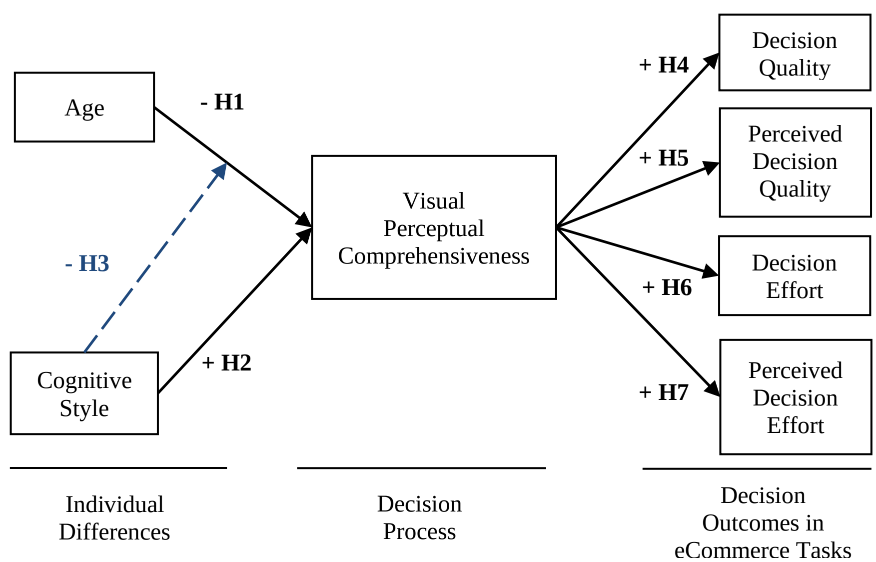


Figure 4: Research Model illustrating the direct effects (solid) and moderating (dashed) relationships of the research variables in the context of e-commerce

It is important to note that the chronological conceptualization of age is the one adopted in this research as discussed in ***Section 2.5.2***. Specifically, the study focuses on the Young Adults and Young-Old Adults chronological age groups that are outlined in ***Table 7***. Unless otherwise stated, the term Older Adults is used throughout this dissertation to refer to the Young-Older Adults chronological age group.

3.2 Hypotheses Development

3.2.1 Age and the E-Commerce Decision Process

Aging is associated with the attenuation of fluid cognitive abilities such as selective attention and working memory capacity (Ghisletta et al. 2012; Salthouse and Babcock 1991). These memory and executive functions are significant determinants of task performance. (Biffi and Tuissi 2006; Bruine de Bruin et al. 2012; Finucane et al. 2002, 2005; Del Missier et al. 2010; Orquin and Loose 2013).

Research consistently shows that higher Age is associated with more processing errors, more risky decisions, and inconsistent preferences (Chevalier et al. 2015; Czaja and Sharit 1993; Finucane et al. 2002; Pachur et al. 2017; Peters et al. 2007; Romano Bergstrom et al. 2013). For example, older adults made three times as many errors as younger adults when making decisions about their health plans, given various forms of information displays [e.g., text, charts, tables (Hibbard et al. 2001)]. In one study, older adults' performance was less accurate than younger adults in decision rule application tasks, which was partly explained by declining fluid abilities (Bruine de Bruin et al. 2012).

While aging is often associated with declines in certain cognitive abilities relevant to decision making, such as working memory, processing speed, and attentional control, research also highlights contexts in which older adults perform as well as or better than their younger counterparts. For example, older adults tend to rely more on accumulated knowledge and experience, which can compensate for declines in cognitive flexibility or deliberative processing. Moreover, some studies suggest that older adults may demonstrate more effective emotional regulation and a greater focus on goal-relevant information. Notably, Bruine de Bruin et al. (2012) found that older adults often show better calibration between confidence and accuracy in decision making tasks, indicating more realistic self-assessments. These findings suggest that while age can negatively affect certain aspects of decision processing, it may enhance others, particularly those involving judgment, emotional regulation, or metacognition. Therefore, age-related differences in decision making are nuanced and context dependent.

Aging is associated with reduced reliance on deliberative thought processes (i.e., System 2) and an increased reliance on intuition (i.e., System 1), rendering older adults more vulnerable to biases (Peters et al. 2007). Older adults consistently seek less information when making decisions or solving problems, and rely less on analytical processing (i.e., System 2) and more on intuitive-based judgements (Biffi and Tuissi 2006). Older adults were found to use less exhaustive strategies and make fewer information requests in decision tasks (Berg et al. 1999). Hence, in the context of multi-alternative multi-attribute e-commerce decisions, older adults are expected to rely more on intuitive based judgement

Age-related declines and the reduced reliance on deliberative processes may cause older adults to be more influenced by bottom-up visual cues (Gazzaley et al. 2005; Madden 2007). Age-related differences in information search effectiveness have been attributed to the decline in older adults' selective attention (Van Gerven et al. 2000; Plude and Doussard-Roosevelt 1989) and working memory (Gazzaley et al. 2005), rather than diminishing physiological abilities such as Useful Field of View (UFoV) (Romano Bergstrom et al. 2013). This can be explained with the knowledge that bottom-up influences can interfere with and trump top-down attentional control (Orquin and Loose 2013) especially with more reliance on decision heuristics which increases with age.

Under cognitive bias conditions, primal and salient alternatives will force a bottom-up attention allocation in their favour, given their position and vividness on the screen (Orquin and Loose 2013), at the expense of higher quality alternatives that might be less vivid or presented later. The Attentional Drift Diffusion Model (aDDM) posits that stimuli fixated earlier in a task will be more likely encoded in working memory than others (Krajbich et al. 2012; Orquin and Loose 2013). This is further exacerbated by the earlier saturation of working memory capacity for older adults compared to younger adults for the same amount of information. Previous studies have demonstrated that by reducing the working memory capacity of decision-makers, through working memory overload interventions, their information-seeking behaviour becomes impaired, driving them to utilize "fixations as an external memory space, thereby reducing demands on cognitive memory" (Orquin and Loose 2013). Researchers have found similar results, of reduced information search effectiveness, by introducing cognitive load in the form of website complexity (Wang et al. 2014).

Given the complexity of e-commerce environments due to the overabundance of choice and information overload (Gudigantala et al. 2010; Walsh and Mitchell 2005), e-commerce decisions can be particularly taxing to older adults. Cognitive fatigue will occur earlier for older adults in e-commerce tasks compared to younger adults, leading them to rely more on heuristics and System 1-based intuitive processes, reducing the likelihood of expanding the information acquisition behaviour towards and deliberation of higher quality alternatives. As a result, older adults will be more susceptible to the order and vividness biases and will thus will generally exhibit lower VPC. Thus:

H1: Older Adults will exhibit lower Visual Perceptual Comprehensiveness compared to Younger Adults in e-commerce tasks

3.2.2 Cognitive Style and the E-Commerce Decision Process

Satisficers settle for a good enough outcome that passes a minimum threshold (Chu and Spires 2000; Iyengar et al. 2006; Schwartz et al. 2002). They tend to stop their information search as soon as that threshold is met (Misuraca and Fasolo 2018). Maximizers, on the other hand, aim for perfection and strive to meticulously consider all available information even when a decision threshold is reached.

Maximizers utilize top-down exhaustive (i.e., System 2-based) strategies (Iyengar et al. 2006; Schwartz et al. 2002). System 2 deliberative top-down processes are characterized by a wider breadth of information search and a broader distribution of attention allocation on available information (Huang and Kuo 2011). Deliberation reduces the influence of bottom-up stimuli, such as the order and salience of information, (Croskerry 2009; Kowler 2011) and thus is expected to mitigate or reduce bias susceptibility.

While individuals on either end of the cognitive style continuum (i.e., satisficers, maximizers) will likely be swayed towards primal and salient alternatives (Orquin and Loose 2013), satisficers are more likely to make a premature decision based on their heavier reliance of decision heuristics [e.g., EBA, SAT (see ***Appendix 8.2***)], and settle for a bias inducing alternative. Maximizers will be more likely to exert additional effort to examine less salient information or lower placed alternatives in a set and exhibit more deliberation and breadth of information-seeking. Hence, satisficers can be more susceptible to order and vividness biases relative to maximizers, which would skew their attention allocation in favour of the lower quality bias-inducing alternatives. As a result, satisficers will exhibit lower VPC. Thus:

H2: Satisficers will exhibit lower Visual Perceptual Comprehensiveness compared to Maximizers in e-commerce tasks

3.2.3 Cognitive Style's Moderation of Age's impact on Visual Perceptual Comprehensiveness

Age and cognitive style have rarely been studied together (de Bruin et al. 2016). The few studies that included those two constructs simply reported that more older adults identified as satisficers compared to younger adults (Bruine de Bruin et al. 2007, 2012; Love 2009; Tanius et al. 2009). No studies examined decision performance and outcomes across satisficers and maximizers by age group or investigated their likely interaction.

Building on the foregoing discussion, satisficers by definition select suboptimal outcomes to conserve effort, which can be partly achieved by frugality in seeking additional evidence (Karimi et al. 2015). Similarly, aging is associated with increased reliance on System 1-based intuitive processes, making older adults less deliberative (Biffi and Tuissi 2006; Queen et al. 2012) and more vulnerable to perceptual biases (Coolin et al. 2015; Peters et al. 2007). Maximizing strategies aim to integrate as much information as possible in their decision making process, aiming towards choosing the best possible alternative in a multi-alternative multi-attribute decision context such as e-commerce (Schwartz et al. 2002; Wan and Nakayama 2023). Since maximizers seek to integrate more information in their decision process by deliberatively controlling their attention, they're bound to assess decision alternatives that are less salient and primal regardless of age, making them less susceptible to representation cognitive biases. For older maximizers, their increased volition to utilize System 2 strategies is expected to reduce their susceptibility to harmful decision biases. While for older satisficers, their reliance on less deliberative System 1-based decision strategies in terms of breadth of information sought, deliberation, and symmetry of attention allocation is expected to be more pronounced. This is expected to make them seek the least amount of information in their decision process, which is likely to be the bottom-up salient and primal alternatives in a considerations set, making them the most vulnerable to decision biases. As a result, satisficers will be more susceptible to the negative influence of age on VPC. Thus:

H3: Cognitive Style will moderate the relationship between Age and Visual Perceptual Comprehensiveness such that Maximizers will be less susceptible than Satisficers to the negative influence of Age on Visual Perceptual Comprehensiveness in e-commerce tasks

3.2.4 VPC and the Quality of E-Commerce Decision Outcomes

Eye movement behaviour in decision-making tasks is not stochastic, it's a combination of top-down and bottom-up processes (Gleasure and Grace 2016; Orquin and Loose 2013; Theeuwes 2010). Decision-makers exert top-down control of attention to seek, fixate, accumulate, and process evidence in a given task following a decision strategy (Orquin and Loose 2013). System 2 exhaustive decision processes require decision-makers to selectively attend to and aggregate more evidence and apply effortful rule-based reasoning to find the optimal, or near optimal, choice (Kahneman 2011; Stanovich and West 2000). However, bottom-up stimuli, such as saliency and position of information, interfere with downstream executive control of foveal vision and warp the attention of the decision-maker in their favour (Orquin and Loose 2013).

As users fall prey to the order and vividness biases, they will dwell on primal and salient alternatives more and gather more evidence in their favour, making primal and salient alternatives more likely to be chosen prematurely (Krajbich et al. 2012; Orquin and Loose 2013). Salient and primal alternatives are not necessarily the most optimal choices; hence, these biases can be detrimental to the quality of consumers' information acquisition quality and ultimately their decision. On the other hand, increasing VPC factors such as the breadth of information acquisition by fixating on other less salient and primal higher quality alternatives would increase their likelihood for selection of the best alternatives and reduce the effect of biases resulting in better decisions. Thus:

H4: Higher Visual Perceptual Comprehensiveness is associated with Higher Decision Quality in e-commerce tasks

According to the Effort/Accuracy Framework, reliance on less information and more heuristics is a trade-off that conserves energy at the cost of reducing quality (Sproles and Kendall 1986). The theory of aDDM posits that top-down deliberative processes trumps bottom-up perceptual biases and allows the integration of more information in the decision making process (Kahneman 2011; Orquin and Loose 2013).

Decision makers are typically aware that they're trading off quality for convenience and understand that they may not be making the most optimal decision when conserving effort (Schwartz et al. 2002; Sproles and Kendall 1986).

In e-commerce contexts, increased product information and diagnosticity resulted in higher levels of perceived decision quality (Xu et al. 2014). In another study, participants who self-reported that they rely on suboptimal decision strategies and less information in their decision-making process expressed regret due to the perceived quality of their purchased products, even when the quality of their chosen products were high (Barta et al. 2023).

Accordingly, it is hypothesized that consumers who rely on more information in their decision-making process are more likely to have higher perceptions of the quality of their decisions regardless of the objective quality of their decision. On the other hand, those who are more susceptible to the order and vividness representation biases, and thus have lower VPC, due to their reliance on decision heuristics understand that they are trading quality to conserve effort and will have lower perceptions of the quality of their decision. Thus:

H5: Higher Visual Perceptual Comprehensiveness is associated with Higher Decision Quality Perceptions in e-commerce tasks

3.2.5 VPC and the Decision Effort Outcomes

The Effort/Accuracy Framework posits that higher decision effort is the result of more complex decision strategies, increased steps of making the decision (i.e., EIPs), and inclusion of more information considered and processed in the decision-making process (Johnson and Payne 1985; Tan et al. 2010). This is evident from pupillometry studies, where more information stored in working memory for processing is associated with higher cognitive load and effort as indicated by the dilation of the pupils (Duchowski et al. 2018; Kahneman 1973, 2011; Kahneman and Beatty 1966; Sirois and Brisson 2014). VPC by definition is the reduced susceptibility to cognitive biases by the integration of more information in the decision-making process. Thus:

H6: Higher Visual Perceptual Comprehensiveness is associated with higher Decision Effort in e-commerce tasks

Increased information acquisition and processing leads to a higher load on working memory and cognitive demands (Johnson and Payne 1985; Kahneman 2011; Kuo et al. 2009; Tan et al. 2010; Tversky et al. 1974). System 2-based processes that are associated with effortful information-seeking and integration are more cognitively demanding relative to System 1-based intuitive processes (Kahneman 2011; Stanovich and West 2000). Additionally, increased breadth of search would lead to the identification of more high quality and relatively similar alternatives that vary slightly on attribute performance. Increased choice similarity in e-commerce is a factor of decision complexity (Xiao and Benbasat 2007) because the evaluation requires the application of effortful deliberation and rule-based reasoning.

As cognitive load increases with more information processing and decision-strategy complexity, it is expected that perceived decision effort increases. For example, objective mental workload measured by EEG in an experiment was shown to increase perceptions of effort and fatigue (Käthner et al. 2014). Similarly, other eye tracking and pupillometry studies showed that higher complexity of software coding and cognitive load leads to higher levels of fatigue (Sharafi et al. 2015). Similar results were found in a study of phishing susceptibility (Zhuo et al. 2024).

It is expected that increased deliberation as reflected in VPC will likely increase how e-commerce users perceive the effort they exerted to make a decision in the same way it does in other domains. Thus:

H7: Higher Visual Perceptual Comprehensiveness is associated with higher Perceptions of Decision Effort in e-commerce tasks

3.3 Summary

Age and cognitive style the exogenous constructs of focus in this e-commerce study, while objective and subjective decision quality and cognitive effort are the endogenous constructs of focus. VPC is introduced as a composite construct that attempts to explain the relationship between these variables in the context of e-commerce decisions. Age is expected to negatively impact VPC, while maximizing is expected to positively impact VPC while negatively moderating the negative impact of age on VPC. VPC is hypothesized to positively impact actual and perceived decision quality and cognitive effort. The research model is empirically validated through a mixed-methods experimental study described in ***Chapter 4***. The study results are outlined and discussed in ***Chapter 5***. In ***Chapter 6***, the theoretical, methodological, and practical contributions of the study are outlined; and the limitations of the study are acknowledged.

4 Research Methodology

A mixed-factorial experimental design was used to test the hypotheses and address the research objectives, utilizing quantitative and eye tracking methods as described in this section. Data collected in each experimental session involved a series of multi-alternative multi-attribute e-commerce decision tasks in a carefully controlled setting.

4.1 Exogenous Variables and Experimental Design

The three independent variables in this study comprise two individual difference factors of age (i.e., younger adults, older adults), cognitive style (i.e., satisficers, maximizers), and decision cognitive biases (i.e., vividness bias, order bias, control/no bias). A controlled e-commerce experiment was conducted using a 2 x 2 x 3 mixed-factorial design. Operationalization of these independent variables and experimental procedures are explained next.

4.1.1 Age

The first factor, Age (chronological), was measured as a dichotomous variable following Tams (2017) in which participants were either young adults (i.e., ages 18-39) or young-older adults (i.e., ages 60-74) as outlined in ***Table 7***. Age groups were categorized following the gerontology and psychology literature recommendations as discussed earlier in ***Section 2.5.2***. The middle-aged adults group (ages 40-59) was not examined for feasibility reasons as they are not the focus of this study, in addition to evidence from the literature regarding lack of sufficient differences in eye tracking behaviour compared to the young adults age group (Bergstrom et al. 2014). The old-old age group (i.e., ages 75+) were also excluded from this study for reasons related to difficulty in recruiting participants from this age group for lab experiments due to mobility limitations as well difficulty in calibration with the eye tracker due to declines in visual acuity.

4.1.2 Cognitive Style

The second factor, Cognitive Style, was measured using the well-established 13 items maximization scale (on a 7-point Likert scale, items are listed in ***Table 8***) introduced by Schwartz et al. (2002) and validated numerously (Barta et al. 2023; Karimi et al. 2015; Love 2009; Misuraca and Fasolo 2018; Parker et al. 2007), in which a composite score for each participant was calculated and a median split was used to categorize participants as either maximizers or satisficers (Iyengar et al. 2006; Karimi et al. 2015; Love 2009; Schwartz et al. 2002).

Table 8: Description and Measurement Items for Cognitive Style

Construct	Description and Measurement Items
Cognitive Style	Maximization Scale (7-points Likert scale) places participants on a Maximizer – Satisficer continuum; median is used as a threshold cut-off value to categorize participants (Iyengar et al. 2006; Karimi et al. 2015; Love 2009; Schwartz et al. 2002). The following items are adapted from Schwartz et al. (2002) and updated to reflect contemporary contexts.
1. When I watch TV or Netflix, I channel surf, often scanning through the available options even while attempting to watch one program. 2. When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to. 3. I treat relationships like clothing: I expect to try a lot on before I get the perfect fit. 4. No matter how satisfied I am with my job, it's only right for me to be on the lookout for better opportunities. 5. I often fantasize about living in ways that are quite different from my actual life. 6. I'm a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.). 7. I often find it difficult to shop for a gift for a friend. 8. When shopping, I have a hard time finding clothing that I really love. 9. Renting or streaming videos is really difficult. I'm always struggling to pick the best one. 10. I find that writing is very difficult, even if it's just writing an email or message to a friend, because it's so hard to word things just right. I often do several drafts of even simple things. 11. No matter what I do, I have the highest standards for myself. 12. I never settle for second best. 13. Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment.	

4.1.3 Cognitive Bias

The third factor, Cognitive Bias, is measured within subjects. The factor has three within-subject levels administered over three experimental tasks. First, a no bias control condition in which all task alternatives were presented in random order without any manipulation of saliency. The two other conditions included the manipulation of two e-commerce tasks' alternatives to induce the Order and Vividness biases. For the Vividness Bias condition, low quality alternative product pictures were very colourful and bright compared to the greyscale pictures of other alternatives. For the Order Bias (Primacy Effect) condition, alternatives were listed sequentially from the worst to the best quality. Task design and manipulations are discussed in ***Section 4.2***. For each participant, the experimental session included one training task and three experimental e-commerce tasks for the three bias conditions, and the sequence of the tasks/biases was counterbalanced between subjects.

To summarize, four independent groups of participants will be required, as illustrated in *Table 9*.

Table 9: Summary of the Experimental Design and Participant Groups

Cognitive Bias Within-Subjects		(Vividness, Order, No Bias Conditions)	
	Age	**Young Adults**	**Older Adults**
Cognitive Style	**Satisficers**	1. Younger Satisficers	2. Older Satisficers
	Maximizers	3. Younger Maximizers	4. Older Maximizers

4.2 Experimental Procedures

Younger and older adults were invited to participate in this study in a controlled lab environment in the Evidence-Based Decision-Making labs at the McMaster Digital Transformation Research Centre (MDTRC). Participants were first briefed on the experimental procedures for the session and had a chance to read and sign the letter of information and consent. Participants were then asked to follow the eye-tracking calibration procedure, then fixate on a cross for 10 seconds to collect their baseline physiological data. The details of the lab environment and experimental procedures are outlined in ***Appendix 8.8***.

After the calibration of the research equipment was successful, the eye tracking software (Tobii Studio Pro) launched a web browser (Firefox) to the study's website which included the digital survey and the research tasks. Participants were then asked to complete the survey comprising the questions and measurement scales for the independent (i.e., Age, Cognitive Style) and control variables (e.g., e-commerce experience.) Participants were then instructed to perform the three e-commerce decision tasks on a designated desktop computer, preceded by a training task to familiarize them with the procedure and task cycle. Each task cycle included a pre-task control variable survey (e.g., product knowledge), followed by the experimental task, followed by a task specific endogenous variables survey (e.g., Perceived Decision Effort). The experimental paradigm is outlined in ***Figure 5***.

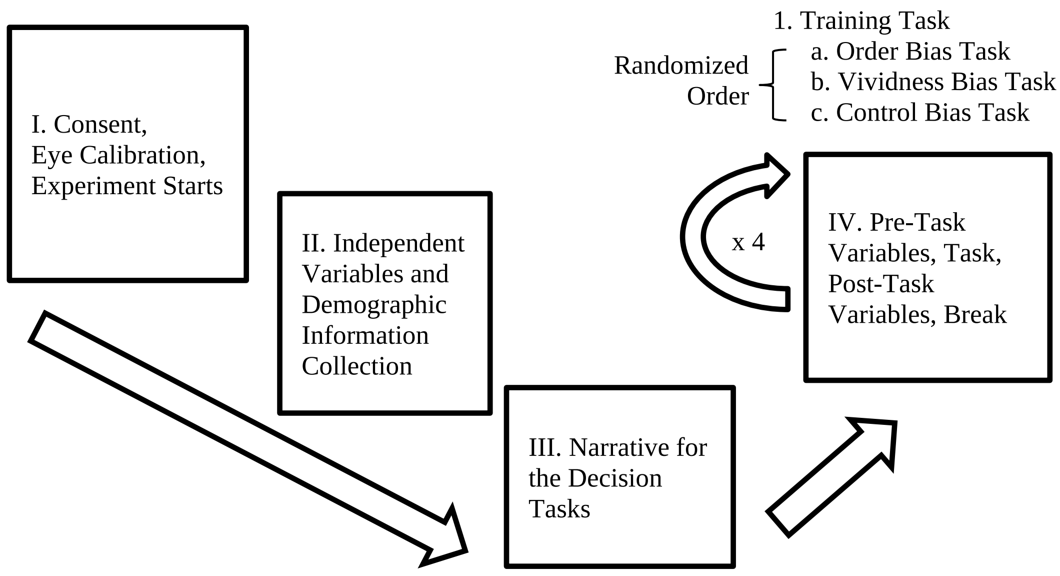


Figure 5. Experimental paradigm for study. Box number IV represents the within-subject cognitive bias decision tasks, so this is repeated four times

4.3 E-Commerce Task Design

The e-commerce tasks followed standard research designs in the IS and psychology bodies of literature with several modifications to suit the current research objectives (Calic et al. 2020; Häubl and Trifts 2000; Olson and Widing 2002; Tan et al. 2010, 2012; Wang and Benbasat 2009; Xu et al. 2014). The four products that were selected for the e-commerce tasks are: ***stove, TV, refrigerator***, and ***washing machine***.

These products were selected for several reasons. First, they are common products that are available in most households, and most subjects regardless of treatment would be most likely familiar with their features (Tan et al. 2010). Second, these products are age and cognitive style agnostic, in that they are likely used by individuals for the same purposes regardless of age or cognitive style. Third, these are durable products that require high decision commitment as they last for a long time increasing the realism of the experiment, and they are not likely to be frequently purchased by the same individual ensuring that all participants have more or less similar experience in purchasing them. Fourth, they come from the top two product categories (i.e., consumer electronics, household appliances) that consumers prefer to research online the most, at 66% and 47%, respectively (Statista 2019), and that are expected to respectively comprise 8.9% and 6.6% (15.4% altogether) of total e-commerce sales (excluding food) by the end of 2025

(Statista 2025b). Fifth, they have sufficiently complex attributes that could be varied to serve the objectives of the experiment to generate the decision task alternatives and consideration sets. Finally, these attributes are comparable across these different products to a certain extent. This helps ensure that possible confounding effects are avoided by achieving consistency in the decision complexity across the three tasks. Alternatives were procedurally generated via a developed algorithm by the systematic variation of seven product attributes as shown in ***Table 10***. This algorithm is discussed later in ***Section 4.3.4***.

Table 10: Products and Attributes* for the E-Commerce Tasks

#	Attribute	Levels	Stove	TV	Refrigerator	Washing Machine
1	**Price**	5	$499.99 to $2,999.99 $250 increments			
2	**Size**	5	**Dimension** > 32” to < 24” 2” increments	**Dimension** > 74 to < 24 5” increments	**Capacity** > 28 to < 8 5 cu. ft. increments	**Capacity** > 5.7 to < 3.5 0.5 cu. ft. increments
3	**Feature A**	3	**Capacity** 5 cu. ft. 4 cu. ft. 3 cu. ft.	**Resolution** 2160p (4K/Ultra HD) 1080p (Full HD) 720p (HD)	**Ice Maker** Water and Ice Cubes Water Only None	**Noise Rating** Quiet Low Noise Moderate Noise
4	**Warranty**	3	3, 2, and 1 Years			
5	**Energy Saving**	3	High, Medium, Low			
6	**Smart**	2	Yes, No			
7	**Feature B**	2	**Self Cleaning** Yes No	**Sound System** Mini-Theater Hi-Fi	**Freezer** Yes No	**Dryer** Yes No

*Attributes are listed from best to worst

4.3.1 Controlling Decision Complexity

Decision complexity and cognitive load are usually manipulated by varying the choice set size (i.e., number of alternatives) and attribute complexity [i.e., number of attributes and levels (Tan et al. 2010, 2012; Wang and Benbasat 2009)]. Thus, controlling difficulty is critical in order to measure cognitive load and avoid any possible confounding effects as a result of high task and webpage design complexity or differences in decision difficulty between participants and tasks (Buettner 2017; Wang et al. 2014).

4.3.1.1 Number of Alternatives

The number of alternatives utilized to create a decision task under normal conditions varies widely in IS research. Alternatives range from as low as a handful (Arnold Kamis et al. 2008; Huang and Kuo 2011), to the 50s (Häubl and Trifts 2000; Xu et al. 2014), to the hundreds (Tan et al. 2010), and as high as thousands (Tan et al. 2012). Increasing the number of alternatives does add to the realism of the experiment. However, a large choice set may influence subjects' decision strategy choices and drive them to be less exhaustive. Additionally, fewer alternatives can allow for better experimental control, particularly with the involvement of eye tracking methods. Eye tracking analysis is laborious and time consuming, and standardization can be extremely beneficial for improving experimental controls and facilitating the analysis of data (Duchowski 2007; Riedl and Léger 2016). Thus, 10 alternatives would strike a reasonable trade-off between mundane realism and experimental control (Tan et al. 2010), which will ultimately enhance the ecological validity of the findings. This was verified in the pilot study discussed later in ***Section 5.1.2***.

4.3.1.2 Number of Attributes and Levels

Additionally, the attributes themselves were carefully selected to avoid any emotion-laden features, as these may induce an imaginability bias, a memory category bias also emanating from the Availability Heuristic (Arnott 2006; Bazerman and Moore 2009; Bhandari et al. 2006), which may contaminate the study results by taxing users' cognitive capacity. For example, the airbag option when buying a car as a safety feature is an emotion-laden attribute that induces imaginability of a risky situation that would influence the decision-maker weighing of attributes (Drolet and Frances Luce 2004; Peters et al. 2007).

Since the average individual can on average handle seven bins of information categories in their working memory at a time (Ghasemaghaei et al. 2019; Miller 1956), seven attributes per alternative is common in decision task designs with normal cognitive load conditions (Ghasemaghaei et al. 2019; Häubl and Trifts 2000; Tan et al. 2010; Wang and Benbasat 2009).

The range and levels of attributes (shown in ***Table 10***) was determined by studying the products available in the top most visited e-commerce sites (see ***Appendix 8.5***). Attributes and their levels were selected to be subjectively and practically as similar or as close to each other as possible across the four products.

Decision sets were created by procedurally generating 10 alternatives via an algorithm developed for this study, by varying these attribute levels for each product category. The method of generating the alternatives relied on an algorithm that was developed to control decision difficulty and other confounding factors (e.g., participant personal affluence and budget preferences). This algorithm is discussed later in ***Section 4.3.4***.

4.3.1.3 Branding and Product Pictures

To avoid brand-related biases, brand names and logos were not included as attributes (Häubl and Trifts 2000; Tan et al. 2010), and only neutral stock images without branding were used for the alternatives. 10 almost identical pictures for each product category were selected to avoid bias, except for three of the ten TV pictures that were modified to show colourful screens to induce the Vividness Bias. All 40 pictures (10 for each product category) are listed in ***Appendix 8.9***.

4.3.1.4 Summary

There are many potential biases and confounding factors that can manifest in an e-commerce decision task experiment. This is a study that focuses on cognitive-biases, and while it is impossible to control for all potential biases and confounding factors, extreme care was taken to control as many biases and factors as possible to the best of the researcher's ability. To the best of our abilities, extreme care was taken to isolate and induce the two biases under investigation separately while removing any others that may contaminate the results. Additionally, a novel algorithm was developed to equalize decision difficulty across participants despite differences in personal product attribute preferences. This algorithm is discussed later in ***Section 4.3.4***.

4.3.2 Experimental Protocol

Participants were provided with a narrative for the decision tasks then familiarized with the four products (i.e., stove, TV, washing machine, refrigerator). The stove task was used to train participants on the user interface and the task cycle (***Figure 5***) that was repeated for the other three product tasks for the three conditions.

Participants were first asked to imagine that they will be moving to a new home and that they need to purchase four household products and appliances. This is consistent with other e-commerce research to induce higher levels of mundane realism (Tan et al. 2010) by simulating a real-life context (Häubl and Trifts 2000; Tan et al. 2010, 2012).

Participants were then asked to set their median budget for the product then indicate the weight of each of the product's seven attributes based on their personal preference. They were informed that the reason a median budget is the middle range of their budget, and was used is because the results will include alternatives with prices varying around that median, both slightly cheaper and more expensive products. A participant mentioned that "… it was really helpful to see the full range of prices that I will see when I set my budget on this screen…". Participants were warned that they cannot change those budget or weight settings when they proceed to the product selection page and were asked to confirm their inputs. Once they clicked submit, the algorithm (outlined in ***Section 4.3.4***) procedurally generated a list of 10 alternatives based on the personal attribute weighting settings for the participant, ensuring that all participants had a consideration set of alternatives with equivalent decision difficulty that's consistent across tasks and participants.

The instructions and preference elicitation screens are illustrated in ***Figure 6***.

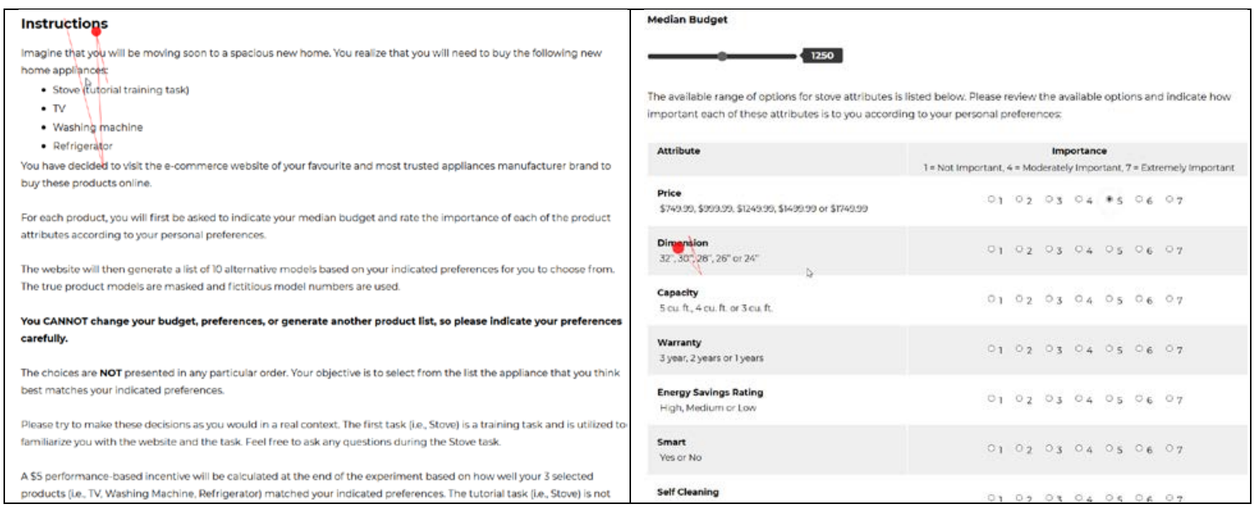


Figure 6: Design for the Task Instructions (left) and Preference Elicitation (right) screens

4.3.3 Real Market Data for Task Realism

For each of the product categories, participants were asked to specify their median personal budget for the product. They were informed that the system will recommend products within a reasonable range of that budget, including varying attributes and slightly higher or lower prices, based on the available products and their criteria preferences. Participants also rated each product through a preference elicitation dialogue

(Tan et al. 2012; Wang and Benbasat 2009). Participants were warned that once they provide their preference and proceed to the decision task screen, they cannot go back and change those preferences.

To simulate a realistic decision set, the range of the product size criterion (e.g., TV dimensions) procedurally generated by the algorithm (discussed in ***Section 4.3.4***) varied dynamically as the user modified their budget, similar to Xu et al. (2014). To simulate a further realistic decision task, the researcher based this variability on real marketplace data. Data from hundreds of products listed on BestBuy.ca[5] was scraped and analyzed it to measure the relationship between product prices and size. ***Figure 7*** illustrates the fit plot regression analysis for the relationship between TV prices and sizes. Each data point represents a real TV model for sale at BestBuy, with the price indicated on the x-axis, and the size (i.e., dimensions in inches) indicated on the y-axis. A regression analysis was done to fit a line through the data and calculate how much price varies by size. The resulting regression equation was used in the experimental algorithm (see ***Section 4.3.4***) to procedurally generate realistic results. Similar analysis was done for the other appliances. As a result, participants were presented with representative decision sets including realistic budgets and their corresponding prices and attributes for each product.

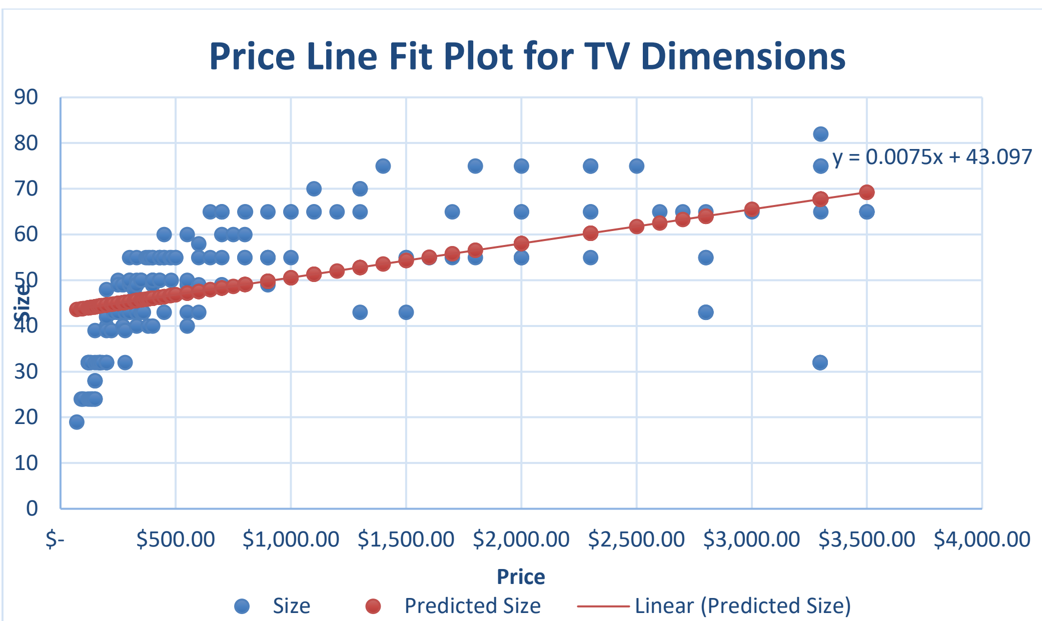


Figure 7: Regression Analysis for TV size and price, used as a basis for generating realistic recommendations

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[5] Accessed February 24th, 2018

Initially, the default budget was set as the median of the available set of prices for each product based on the market data. Participants can move a slider to change their budgets in steps of $250, starting at the median price. The set of product prices and sizes from the generated list of alternatives varied based on real marketplace information as follows. Each price point has a corresponding product size depending on the regression data. Each budget increment step generated products varying in product price and size to include sizes at the median, and up to two steps higher and down to two steps lower than the median. These represent the five ranked levels of the two product attributes (i.e., price, size) that are used to simulate realistic decision sets.

To demonstrate how this works, an example is provided in ***Table 11***. In this example, a participant chose B ($1,249.99) on the median budget slider. If they proceed to the decision task, the range of prices for alternative in the decision task will be from $749.99 – $1,749.99 which are ranked from lowest and best (price: $749.99, rank: 1) to highest and worst (price: $1749.99, rank: 5), respectively. These prices in real marketplaces happen to correspond to the TV dimensions 49" – 56" which are ranked from smallest and worst (dimension: 49", rank: 5) to largest and best (dimension: 56", rank: 1), respectively. The interface provides the range of prices and dimensions to the participants. However it does not provide these ranks to the participants. Participants are able to compare and consider these values as part of their decision making process.

Table 11. Visualization of the budget decision and the resulting range of prices and dimensions for TVs

Participant Price Slider Options	**N/A**		**A**	**B**	**C**	**D**	**E**	**F**	**G**	**N/A**	
TV Prices	499.99	749.99	999.99	1249.99	1499.99	1749.99	1999.99	2249.99	2499.99	2749.99	2999.99
Price Ranks		1	2	3	4	5					
Corresponding TV Dimensions	47"	49"	51"	52"	54"	56"	58"	60"	62"	64"	66"
TV Dimensions Ranks		5	4	3	2	1					

If the participants were to move the slider and change their preferred median budget to E ($1,999.99) and proceed to the decision tasks, the following changes will happen as illustrated in ***Table 12***. The range of prices for alternative in the decision task will be from $1,499.99 – $2,499.99 which are ranked from lowest and best (5) to highest and worst (1), respectively. The range of generated TV dimensions, as per real market data, will range from 49" – 56" which are ranked from smallest and worst (1) to largest and best (5), respectively. The same logic applies to all other products.

Table 12. Visualization of the changes in prices and dimensions of TVs by changing the median budget to E

Participant Price Slider Options	N/A		A	B	C	D	E	F	G	N/A	
TV Prices	499.99	749.99	999.99	1249.99	1499.99	1749.99	1999.99	2249.99	2499.99	2749.99	2999.99
Price Ranks					1	2	3	4	5		
Corresponding TV Dimensions	47"	49"	51"	52"	54"	56"	58"	60"	62"	64"	66"
TV Dimensions Ranks					5	4	3	2	1		

The resulting price and size changes for generated alternatives is purely cosmetic, just to simulate a realistic decision set for the task and the participant, giving them the impression that budget impacts size as it does in real marketplaces. However, what is used in determining how each alternative fits the participant best (fit score, discussed in ***Section 4.3.4***) and the decision quality is the relative rank of each of the five listed prices to control variation in affluence and budget preferences between participants. The rankings of the five levels of the two attributes (i.e., price, size) simply move with the slider and applies to whichever price range corresponds to the median budget.

In addition to the preferred median budget, the preference elicitation dialogue also displays a list of the product attributes and their possible values. These values (e.g., HD) are unique for each product (e.g., TV) and attribute (e.g., Feature A) as outlined in ***Table 10***. Unlike size, they are static and do not change as a factor of any other variable. For each product, each attribute value (i.e., level) has a unique ranking, which is also used to calculate decision quality in the following section. For example, the TV Resolution attribute has the following three levels: 2160p (4K/Ultra HD), 1080p (Full HD), and 720p (HD). The first level is the highest quality, best, and dominant level. Thus, all participants would prefer it over the other two levels and it's assigned the highest rank (i.e., 1). While 720p (HD) is the worst quality and least favourable of the three levels to all participants. Thus, it's assigned the worst rank (i.e., 3).

Participant were required to rate the importance of each attribute on a 7-point scale. Once the participants confirm their preferences, they will advance to the recommendations page to make a decision.

They are warned that if they choose to proceed from the preference elicitation screen to the decision task screen, they cannot go back or modify their preferences beyond this step, since this is a limitation of the eye-tracking software and how the experiments can be designed within it. Participants are required to confirm again that they want to proceed.

4.3.4 Algorithm for Generating a Recommendation Set

The novel algorithm I developed for this study procedurally generates 10 alternatives based on each participant's median budget and attribute weighting, which they provided as their personal preference in the preference elicitation page. It controls confounding factors (e.g., decision difficulty, affluence, budget preference) across participants. The rationale of the algorithm and how it generates the alternatives is illustrated with an example in ***Appendix 8.10***.

To further simulate a complex realistic e-commerce decision task, the generated list comprises 10 choices that have a good, but not perfect, fit to the participant requirements. They also relatively vary in terms of their attributes closely enough to simulate a realistic complex e-commerce task. Each of these alternatives is assigned a unique fit score relative and a unique rank relative to the participant's personal preference, such that every alternative is dominated by another except the most dominant and higher scoring alternative. These alternatives and their attributes are drawn randomly from sets of fit scores of potential alternatives ranging between 0.6 and 0.84, in 0.3 fit score increments, standardizing the task decision difficulty across participants. Participants are not given any information regarding the fit scores, the product rankings, or how the order and sorting of the results was determined.

For further realism, the algorithm also varies attribute values such that no alternative dominates the others on every attribute value, no alternatives with equal fit scores are generated, and the full range of every attribute (e.g., Smart: Yes and No; Price: all 5 levels) must be presented at least once across alternatives. This procedure ensured that regardless of task, participant, or unique product preference; the decision was equally complex and standardized across tasks and participants. The range of fit scores for alternatives was consistent across participants and tasks, and every task has equally variable products that match different participant requirements. The algorithm ensures that the generated list of alternatives in each experimental task will always have 10 products the are uniquely scored and ranked to fit each participant. The fit score and rank of the alternative that each participant chooses determines their decision quality as explained in ***Section 4.4.2***. To the best of my knowledge, this is the first algorithm of its kind to be used in an e-commerce experiment.

4.3.5 Algorithm Results: The Decision Alternatives Page

As discussed in ***Section 4.3.1.3***, product models and brand logos were removed to avoid brand effects, and the 10 neutral product pictures were randomly assigned to the 10 alternatives in the consideration set. The exception was the three Vividness Bias inducing TV pictures, which were assigned to specific alternatives depending on their ranks as explained in ***Section 4.3.6***.

The 10 alternatives were provided in a continuous list view following common e-commerce website designs, and no RA or DSS affordances were provided. The 10 alternatives were displayed in 1 page, eliminating the need for navigation to different pages, to facilitate and simplify the task for the participant and the eye-tracking data analysis for the researcher. The display size of the screen was 21” and the resolution was set to 1920 x 1080 pixels for all participants for consistency (Tobii 2016). At this resolution, the page was designed to show 2 full results (i.e., alternatives), partial info on the third result, and a scroll bar. Thus, participants knew that there are more results on the page. This was complemented by a result number label (e.g., result 1 of 10). The participant needed to scroll down to evaluate alternatives placed lower in the list. The sorting order of the alternatives is also dependent on the cognitive bias manipulation for the task, which is discussed in ***Section 4.3.6***. The alternatives were listed sequentially form top to bottom in one column, and no product were listed next to each other despite the available space on this screen. This was to avoid confounding effects of primacy between top-bottom and left-right order and to ensure that the order bias is unidimensional. The text was large enough for readability to all participants without the need for assistive technology (e.g., magnifier) and to allow the accurate collection of eye-fixation data with high spatial precision. The design of the decision task page follows standard filtering RA designs in e-commerce and is provided in ***Figure 8***.

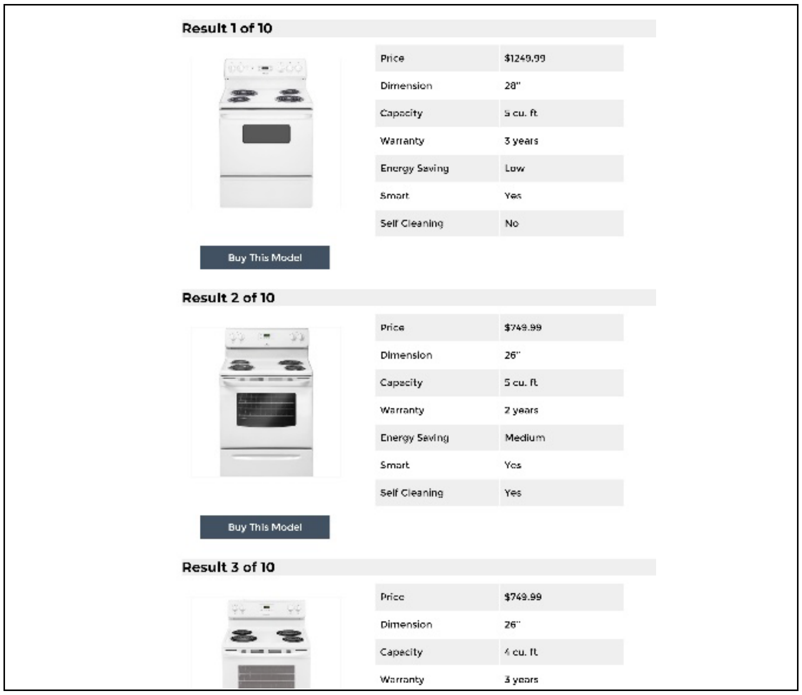

Figure 8: The design of the results page for the multi-alternative multi-attribute e-commerce decision task.

4.3.6 Bias Manipulations

In the Order Bias (i.e., Primacy Effect) condition task (i.e., washing machine), alternatives were sorted based on their fit score, sorted from those with the lowest fit score (i.e., worst alternative) at the top of the screen to the highest and best alternative at the bottom of the screen (i.e., ascendingly). This is also similar to standard order bias inducing tactics in e-commerce (***Appendix 8.7***).

In the no bias control condition (i.e., refrigerator) and the vividness bias condition (i.e., TV), alternatives were randomly sorted. For the Vividness Bias condition manipulation, the product pictures displayed on three Vividness Bias inducing alternatives were modified to be vibrant and colour rich to increase their saliency, to bias and attract the bottom-up perceptual processes of the participant interfering with their top-down deliberate decision strategy. This is consistent with common saliency tactics that are used in e-commerce websites (***Appendix 8.6***). These three of the 10 pictures of the TVs displayed a unique and colour rich picture on the TV display to attract visual attention, instead of a bland blue screen displayed on the other seven TV alternatives (see ***Figure 9*** for a sample, and ***Appendix 8.9*** for the full set). For consistency, the three alternatives that were assigned the Vividness Bias inducing pictures are the 4th, 6th, and 8th best ranking alternatives for each participant. Thus, they are neither the best nor the worst performing alternatives in the set but are equally low-quality alternatives relative to all participants ensuring that the bias manipulation reduces decision quality as intended.

 4th, 6th, and 8th top fit results with a picture	 All other 7 results without a picture
Vividness Bias inducing	Not bias inducing

Figure 9. Sample of the Vividness Bias TV Display Manipulation

The three cognitive bias tasks and their manipulations are summarized in ***Table 13***, preceded by a training task that was identical for all participants as explained earlier in ***Section 4.3.2***.

Table 13. Task Manipulations to Induce Cognitive Biases

Cognitive Bias	Product	Manipulation
Training	Stove	A randomly drawn set of alternatives that was identical for all participants
Vividness	TV	Order: Random Vivid product images for specific models (4th / 6th / 8th highest fits)
Order	Washing Machine	Order: Worst/lowest fit (top) to best/highest fit (bottom) Neutral product images
No Bias	Refrigerator	Order: Random Neutral product images

4.4 Endogenous Variables Operationalization

4.4.1 Visual Perceptual Comprehensiveness

As discussed in ***Section 2.7.2***, VPC is proposed as a composite objective measure of Decision Process in the conceptual framework. The underlying latent phenomenon of interest is the specific cognitive effort components and steps exerted by the individual towards making a decision. Building on the theoretical discussion earlier, the two measures identified for VPC are the breadth and depth of information-seeking behaviour (Huang and Kuo 2011). The relationship between VPC and its indicators implies that VPC is a formative construct because (i) the causal relationship is from the indicators to the construct; and (ii) the indicators may not necessarily correlate (Cenfetelli et al. 2009; Petter et al. 2007). The two indicators of VPC are operationalized by performing calculations utilizing some of the commonly utilized eye-tracking metrics described in ***Appendix 8.11***. Eye tracking methods are discussed in more depth in ***Section 4.5***.

With regards to the selection of fixation-derived metrics to compute VPC, the number of fixations is used to compute breadth of information search, while fixation duration is more appropriate for depth of search. Fixation frequency metrics can be problematic and have conflicting interpretations in terms of deliberation (Duchowski 2007; Poole and Ball 2006; Sharafi et al. 2015). For example, a major distinction must be made with regards to total fixations between amount of inspected information and repeated fixations. Fixations increase with increased breadth of information inspected as well as repeated information inspections (Duchowski 2007; Horstmann et al. 2009). A larger amount of information inspected reflects a more deliberative and effortful decision strategy, where more information is utilized in the decision-making process. On the other hand, repeated information inspections and fixations can either be indicative of exhaustive decision processes in which information is repeatedly compared (Horstmann et al. 2009), or it can be indicative of poor information quality (Duchowski 2007) or a failure by the decision-maker to retain the information in memory for future comparison where fixations are utilized as an external memory space (Droll and Hayhoe 2007; Orquin and Loose 2013). Thus, fixation frequency is more appropriate to calculate the breadth of information sought, while durations are more appropriate for comparing deliberation across alternatives. This is consistent with Huang and Kuo's principle component analysis of eye metrics (2011), in which two higher order eye behaviour factors were found (i.e., breadth of research with fixation frequency metrics, depth of processing and deliberation using fixation duration metrics).

Additionally, this study is interested in comparing the decision-making performance between two age groups that vary in terms of cognitive fluid and crystalized abilities (adult cognitive abilities are summarized and defined in ***Appendix 8.12***), where these differences vary across groups and within individuals in each group (Bruine de Bruin et al. 2012), which might influence eye tracking metrics.

4.4.1.1 Breadth

The first indicator of VPC is **breadth** of information-seeking. Breadth is calculated based on the amount of information attended to as a proportion of the full information available. The information available is constrained to the product-relevant information, which are the product attributes. Information is considered attended to if it was fixated for at least once. The following formula is used to calculate Breadth:

$$\boldsymbol{Breadth} = \frac{\boldsymbol{Information\ Attended}}{\boldsymbol{Information\ Available}}$$

$$0 \leq \boldsymbol{Breadth} \leq 1$$

Equation 1: Breadth of Information-Seeking

4.4.1.2 Deliberation

The second indicator of VPC is **deliberation** of attended information. This is a reflection of the depth and exhaustiveness of information processing. Deliberation is a factor of time spent evaluating attended information towards making a decision. Thus, deliberation is calculated as the total fixation duration for product-relevant information. Information such as titles and navigation cues are not specifically relevant to the task but are more guidelines for browsing and navigating.

4.4.2 Decision Quality

In the conceptual framework, Decision Quality (DQ) is utilized as an objective decision outcome measure. For each task, the generated 10 alternatives were ranked based on their fit score. The quality of the decision is measured as the distance in ranking between the fit score for the chosen alternative and the fit score for the best possible alternative in the set (Tan et al. 2012). DQ will be calculated as:

$$\boldsymbol{DQ} = \frac{(10 - Rank\ of\ Chosen\ Alternative)}{(\ 10 - 1\ )}$$

$$0 \leq \boldsymbol{DQ} \leq 1$$

Equation 2: Decision Quality

4.4.3 Perceived Decision Quality

Perceived Decision Quality is a subjective Decision Outcome measure in the conceptual framework. It was measured using a scale validated in previous IS research as shown in ***Table 14***.

Table 14: Description and Measurement Items for Perceived Decision Quality

Construct	Description and Measurement Items
Perceived Decision Quality	Perceived Decision Quality , adapted from Xu et al. (2014) and Tan et al. (2010). The items were modified to fit the product for each task.
1. I believe I have made the best choice at this website. 2. I would make the same choices if I had to do it again. 3. I believe I have selected the best [TV]* model.	

*The product between box brackets will vary appropriately depending on the task

4.4.4 Decision Effort

Decision Effort is the objective amount of effort exerted by the participant to complete the task, which is a Decision Outcome variable. There are numerous methods in the extant literature to measure objective decision effort. The most straightforward method is to use Decision Time as a proxy or indicator of Decision Effort (Glaholt and Reingold 2011; Rydzewska et al. 2024; Xiao and Benbasat 2014). While there is a significant correlation between the two variables, the correlation coefficients are typically only in the medium range (Wang and Benbasat 2009). This is to be expected given that Decision Time can be influenced by many other factors (e.g., language proficiency, reading and comprehension skills, vision acuity). This study will utilize Decision Time as the objective measure for Decision Effort.

Other objective measures of Decision Effort include Pupil Dilation and EEG. Under equiluminant and equidistant conditions, pupils dilate as function of the ANS response to cognitive effort and strain (Duchowski et al. 2018; Kahneman 2011; Kahneman and Beatty 1966; Piquado et al. 2010). For EEG, parietal oscillations in the Alpha band (i.e., 8 Hz to 13 Hz) are associated with low cognitive effort, while prefrontal-cortex oscillations in the Theat band (i.e., 4 Hz to 8 Hz) indicate high load and strain (Cavanagh and Frank 2014; Kahana 2006; Williams et al. 2019). These methods are not utilized in this study.

4.4.5 Perceived Decision Effort

Perceived Decision Effort represents another subjective Decision Outcomes measure outlined in the conceptual framework. It was measured using a scale validated in previous IS research as shown in *Table 15*.

Table 15: Description and Measurement Items for Perceived Decision Effort

Construct	Description and Measurement Items
Perceived Decision Effort	Perceived Cognitive Effort, adapted from Pereira (Pereira 2000), Wang and Benbasat (2009), and Xu et al. (2014). The items will be modified to fit the product for each task.
1. The task of selecting a [TV]* using this recommendation agent took too much time 2. The task of selecting a [TV]* using this website was very easy (reversed) 3. Selecting a [TV]* using this recommendation agent required too much effort 4. The [TV]* selection task that I went through was too complex	

*The product between box brackets will vary appropriately depending on the task

4.5 Eye Tracking

4.5.1 Eye Trackers and Experimental Procedures

Tobii Pro X2-60 was the eye-tracking system available in the Evidence-Based Decision-Making Labs at MDTRC at the time of data collection for this study. The tracker is shown attached to the display in ***Figure 10***. The system is unobtrusive, standalone, and remote (i.e., no contact with the participant). The tracker uses infrared diodes or LEDs to generate reflection patterns on the corneas of the participants' eyes. These reflection patterns, together with other visual data about the participants, are collected by the device's image sensors at 60 Hz (i.e., data points per second), and allow it to accurately calculate the participants' gaze point and pupil size with high temporal and spatial precision. Its large head movement box allows the subject to move during recording while maintaining accuracy and precision. The eye trackers provide a rich stream of data (e.g., saccadic movements, gaze points, pupil dilation). The system is commonly used in eye tracking research publications and poses no risks to participants beyond those of daily life.

Figure 10: Tobii Pro X2-60

Two steps were performed for eye tracking calibration. First, participants were asked to wear their corrective lenses (mono-focal only), if required, at the start of the experimental session. For best gaze data accuracy, participants were asked to be comfortably seated around 63 cm away from the display, which is the optimal distance for highest gaze point accuracy (Tobii 2016). The recording and analysis software (i.e., Tobii Pro Studio) was used to guide the adjustments to the seat, display height, and footrest for optimal distance and comfort for participant's posture (see ***Figure 11***).

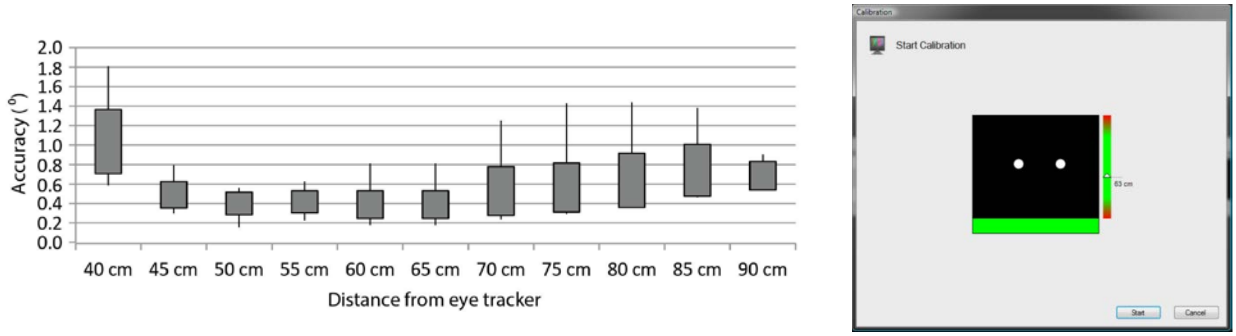

Figure 11: Optimal Distance from Eye Trackers (left) and Software Guidance for Distance (right)

The second step was to calibrate the eye tracking system with the participant eye gaze direction and the screen coordinates. This is achieved by asking the participant to fixate, and follow with their eye gaze, a red circle moving on a white blank screen. Recalibration of some points is sometimes necessary (see ***Figure 12***). The experiment commenced once calibration is successful. This process on average took about 3 minutes.

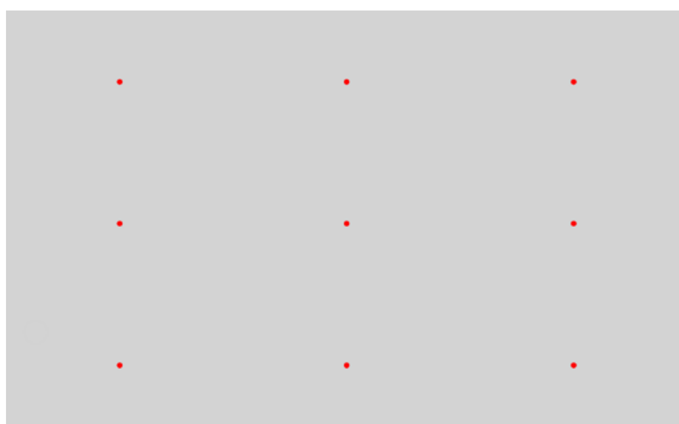

Figure 12: Calibration Test Screen

4.5.2 Eye Calibration Confirmation Screen

This step was done to confirm the success and accuracy of the eye tracking calibration test. After the eye-tracking calibration process, participants were then asked to fixate and focus on a black cross at the centre of a white screen (***Figure 13***) while relaxing. The cross was displayed for around 10 seconds. It served as a confirmation that the calibration was successful, as the researcher could check whether the participant gaze-point overlay was appropriately located over the fixation cross using the live viewer in the software. If not, the calibration process was restarted early on in the data collection process to avoid loss of valuable data due to poor quality. This also helped identify some participants who did not disclose important eye health related information that would have excluded them from the research as discussed below in ***Section 5.1.3***. Gaze data for such participants with problematic or erroneous calibrations was excluded from eye-tracking-related analyses.

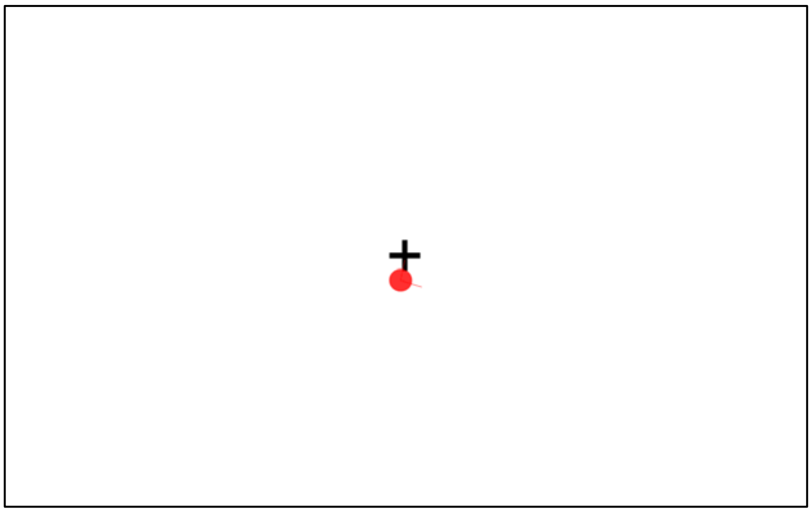

Figure 13: Baseline Fixation Cross

4.5.3 Task Sequence

After the initial survey described in ***Section 4.2***, participants were then asked to complete a training task (i.e., stove) to familiarize them with the experimental procedure and task cycle. Then they were asked to complete the three e-commerce tasks. An optional rest break between the tasks was offered for all participants. Experiment tasks' sequence was randomized across participants. Each was assigned to one of the 6 (i.e., 3!) testing sequences listed in ***Table 16*** at random. Balance of sequences across participants was maintained to minimize any presentation effects.

Table 16: Randomized Tasks Sequence

Sequence	Task 1	Task 2	Task 3
1	TV	WM	RF
2	TV	RF	WM
3	WM	TV	RF
4	WM	RF	TV
5	RF	TV	WM
6	RF	WM	TV

4.5.4 Analysis in Tobii Studio

Areas of Interest (AOIs) were utilized to categorize information on each page and perform quantitative analyses on oculometric data. AOIs are shapes that are overlaid on stimuli (e.g., product attributes, pictures) to define their locations for the analysis software (Tobii 2016). Using Tobii Studio guidelines, AOIs were defined for all product relevant stimuli (i.e., product images, product attributes). AOIs were also grouped by alternative to facilitate both attribute level and alternative level quantitative analyses (see ***Figure 14***).

Figure 14: Section of the product selection interface with the Areas of Interests (AOI) indicated in various colours and uniquely coded for quantitative analysis

The decision page for all tasks was designed such that all relevant stimuli and information coordinates on the screen are standard across and that there was no dynamic content. The sizes and coordinates of AOIs were standard and accurate to the pixel across alternatives, tasks, and participant sessions ensuring eye tracking data quality and accuracy. This explicitly followed Tobii Studio guidelines. Using AOIs and AOI groups, statistical analyses were performed on the ocular metrics (***Appendix 8.11***), and VPC and its indicators were measured accordingly.

4.6 Control Variables

Given the complexity of eye tracking methods and the time required for analysis, only the most relevant constructs in the nomological network are included in this study (Riedl and Léger 2016). However, several relevant control variables will be considered to statistically account for their influence on the dependent variables and to facilitate post-hoc analyses (Creswell 2009). These variables are summarized in ***Appendix 8.13***.

4.7 Study Design

A mixed-methods experiment was designed for this study. The experimental procedures and protocol were described, as well as the rigorous steps taken to ensure the validity of the results. This includes the development of a novel algorithm to control several confounding variables. The results of the experiment are outlined and discussed next.

4.7.1 Required Sample Size

To detect a medium effect size at high statistical power (i.e., $1 - \beta = 0.8$, $f = 0.25$) and α of .05, a minimum of 30 participants per cell are required (i.e., accounting for an additional 10% for incomplete experiments or data spoilage).

Participants were recruited from the Halton and Hamilton Region communities after screening for eye-related (see Verbal Screener Questionnaire in ***Appendix 8.14***) health issues that interfere with eye-tracking. These include eye implants, the need for bi- or trifocals, assistive technology, or assessing whether they suffer from other relevant diseases such as glaucoma, cataracts, permanent pupil dilation, diabetic retinopathy, and macular degeneration. Participants were invited to the Evidence-Based Decision-Making Labs at McMaster Digital Transformation Research Centre (MDTRC) to partake in the study.

Recruitment material included flyers, ads on the DeGroote School of Business information displays around campus, ads in the free “Coffee News” paper that is distributed across the local communities, social media posts, snowball sampling, MDTRC website ads, reaching out to participants in the MDTRC participant pool as well as the SONA pool for the School of Psychology, Neuroscience, and Behaviour at McMaster University, among others. Samples of the recruitment material are provided in ***Appendix 8.15***.

4.7.2 Pilot Study

A total of 17 participants were recruited for the pilot study and pre-tests. The purpose of the study was to validate the study design and measurement instruments as well as to identify and address challenges that may arise during the main study. For example, despite screening for age prior to recruitment, three participants revealed during the experiment that they were middle aged and thus were dropped from the analysis. This led to a revision of the phone screening questionnaire to emphasize the appropriate age brackets required for the study. The cognitive style score for the remaining participants was calculated by averaging their Likert-scale item scores. The mean score was ($M = 3.77$) and the median score was ($M_d = 3.84$) which is lower than those of typical cognitive style research (Barkhi 2002; Karimi et al. 2015; Love 2009), but is not unexpected given the small sample size. None of the cognitive style scale items were reverse-coded. The internal consistency reliability of the scale was assessed based on Cronbach's Alpha ($\alpha = 0.77$), exceeding the recommended threshold of (0.7). Dropping any item from the scale lowered the alpha value, thus all items were retained consistent with prior research such as Karimi et al. (2015). A median split was conducted to identify the cognitive style of participants. The results are illustrated in ***Table 17***.

Table 17. Cognitive Style by Age Group for the Pilot Study

		Cognitive Style		
		Satisficer Count	Maximizer Count	Total Count
CHR Age Group	Young Adults	3	3	6
	Older Adults	4	4	8
	Total	7	7	14

For the Perceived Decision Effort scale, item 2 was reverse coded which posed a problem. The Cronbach's Alpha of the scale was below the threshold and exceeded the threshold to ($\alpha = 0.84$) when the item was reverse coded and to ($\alpha = 0.85$) when the item was dropped. The same true for the other reverse coded item for the control variable Product Knowledge item 5. Thus, all initially reverse coded items were reversed for the main study moving forward.

5 Main Study and Results

5.1 Data Collection

5.1.1 Recruitment Challenges

One major challenge for this study was recruiting older adults. The eye-tracking screening process excluded many potential older adult participants, predominantly due to cataract disease or the need of bifocals. Several approaches to boost recruitment were utilized. First, recruitment was expanded to include an advertisement in the local newspaper "Coffee News" that is distributed for free at local shops (e.g., Tim Hortons). Second, sister research centres and institutions (e.g., Gilbrea Centre for Aging, McMaster Institute for Research on Aging) promoted the study to their participant base. Further, the recruitment compensation for the study was increased from $20 to $50, which significantly helped boost recruitment. Despite screening for eye tracking issues, some participants chose not to disclose them until issues were faced during the eye calibration or fixation cross stages of the study as discussed earlier. Upon discussions with these participants, it became clear that some participants, predominantly older adults, chose not to disclose these issues to avoid being screened out and losing the opportunity for the compensation. After months of struggling with these recruitment challenges, the COVID-19 lockdowns completely prohibited further collection of in-person data at research labs which led to the termination of the data collection phase of this study.

5.1.2 Accessibility & Inclusion Research Opportunity for IS

In addition to the recruitment challenges mentioned above, many older adults were willing but unable to participate in the study (prior to the COVID-19 lockdowns) due to several barriers including accessible transportation, financial, or physical barriers among others. These older adults would particularly benefit greatly from the advantages of using e-commerce to fulfill their daily needs. This benefits them particularly since they suffer from prohibitive disabilities, phenotypes, pathological diseases, or decreased motor functions that prevent them from being able to physically shopping at brick-and-mortar stores. Unfortunately, they were excluded from this study due to the aforementioned barriers. It's an unfortunate paradox. User groups who would arguably benefit the most from IS and UX research are excluded from said research. Thus, their different abilities, limited range of interactions, and needs are not taken into consideration when designing IS artefacts such as DSS.

This paradox inspired the author to conceptualize and develop an accessible mobile research lab that takes IS research to these disadvantaged groups in situ. Working with my mentors (i.e., Dr. Hassanein: co-founder and former Director of MDTRC, Dr. Head: co-founder and current Director of MDTRC), we secured funding for and established the Mobile User Experience Lab (MUXL) which launched in the Summer of 2023. This was after the conclusion of the data collection phase of this study, so the MUXL was not utilized for this research. This facility will allow researchers to collect more data, engage the community, as well as include many disadvantaged IS user groups that are otherwise unable to participate and reap the full benefit of IS research (El Shamy et al. 2024). See ***Appendix 8.16*** for more details about the project.

5.1.3 Participants

A total of 54 participants were recruited for the main study. The sample is slightly biased against women (almost 4:7 male participants). It is not clear why more men were motivated to partake in the study than women.

Tables 18, ***19***, and ***20*** below provide the descriptive summaries of the participants' demographics.

Table 18. Participants by Age Group and Gender

		Gender		
		Female	Male	Total
		Count	Count	Count
Chronological Age Group	Younger Adults	11	26	37
	Older Adults	8	9	17
	Total	19	35	54

Table 19: Participants by Highest Degree Achieved

		CHR Age Group		
		Young Adults	Older Adults	**Total**
Degree	None	0	0	**0**
	High School	4	8	**12**
	College	0	5	**5**
	Bachelor's	24	3	**27**
	Master's	9	1	**10**
	Ph.D.	0	0	**0**

Table 20: Participants by Occupation

		CHR Age Group		
		Young Adults	Older Adults	**Total**
Employment	Employed	4	4	**8**
	Homemaker	1	1	**2**
	Not Employed	0	0	**0**
	Retired	0	11	**11**
	Self-Employed	1	1	**2**
	Student	31	0	**31**
	Unable to Work	0	0	**0**

Table 21 outlines the number of participants, usable eye-tracking data points. Despite screening participants, it seems that some decided not to disclose or conceal their optometry diseases. Their eye calibration process typically failed, the overlay did not focus on the fixation cross, or the quality of their gaze data is very poor and contains a lot of missing value. Those were excluded from the eye tracking data analyses components.

Table 21. Number of Participants Opting into Study Methods

				Subject Count	Eye Tracking Count
Chronological Age Group	Younger Adults	Cognitive Style	Satisficer	15	13
			Maximizer	22	20
			Total	**37**	**33**
	Older Adults	Cognitive Style	Satisficer	12	7
			Maximizer	5	4
			Total	**17**	**11**
	Total	Cognitive Style	Satisficer	27	20
			Maximizer	27	24
			Total	**54**	**44**

5.2 Data Screening

Typically, missing data is a common problem in survey studies. Interestingly, there were no missing entries in the survey data set for this study despite the numerous optional fields. Similarly, there were no observed gaming patterns or rushed responses. One explanation could be that the participants are feeling that they are monitored by the eye tracking live viewer and were encouraged to ask questions and to respond truthfully since they are being observed in the experimental lab environment.

5.2.1 Exogenous Variables Data Screening

5.2.1.1 Age

As explained above in ***Section 4.1.1***, only young adult (ages 18 to 39) and young-old adult (60-74) participants were included in the analysis of this study. ***Table 22*** provides a descriptive summary of participants chronological age in each age group. Chronological age was normally distributed for both age groups. For younger adults, the Shapiro-Wilk test of normality was not significant at (p = 0.46). Similarly for older adults, the Shapiro-Wilk test was not significant at (p = 0.41). The distribution of chronological age by group is visualized in ***Figure 15***.

Table 22: Descriptive Statistics of Participants' Ages

		Chronological Age				
		Mean	Minimum	Range	Maximum	Standard Deviation
Chronological Age Group	Young Adults [18 – 39]	27	18	17	35	3.58
	Older Adults [60 – 74]	66	60	13	73	3.8
	Total	**39**	**18**	**55**	**73**	

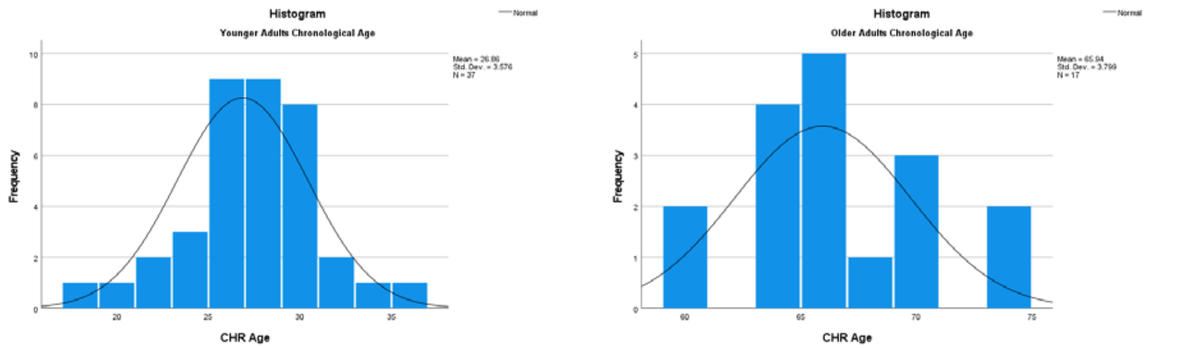

Figure 15: Distributions of Chronological Age by Age Group

As illustrated in ***Table 23*** and ***Figure 16***, there are no chronological age outliers for the older adults group, while the younger adults group only has a single outlier, at age 18 (*#32*, *Younger Adult*, *Satisficer*). The fact that the participant is 18 years old doesn't preclude them from being part of the study since the participant falls within the recruitment age range for younger adults. Additionally, are moving the outlier does not significantly impact the descriptives of the Younger Adults group data (mean slightly increases from 26.9 to 27.1), and the next lowest non-outlier chronological age value is 19. Their data did not significantly deviate from that of other participants in any way. Given the challenges faced while collecting data for this study, this outlier was retained and included in all further analyses, especially given the already small sample size.

Table 23: Percentiles of Age by Age Group

			Percentiles						
		Chronological Age	5	10	25	50	75	90	95
Weighted Average (Definition 1)	CHR Age	Younger Adults	18.90	21.80	25.00	27.00	29.00	31.20	34.10
		Older Adults	60.00	60.00	63.00	66.00	69.00	73.00	.
Tukey's Hinges	CHR Age	Younger Adults			25.00	27.00	29.00		
		Older Adults			63.00	66.00	69.00		

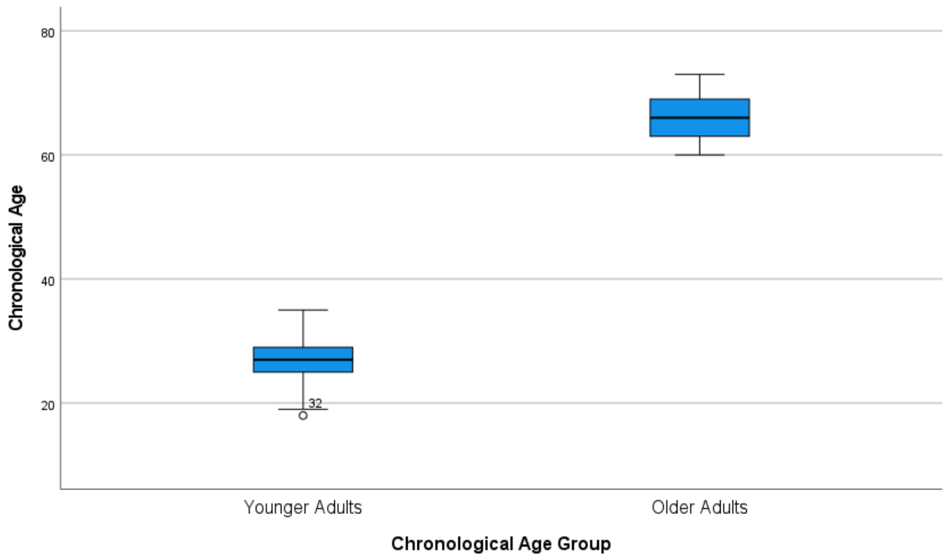

Figure 16: Boxplot of Age by Age Group

Figure 17 illustrates some interesting differences in e-commerce related behaviours between younger and older adults. Generally, younger adults seemed to utilize e-commerce more frequently and recently for both purchasing and product research compared to older adults, which is consistent with the findings in other studies and reports (Statista 2023).

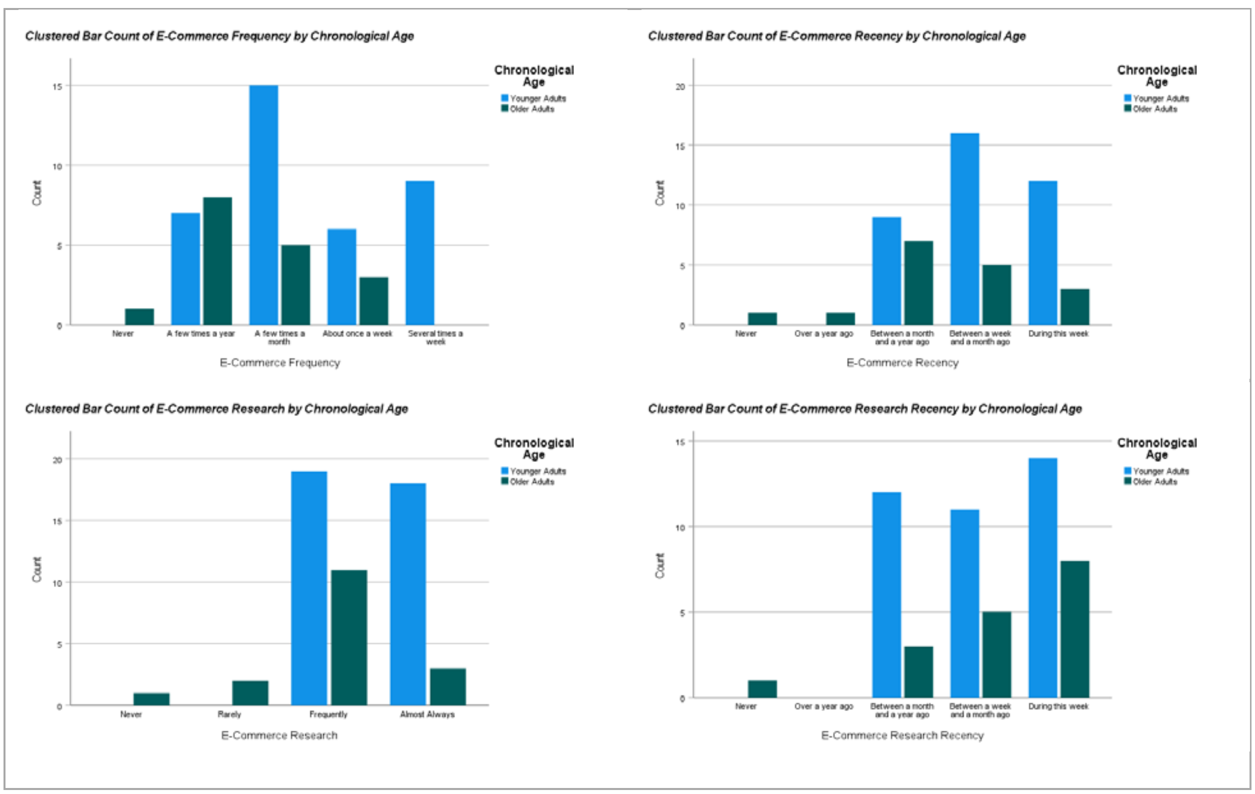

Figure 17: E-Commerce Related Behaviours by Age Group

5.2.1.2 Cognitive Style

None of the cognitive style scale items were reverse-coded, as recommended from the pilot study results. The internal consistency reliability of the 13-item scale was assessed based on Cronbach's Alpha ($\alpha = 0.72$), exceeding the recommended threshold of (0.7). Dropping any item from the scale lowered the alpha value below the threshold, thus all items were retained consistent with Karimi et al. (2015). The inter-item correlation matrix of the cognitive style scale items is illustrated in ***Table 24***.

Table 24: Inter-Item Correlation Matrix

	COG Style 01	COG Style 02	COG Style 03	COG Style 04	COG Style 05	COG Style 06	COG Style 07	COG Style 08	COG Style 09	COG Style 10	COG Style 11	COG Style 12	COG Style 13
COG Style 01	1.000	.441	.127	.236	.101	.187	.374	.289	.331	.296	-.108	-.033	.236
COG Style 02	.441	1.000	.092	.256	-.072	.160	.234	.260	.323	-.049	.066	.183	.037
COG Style 03	.127	.092	1.000	.385	.258	.100	.153	.244	.387	.216	-.116	-.002	.165
COG Style 04	.236	.256	.385	1.000	.300	.195	-.032	.128	.085	-.058	.167	.223	.200
COG Style 05	.101	-.072	.258	.300	1.000	.201	.193	.191	.039	.047	.027	.055	.072
COG Style 06	.187	.160	.100	.195	.201	1.000	.160	.051	.210	.194	.274	.316	-.004
COG Style 07	.374	.234	.153	-.032	.193	.160	1.000	.382	.332	.382	-.108	-.048	.081
COG Style 08	.289	.260	.244	.128	.191	.051	.382	1.000	.333	.207	.133	.143	.228
COG Style 09	.331	.323	.387	.085	.039	.210	.332	.333	1.000	.220	.087	.108	.183
COG Style 10	.296	-.049	.216	-.058	.047	.194	.382	.207	.220	1.000	-.028	.059	.094
COG Style 11	-.108	.066	-.116	.167	.027	.274	-.108	.133	.087	-.028	1.000	.460	.216
COG Style 12	-.033	.183	-.002	.223	.055	.316	-.048	.143	.108	.059	.460	1.000	.100
COG Style 13	.236	.037	.165	.200	.072	-.004	.081	.228	.183	.094	.216	.100	1.000

The following procedure was done to identify the cognitive style of each participant as per Schwartz et al (2002). First, the mean score of the cognitive style items was calculated for each participant. The cognitive style score distribution followed a normal curve as per the Shapiro-Wilk test of normality (p = 0.186) as illustrated in ***Figure 18***. A median score ($M_d = 4.42$) was calculated for all participants, and a median split was done. Participants who scored higher than the median were classified as Maximizers, while those who scored lower than the median were classified as Satisficers. The median score is consistent with those reported in other studies, such as 4.2 (Schwartz et al. 2002), 4.46 (Karimi et al. 2015), and 4.15 (Love 2009).

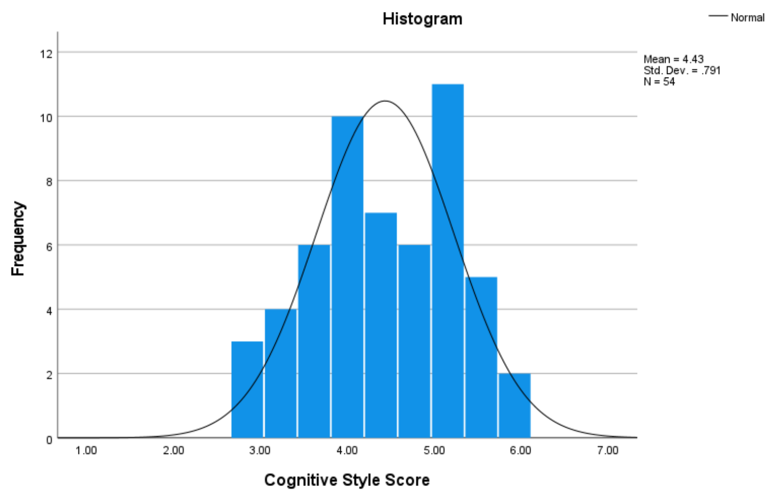

Figure 18: Distribution of Cognitive Style Scale Scores

Table 25 provides a descriptive summary of the cognitive style scores.

		Cognitive Style Scale Score					
		Mean	Median	Minimum	Range	Maximum	Standard Deviation
Cognitive Style	Satisficer	3.76	3.92	2.85	1.54	4.38	.44
	Maximizer	5.11	5.15	4.46	1.46	5.92	.38
	Total	**4.43**	**4.42**	**2.85**	**3.08**	**5.92**	**.79**

Table 25: Cognitive Style Descriptive Statistics

Cognitive styles did not statistically vary significantly between genders, the distribution is outlined in ***Figure 19***.

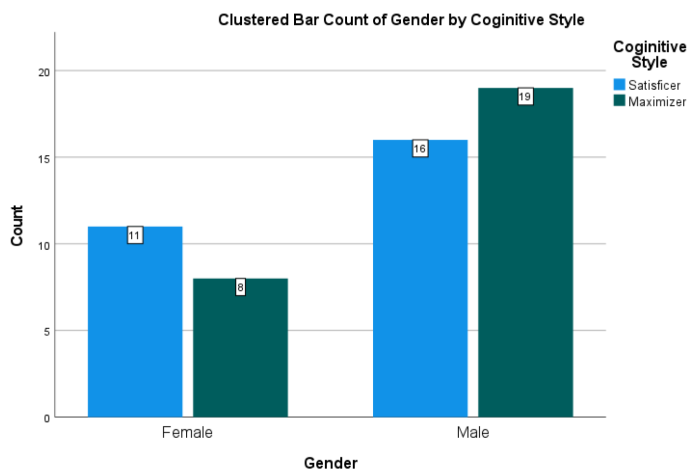

Figure 19: Cognitive Styles by Gender

Figure 20 illustrates consistent e-commerce related behaviours between satisficers and maximizers, and there were no significant differences between the two groups.

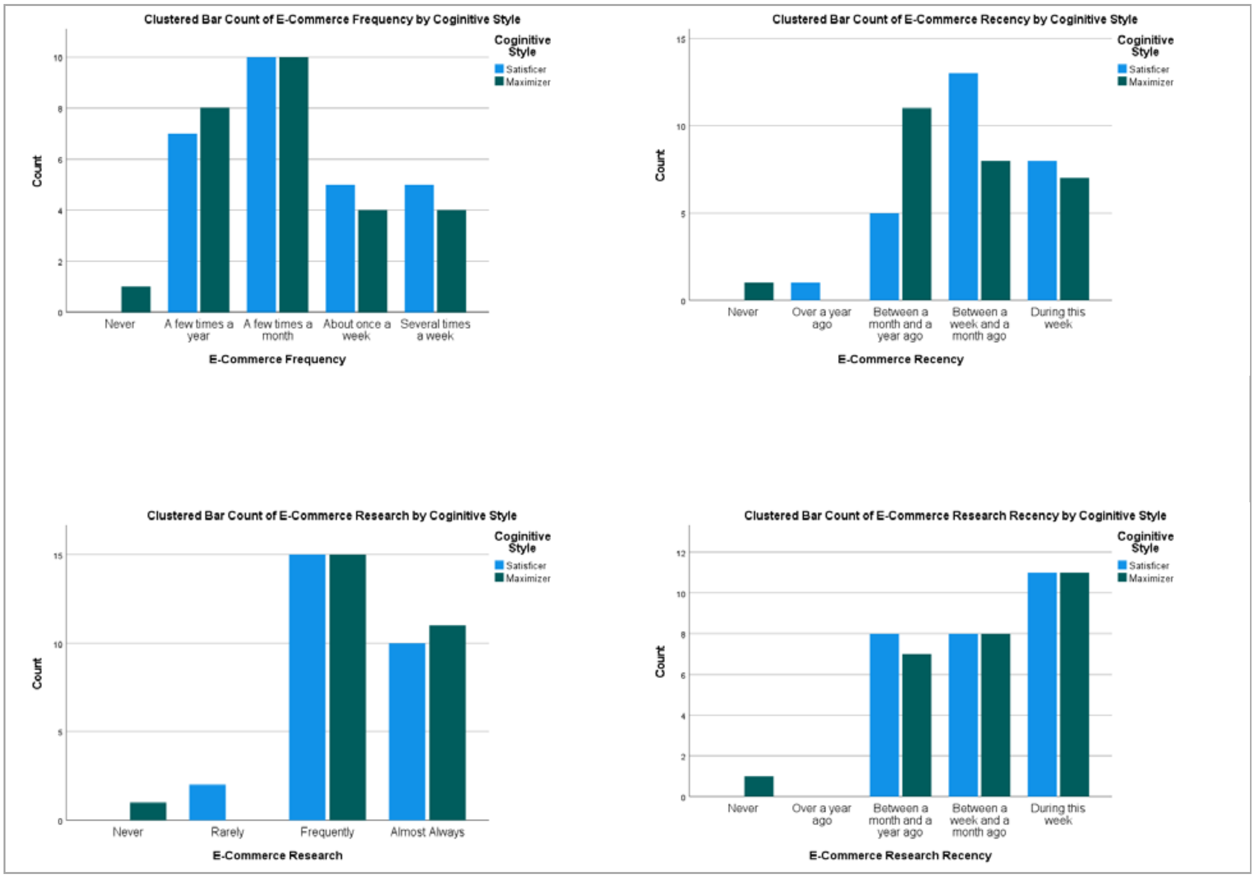

Figure 20: E-Commerce Related Behaviours by Cognitive Style

5.2.1.3 Age and Cognitive Style

Figure 21 and ***Table 26*** provide a summary of the association between age groups and cognitive styles. Utilizing Pearson's Chi-Square analysis, cognitive style is statistically dependent on age group with a significant level of (p = 0.04). Older adults are statistically more likely to be satisficers while younger adults are more likely to be maximizers. The relationship is moderate at an effect size Phi value of (φ - 0.28). These results were obtained despite the small sample size for older adults.

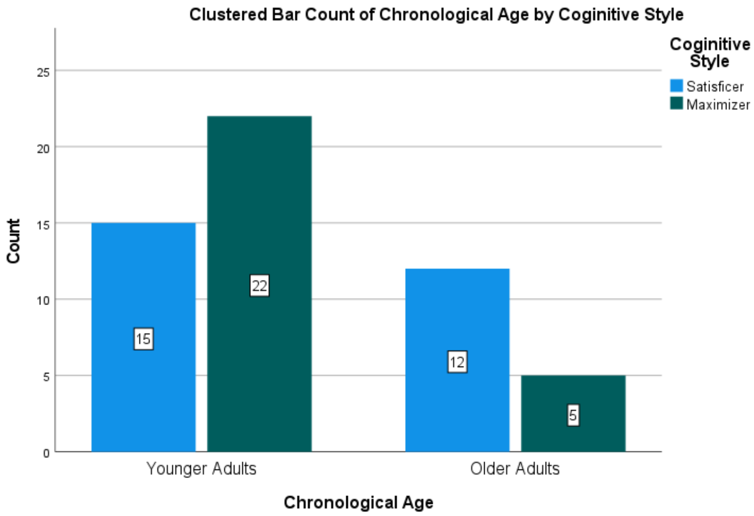

Figure 21. Clustered Bar Count of Chronological Age Groups by Cognitive Style

Table 26: Frequency Table for Independent Variables

		Cognitive Style		
		Satisficer	Maximizer	**Total**
CHR Age Group	Young Adults	15	22	**37**
	Older Adults	12	5	**17**
	Total	**27**	**27**	**54**

Conducting a two-sided independent samples T-Test revealed a statistically significant difference ($p = 0.025$) between the cognitive style scale score means of 4.59 and 4.08 for the younger and older adults, respectively. This is in line with the chi-square analysis results between the two sets of groups discussed above. ***Table 27*** provides a descriptive summary of the scale scores by age group. Younger adults seem to score higher than older adults on the scale and thus are more likely to be categorized as maximizers, while order adults are contrarily more likely to be categorized as satisficers.

Table 27. Cognitive Style Descriptive Statistics by Chronological Age

		Cognitive Style Score					
		Mean	Median	Minimum	Range	Maximum	Standard Deviation
CHR Age Group	Young Adults	4.59	4.85	2.85	2.92	5.77	.76
	Older Adults	4.08	3.92	3.00	2.92	5.92	.76
	Total	**4.43**	**4.42**	**2.85**	**3.08**	**5.92**	**.79**

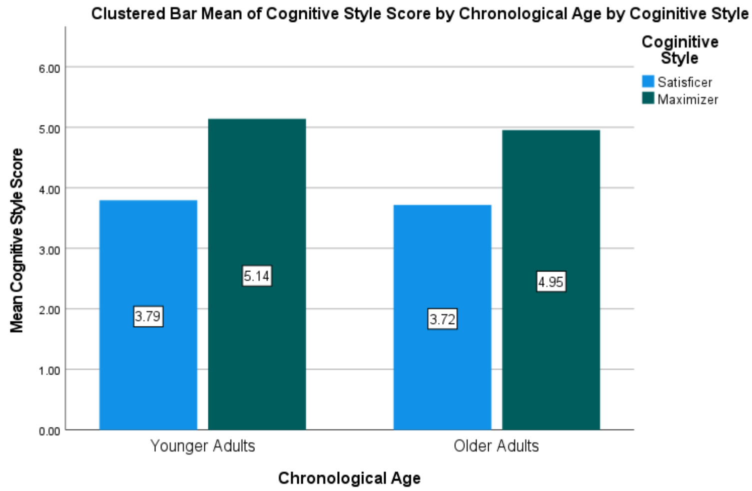

Figure 22: Mean Cognitive Style Score by Age Group Clustered on Cognitive Style

5.2.2 Endogenous Variables Data Screening

Due to technical issues after the initial independent variables survey, one participant *(#42: Younger Adult, Maximizer*, from the factorial cell with the largest sample size) only performed the first task (i.e., Stove) and could not proceed to the other experimental tasks. Their data was thus removed from all further analyses for the remaining three tasks (i.e., TV, Washing Machine, Refrigerator). ***Table 28*** provides a frequency summary of completed tasks.

Table 28. Frequency statistics for completed tasks by participants

		Subject	Stove Decision Quality	Stove Perceived Decision Quality	Stove Perceived Decision Effort	TV Decision Quality	TV Perceived Decision Quality	TV Perceived Decision Effort	WMachine Decision Quality	WMachine Perceived Decision Quality	WMachine Perceived Decision Effort	Refrigerator Decision Quality	Refrigerator Perceived Decision Quality	Refrigerator Perceived Decision Effort
N	Valid	54	54	54	54	53	53	53	53	53	53	53	53	53
	Missing	0	0	0	0	1	1	1	1	1	1	1	1	1

5.2.2.1 Decision Quality

Tests of normality for decision quality by age group, summarized in ***Table 29***, reveal some interesting insights. Decision quality results for younger adults are positively skewed and not normally distributed for each decision task as well as for all four tasks. However, the data distributions follow the normal pattern when aggregated only for the three experimental tasks without the first training task. While the distribution of decision quality for older adults for the first task is normally distributed. This might suggest that younger adults were able to get familiar with the experimental procedure and perform better on the first task compared to older adults. The distribution of decision quality results for older adults is positively skewed for all tasks except the refrigerator task (no bias condition), suggesting that older adults may not perform as well when the alternative decision set is randomly ordered. All this may also simply be an artefact of the small sample size.

Table 29. Tests of Decision Quality Data Normality for Chronological Age Groups

		Shapiro-Wilk		
	Chronological Age Group	Statistic	df	Sig.
Stove Decision Quality	Younger Adults	.705	37	<.001
	Older Adults	.895	17	.056
TV Decision Quality	Younger Adults	.818	36	<.001
	Older Adults	.870	17	.022
WMachine Decision Quality	Younger Adults	.804	36	<.001
	Older Adults	.884	17	.036
Refrigerator Decision Quality	Younger Adults	.800	36	<.001
	Older Adults	.893	17	.051
Overall Decision Quality	Younger Adults	.931	36	.026
	Older Adults	.894	17	.054
All Experimental Tasks Decision Quality	Younger Adults	.917	36	.010
	Older Adults	.935	17	.259

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Tests of normality for decision quality by cognitive style are summarized in ***Table 30***. Decision quality results for maximizers are positively skewed for each task but follow a normal pattern when aggregated. While the results for satisficers are positively skewed for all tasks except the refrigerator task (no bias) suggesting that the proportion of satisficers that tend to perform better is higher for all tasks except when alternatives are randomized. Interestingly, for all experimental tasks, satisficers data is positively skewed, while maximizers results are normally distributed. This may suggest there's more homogeneity in task performance for satisficers than maximizers.

Table 30. Tests of Decision Quality Data Normality for Cognitive Style Groups

		Shapiro-Wilk		
	Cognitive Style	Statistic	df	Sig.
Stove Decision Quality	Satisficer	.852	27	.001
	Maximizer	.581	27	<.001
TV Decision Quality	Satisficer	.850	27	.001
	Maximizer	.799	26	<.001
WMachine Decision Quality	Satisficer	.815	27	<.001
	Maximizer	.850	26	.001
Refrigerator Decision Quality	Satisficer	.934	27	.085
	Maximizer	.714	26	<.001
Overall Decision Quality	Satisficer	.903	27	.016
	Maximizer	.947	26	.200
All Experimental Tasks Decision Quality	Satisficer	.916	27	.032
	Maximizer	.972	26	.677

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Analysis of the univariate main and interaction effects of age and cognitive style on decision quality revealed no significant interaction or main effects on cognitive style. Only the main effect of age on decision quality was significant in the first training task (p < 0.001), all four tasks (p < 0.001), and all three experimental tasks (p = 0.02).

The boxplot in ***Figure 23*** was generated to identify extreme cases and outliers. Many cases, mainly in the younger adult sample, are flagged as outliers for the study tasks. Unfortunately, excluding many cases from analyses will reduce the sample size significantly, which is already below the statistical minimum required. Some cases (e.g., *#39: Younger Adult, Satisficer*) appeared several times consistently on one end of each plot. Z-scores were calculated and reviewed for some control variables (e.g., product evaluation time, decision time, breadth, deliberation) to determine whether the participant wasn't taking the experiment seriously. Additionally, video and screen recordings were reviewed and nothing stood out as an issue. Finally, a Mann-Whitney U test was conducted to calculate the 2-tailed asymptotic significance values for numerous dependent variables. This non-parametric test is more robust to smaller sample sizes and is suitable when the assumption of normality is violated, which is the case for most tasks. There were no significant differences between those participants and the rest of the sample (e.g., the p values for outlier *#39* for three tasks in the boxplot are 0.85, 0.67, and 0.43, respectively), suggesting that the participant data shouldn't be dropped from the analyses.

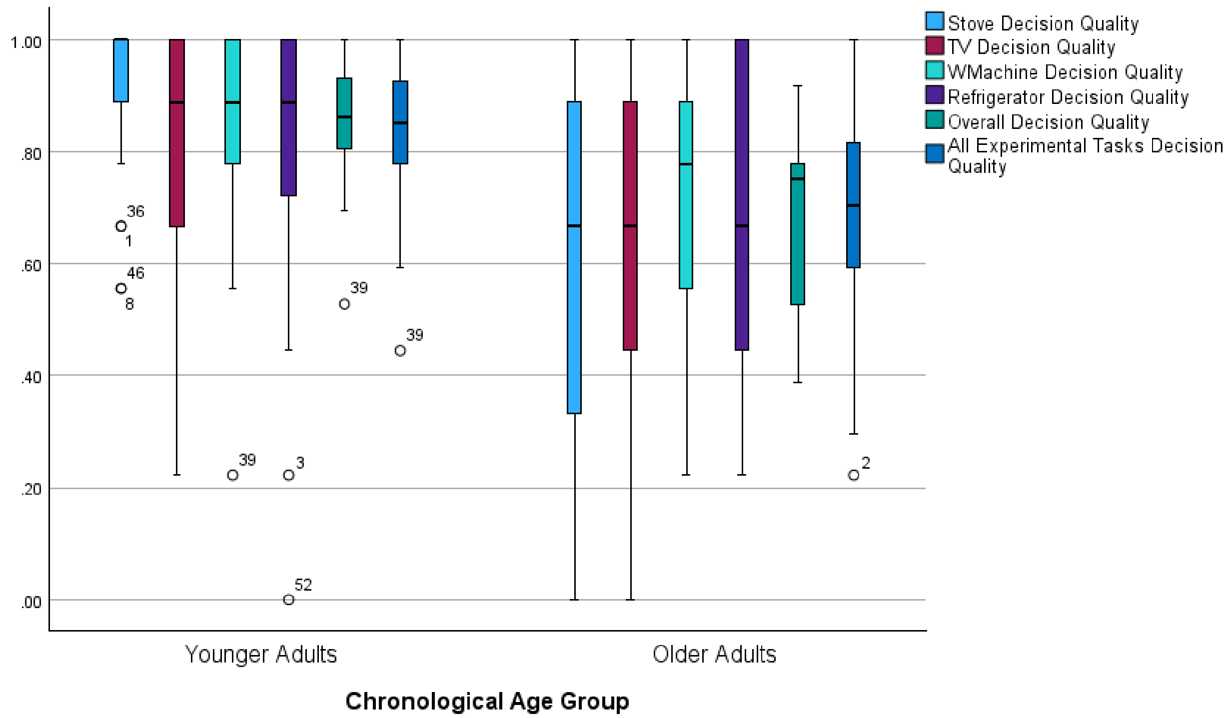

Figure 23. Boxplot of Task Decision Quality by Age Group

The boxplot in ***Figure 24*** shows multiple decision-quality extreme values and outliers for each cognitive style. The same outlier screening and handling process applied to age was applied to cognitive style. Similarly, no cases were unusual or flagged as candidates for deletion. As a result, all data will be retained.

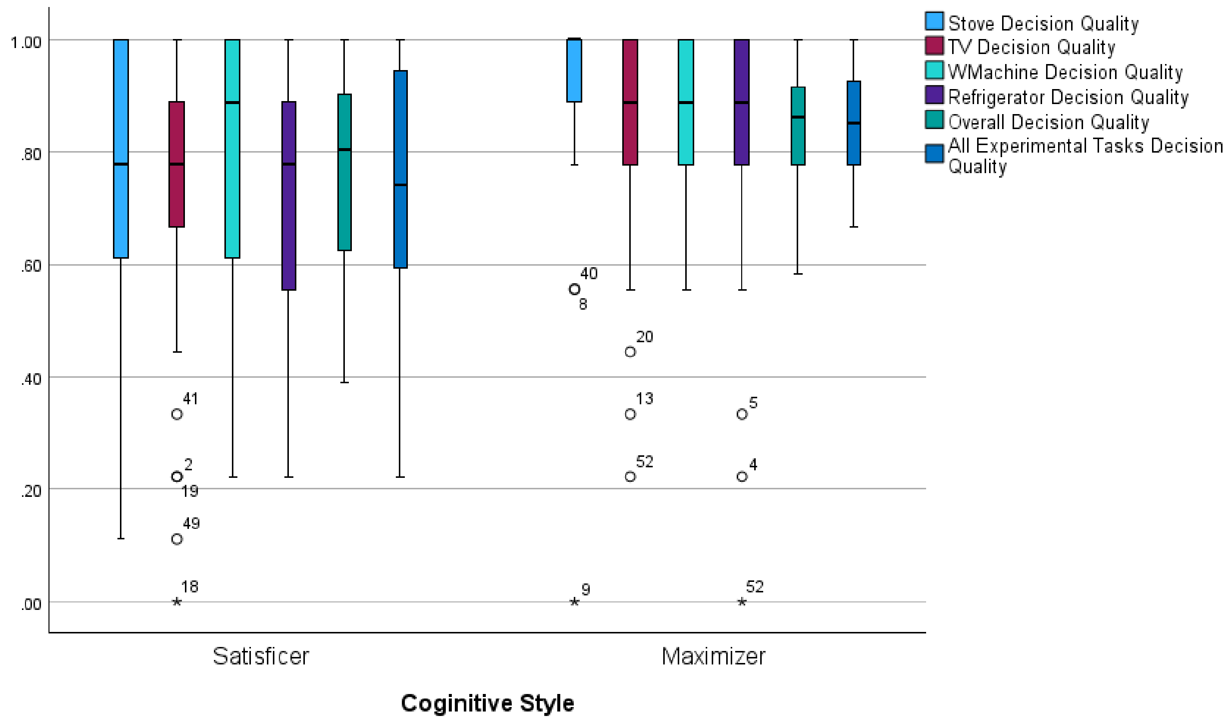

Figure 24. Boxplot of Task Decision Quality by Cognitive Style

5.2.2.2 Perceived Decision Quality

Cronbach's Alpha was used to measure the reliability of the perceived decision quality scale for each of the four experimental tasks, and all exceeded the reliability threshold except for the training task. The scale's alpha values for the Stove (Training), Refrigerator (Control), TV (Vividness Bias), and Washing Machine (Order Bias) tasks are (α = 0.68, 0.84, 0.88, and 0.89) respectively, with strong inter-item correlation values for each scale for the main experimental tasks.

Since perceived decision quality was collected four times throughout the experiment, as a repeated measure, parallel form reliability analysis was conducted. The results in ***Table 31*** show poor test-retest reliability for the scale. The intuitive explanation is that participants are not necessarily equally confident in all their four decisions and thus report different levels of perceived decision quality for the different tasks.

Table 31. Parallel Form Reliability Analysis for Perceived Decision Effort

		Stove Perceived Decision Quality	TV Perceived Decision Quality	WMachine Perceived Decision Quality	Refrigerator Perceived Decision Quality
Stove Perceived Decision Effort	Pearson Correlation	1	.224	.377	.181
	Sig. (2-tailed)		.107	.005	.194
	N	54	53	53	53
TV Perceived Decision Effort	Pearson Correlation	.224	1	.328	.324
	Sig. (2-tailed)	.107		.016	.018
	N	53	53	53	53
WMachine Perceived Decision Effort	Pearson Correlation	.377	.328	1	.223
	Sig. (2-tailed)	.005	.016		.109
	N	53	53	53	53
Refrigerator Perceived Decision Effort	Pearson Correlation	.181	.324	.223	1
	Sig. (2-tailed)	.194	.018	.109	
	N	53	53	53	53

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Tests of normality for perceived decision quality by age are summarized in ***Table 32*** . Most perceived decision quality results follow a normal distribution. Younger adults perceived decision quality for the TV (vividness bias) task was positively skewed. While younger adults perceived decision quality for the washing machine (order bias) task and older adults perceived decision quality for the refrigerator (no bias) task was negatively skewed. This indicates that the majority of younger adults reported higher confidence in their decisions for the TV task, while reporting lower confidence in the washing machine task. This also indicates that the majority of older adults reported lower confidence in their decision for the refrigerator task.

Table 32. Tests of Normality for Perceived Decision Quality by Age Group

	Chronological Age Group	Shapiro-Wilk Statistic	df	Sig.
Stove Perceived Decision Quality	Younger Adults	.924	36	.017
	Older Adults	.892	17	.050
TV Perceived Decision Quality	Younger Adults	.869	36	<.001
	Older Adults	.904	17	.080
WMachine Perceived Decision Quality	Younger Adults	.870	36	<.001
	Older Adults	.914	17	.119
Refrigerator Perceived Decision Quality	Younger Adults	.929	36	.023
	Older Adults	.818	17	.004
Overall Perceived Decision Quality	Younger Adults	.981	36	.774
	Older Adults	.969	17	.799
Experimental Tasks Perceived Decision Quality	Younger Adults	.954	36	.138
	Older Adults	.967	17	.773

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Tests of normality for perceived decision quality by cognitive style group are summarized in ***Table 33***. All perceived decision quality results for the three experimental tasks for satisficers are negatively skewed. The same isn't true for their first training (Stove) task, or when that data is aggregated with all their other perceived decision quality results. This may indicate that most satisficers were not as confident in the quality of their decisions after getting familiar with the experimental procedure and task design. Most maximizers also reported lower confidence in the quality of their decisions for the refrigerator task.

Table 33. Tests of Normality for Perceived Decision Quality by Cognitive Style

	Cognitive Style	Shapiro-Wilk Statistic	df	Sig.
Stove Perceived Decision Quality	Satisficer	.934	27	.085
	Maximizer	.926	26	.062
TV Perceived Decision Quality	Satisficer	.855	27	.001
	Maximizer	.906	26	.021
WMachine Perceived Decision Quality	Satisficer	.882	27	.005
	Maximizer	.917	26	.038
Refrigerator Perceived Decision Quality	Satisficer	.823	27	<.001
	Maximizer	.912	26	.029
Overall Perceived Decision Quality	Satisficer	.984	27	.937
	Maximizer	.979	26	.861
Experimental Tasks Perceived Decision Quality	Satisficer	.961	27	.391
	Maximizer	.937	26	.115

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Data was restructured to analyze the scale by treating every task as an independent case. The scale's alpha value for all tasks is ($\alpha = 0.8$), with the alpha value dropping below that value for each item if it were to be deleted. ***Table 34*** shows good inter-item correlation values for the scale.

Table 34. Inter-item Correlation Matrix for Perceived Decision Quality

	Product Perceived Decision Quality 01	Product Perceived Decision Quality 02	Product Perceived Decision Quality 03
Product Perceived Decision Quality 01	1.000	.606	.484
Product Perceived Decision Quality 02	.606	1.000	.660
Product Perceived Decision Quality 03	.484	.660	1.000

5.2.2.3 Decision Effort

Decision effort is operationalized as the time it takes the participant to make their decision in each task. ***Table 35*** provides a breakdown of decision time means by age and cognitive style. The results are not surprising. Younger adults and satisficers typically made task decisions faster than their older adult and maximizer counterparts.

Table 35. Decision Effort by Age and Cognitive Style

				Stove Decision Time in Minutes Mean	TV Decision Time in Minutes Mean	WMachine Decision Time in Minutes Mean	Refrigerator Decision Time in Minutes Mean
Chronological Age Group	Younger Adults	Cognitive Style	Satisficer	1.89	2.01	2.30	2.03
			Maximizer	2.15	2.10	2.35	2.01
			Total	2.05	2.06	2.33	2.02
	Older Adults	Cognitive Style	Satisficer	2.61	2.52	2.50	2.38
			Maximizer	3.65	2.69	2.89	2.69
			Total	2.92	2.57	2.62	2.47
	Total	Cognitive Style	Satisficer	2.21	2.24	2.39	2.19
			Maximizer	2.43	2.21	2.45	2.14
			Total	2.32	2.22	2.42	2.16

Tests of normality for decision effort are listed in ***Table 36***. Most of the data doesn't follow a normal distribution. Except for the washing machine task for older adults and the refrigerator task for all participants, all data is positively skewed. This indicates that there was more variability in the times it took participants to make these decisions within these groups.

Table 36. Tests of Normality for Decision Effort by Age

		Shapiro-Wilk		
	Chronological Age Group	Statistic	df	Sig.
Stove Decision Time Minutes	Younger Adults	.927	36	.020
	Older Adults	.807	17	.003
TV Decision Time Minutes	Younger Adults	.907	36	.005
	Older Adults	.888	17	.043
WMachine Decision Time in Minutes	Younger Adults	.874	36	<.001
	Older Adults	.911	17	.102
Refrigerator Decision Time in Minutes	Younger Adults	.942	36	.059
	Older Adults	.954	17	.525

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Figure 25 illustrates a boxplot of decision effort by task and age group. Several cases stand out as outliers which might explain why the data isn't normally distributed. Upon reviewing these cases, nothing stands out as grounds for exclusion from the analysis. Given the challenges encountered in data collection and the low sample size, these cases were not excluded in the analysis.

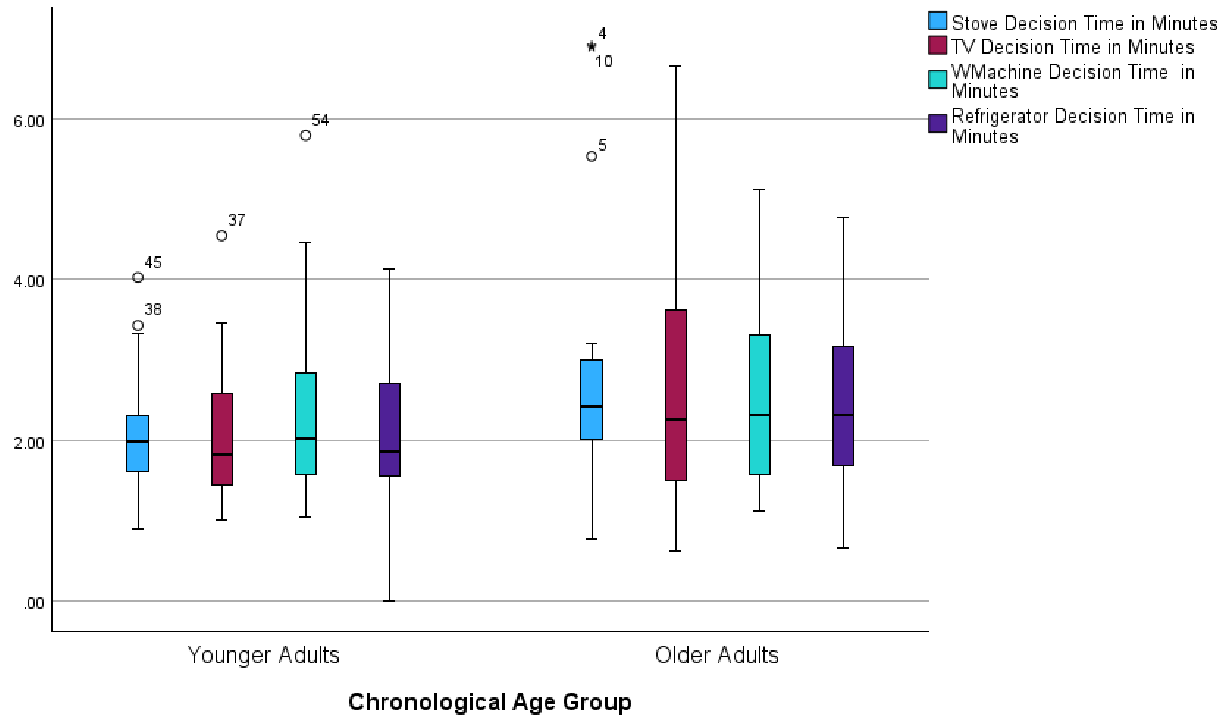

Figure 25. Decision Effort by Task and Age Group

Table 37 illustrates the results for the test of normality for decision effort, as measured by the time it took participants to make decisions. All results were positively skewed for all groups except for the three experimental tasks (TV, washing machine, and refrigerator) for maximizers, where they were normally distributed.

Table 37. Tests of Normality for Decision Effort by Cognitive Style

		Shapiro-Wilk		
	Cognitive Style	Statistic	df	Sig.
Stove Decision Time Minutes	Satisficer	.690	27	<.001
	Maximizer	.817	26	<.001
TV Decision Time Minutes	Satisficer	.819	27	<.001
	Maximizer	.946	26	.188
WMachine Decision Time in Minutes	Satisficer	.834	27	<.001
	Maximizer	.935	26	.099
Refrigerator Decision Time in Minutes	Satisficer	.911	27	.024
	Maximizer	.938	26	.122

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Figure 26 provides a boxplot for decision effort by task and cognitive style. Similar to the previous analysis, there were no grounds to justify the exclusion of cases from the analysis. This is particularly true given the low sample size.

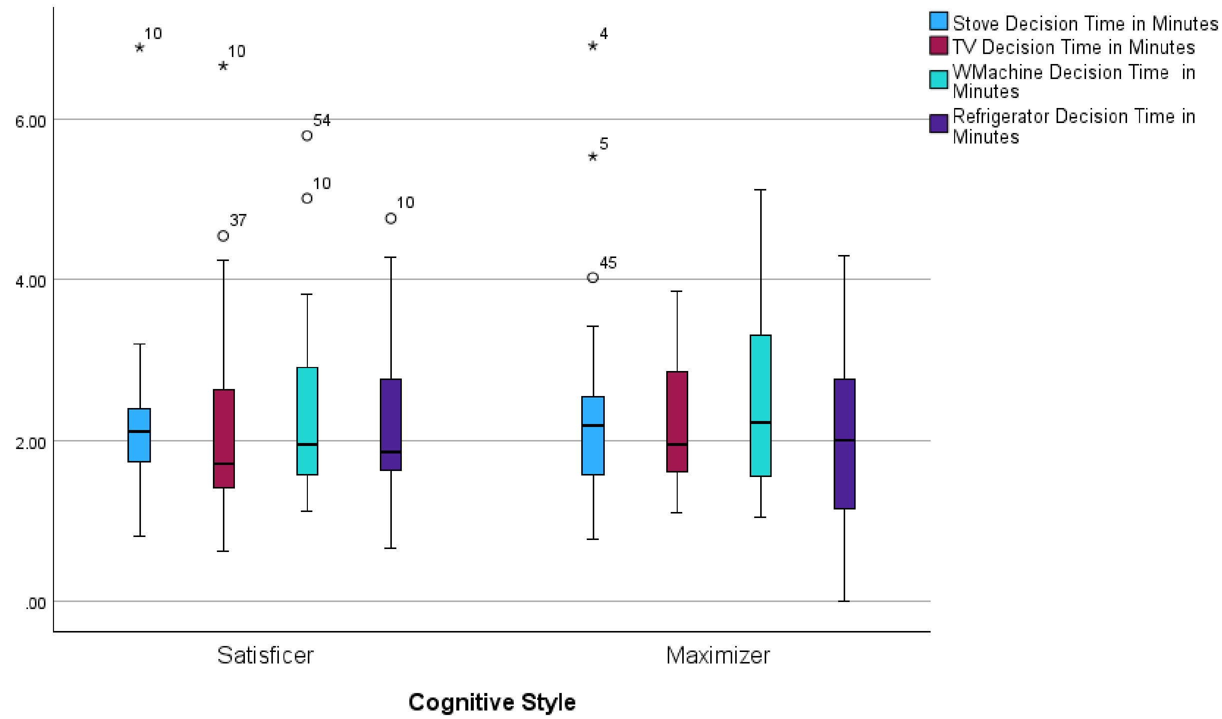

Figure 26. Decision Effort by Task and Cognitive Style

It is worth noting that Deliberation and Decision Effort are both time-based measures. Correlation existed between the two measures, however they did not completely overlap since Deliberation only measured fixation times on product-relevant information, while Decision Effort measured the entire time for task completion.

5.2.2.4 Perceived Decision Effort

As discussed in the Pilot analysis in ***Section 5.1.2***, one of the items (i.e., item 2) was initially reverse-coded, which proved problematic. The reliability analyses led to dropping that item due to poor internal consistency and low inter-item correlations with the other items. It was unreversed for the main study to avoid this issue.

Cronbach's Alpha was used to measure the reliability of the perceived decision effort scale for each of the four experimental tasks, and all exceeded the reliability threshold. The scale's alpha values for the Stove (Training), Refrigerator (Control), TV (Vividness Bias), and Washing Machine (Order Bias) tasks are (α = 0.88, 0.95, 0.96, 0.94) respectively, with strong inter-item correlation values for each scale.

Since perceived decision effort was collected four times throughout the experiment, as a repeated measure, parallel form reliability analysis is appropriate. The results in ***Table 38*** show strong reliability for the scale for the three experimental tasks ($r >= 0.80$). However, the Pearson correlation coefficient for the initial training task only indicates moderate correlation ($0.60 =< r < 0.80$) with the rest. This is the result of the higher mean value for the Stove (Training) compared to the TV (Vividness Bias), Washing Machine (Order Bias), and Refrigerator (Control) tasks (μ = 3.03, 2.67, 2.71, and 2.63, respectively). The intuitive explanation is that participants are learning the instructions and the experimental procedure in the first task which takes more effort than repeating the task. Z-scores were calculated for the scales for each participant to detect outliers, and only one participant (*#13, Younger Adult, Maximizer*) was flagged as one for the four scales. However, their data did not deviate from that of the rest of the participants in any meaningful way, and it was not dropped from the analysis.

Table 38. Parallel Form Reliability Analysis for Perceived Decision Effort

		Stove Perceived Decision Effort	TV Perceived Decision Effort	WMachine Perceived Decision Effort	Refrigerator Perceived Decision Effort
Stove Perceived Decision Effort	Pearson Correlation	1	.616**	.576**	.695**
	Sig. (2-tailed)		<.001	<.001	<.001
	N	54	53	53	53
TV Perceived Decision Effort	Pearson Correlation	.616**	1	.815**	.819**
	Sig. (2-tailed)	<.001		<.001	<.001
	N	53	53	53	53
WMachine Perceived Decision Effort	Pearson Correlation	.576**	.815**	1	.750**
	Sig. (2-tailed)	<.001	<.001		<.001
	N	53	53	53	53
Refrigerator Perceived Decision Effort	Pearson Correlation	.695**	.819**	.750**	1
	Sig. (2-tailed)	<.001	<.001	<.001	
	N	53	53	53	53

**. Correlation is significant at the 0.01 level (2-tailed).

Tests of normality for perceived decision effort by age are summarized in ***Table 39***. Most perceived decision effort results follow a normal distribution. Younger adults' perceived decision effort for the TV (vividness bias) and refrigerator (no bias) tasks was negatively skewed (p < 0.003), the same as that of their overall tasks (p < 0.033). This indicates that the majority of younger adults reported lower effort for these tasks compared to the younger adult sample as a whole. All older adult results followed a normal distribution.

Table 39. Tests of Normality for Perceived Decision Effort by Age Group

	Chronological Age Group	Shapiro-Wilk Statistic	df	Sig.
Stove Perceived Decision Effort	Younger Adults	.944	37	.064
	Older Adults	.960	17	.638
TV Perceived Decision Effort	Younger Adults	.899	36	.003
	Older Adults	.936	17	.274
WMachine Perceived Decision Effort	Younger Adults	.918	36	.011
	Older Adults	.951	17	.472
Refrigerator Perceived Decision Effort	Younger Adults	.896	36	.003
	Older Adults	.934	17	.253
Overall Tasks Perceived Decision Effort	Younger Adults	.934	36	.033
	Older Adults	.955	17	.533
Experimental Tasks Perceived Decision Effort	Younger Adults	.916	36	.010
	Older Adults	.948	17	.423

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Tests of normality for perceived decision effort by cognitive style group are summarized in ***Table 40***. All perceived decision effort results for the three experimental tasks for maximizers, as well as their aggregation, are negatively skewed. The same isn't true for their first training (Stove) task, or when that data is aggregated with all their other perceived decision effort results. This may indicate that most maximizers were able to become familiar with the experimental procedure and task design and reported less effort in the following tasks.

Table 40. Tests of Normality for Perceived Decision Effort by Cognitive Style Group

	Cognitive Style	Shapiro-Wilk Statistic	df	Sig.
Stove Perceived Decision Effort	Satisficer	.967	27	.527
	Maximizer	.939	27	.114
TV Perceived Decision Effort	Satisficer	.893	27	.010
	Maximizer	.908	26	.023
WMachine Perceived Decision Effort	Satisficer	.947	27	.178
	Maximizer	.909	26	.025
Refrigerator Perceived Decision Effort	Satisficer	.924	27	.051
	Maximizer	.917	26	.038
Overall Tasks Perceived Decision Effort	Satisficer	.963	27	.442
	Maximizer	.936	26	.110
Experimental Tasks Perceived Decision Effort	Satisficer	.964	27	.464
	Maximizer	.921	26	.046

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Data was restructured to analyze the scale by treating every task as an independent case. The scale's alpha value for all tasks is ($\alpha = 0.92$). ***Table 41*** shows good inter-item correlation values for the scale.

Table 41. Inter-item Correlation Matrix for Perceived Decision Effort

	Product Perceived Decision Effort 01	Product Perceived Decision Effort 02	Product Perceived Decision Effort 03	Product Perceived Decision Effort 04
Product Perceived Decision Effort 01	1.000	.723	.800	.715
Product Perceived Decision Effort 02	.723	1.000	.796	.649
Product Perceived Decision Effort 03	.800	.796	1.000	.795
Product Perceived Decision Effort 04	.715	.649	.795	1.000

5.2.2.5 Visual Perceptual Comprehensiveness (VPC)

As discussed in ***Section 4.4.1***, the VPC composite is operationalized as the relative Breadth and Deliberation of gaze data. Each metric is initially analyzed separately for each task before combining it into a composite score for VPC.

Given that gaze data is central to the study and the hypotheses testing, some participants had to be dropped from the study due to disqualifying eye diseases disclosed only upon poor calibration results, or due to technical errors.

Table 42. List of Excluded Participants

Participant	Age	Cognitive Style	Reason for Exclusion
#5	Older Adult	Maximizer	Technical Error
#18	Older Adult	Satisficer	Trifocals
#19	Older Adult	Satisficer	Trifocals
#21	Younger Adult	Satisficer	Lazy Eye
#29	Older Adult	Satisficer	Poor Calibration
#33	Younger Adult	Satisficer	Technical Error
#37	Younger	Satisficer	Technical Error
#42	Younger Adult	Maximizer	Technical Error
#49	Older Adult	Satisficer	Cataracts
#51	Older Adult	Satisficer	Technical Error

Table 43 provides a breakdown of the remaining data points by the endogenous variables, namely age and cognitive style.

Table 43. Remaining Participant Data After Screening

		Cognitive Style		
		Satisficer Count	Maximizer Count	**Total Count**
Chronological Age	Younger Adults	13	20	**33**
	Older Adults	7	4	**11**
	Total	**20**	**24**	**44**

5.2.2.5.1 Breadth

The first component of VPC is Breadth, which indicates the percentage of information attended compared to all product-relevant information available. This is measured by whether each piece of presented information was fixated upon by the participant at least once. ***Table 44*** provides a breakdown of the breadth of information attended by age and cognitive style. As expected, it seems that younger adults on average attended to more product-relevant information compared to their older counterparts. However, it seems that maximizers attended to less product-related information on average compared to satisficers, which is counter intuitive.

Table 44. Mean Gaze Breadth for Product-Relevant Information by Age and Cognitive Style

				Stove Info Breadth Gaze Percentage Mean	TV Info Breadth Gaze Percentage Mean	WMachine Info Breadth Gaze Mean	Refrigerator Info Breadth Gaze Mean
Chronological Age Group	Younger Adults	Cognitive Style	Satisficer	.73	.78	.78	.73
			Maximizer	.63	.73	.73	.68
			Total	**.67**	**.75**	**.75**	**.70**
	Older Adults	Cognitive Style	Satisficer	.60	.70	.70	.70
			Maximizer	.42	.66	.66	.55
			Total	**.53**	**.69**	**.69**	**.65**
	Total	Cognitive Style	Satisficer	.69	.75	.75	.72
			Maximizer	.60	.72	.72	.66
			Total	**.64**	**.73**	**.73**	**.69**

Table 45 provides a breakdown of the tests of normality for breadth gaze data by age group. The results indicate that all data are negatively skewed, meaning that most of the data is grouped together around the relatively high median with few exceptions. This shows that in each group, some participants attended to less information compared to their group.

Table 45. Tests of Normality for Gaze Breadth by Age

	Chronological Age Group	Shapiro-Wilk Statistic	df	Sig.
Stove Info Breadth Gaze Percentage	Younger Adults	.877	34	.001
	Older Adults	.834	11	.026
TV Info Breadth Gaze Percentage	Younger Adults	.867	34	<.001
	Older Adults	.770	11	.004
WMachine Info Breadth Gaze	Younger Adults	.867	34	<.001
	Older Adults	.770	11	.004
Refrigerator Info Breadth Gaze	Younger Adults	.894	34	.003
	Older Adults	.844	11	.036

a. Lilliefors Significance Correction

Upon further examination, several cases stand out as the cause of this distribution. As shown in ***Figure 27***, several participants (e.g., #23, #25, #40) only considered a relatively small proportion of the information presented when making their decisions.

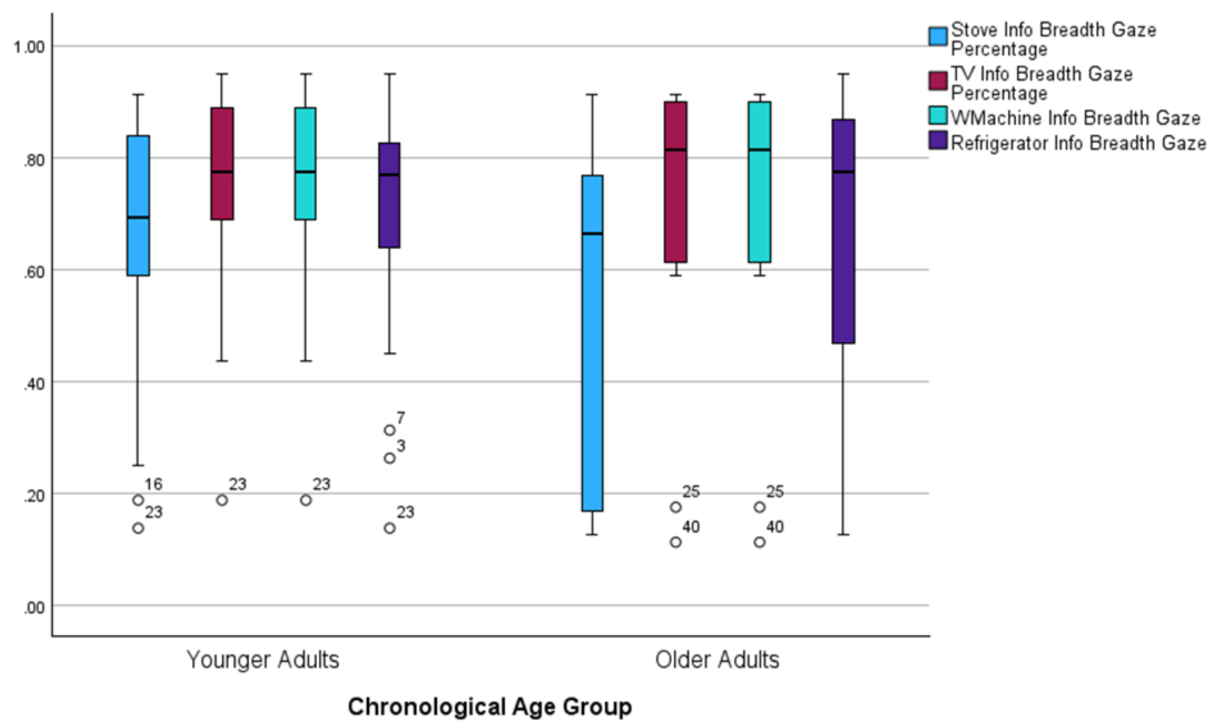

Figure 27. Breadth Gaze Data Boxplot by Task and Age Group

Table 46 shows the normality test breakdown for breadth data by task and cognitive style. ***Figure 28*** provides a deeper dive into the boxplots of breadth data by task and cognitive style. A similar trend was observed in some of the same cases.

Table 46. Tests of Normality for Gaze Breadth by Cognitive Style

Tests of Normality

		Shapiro-Wilk		
	Cognitive Style	Statistic	df	Sig.
Stove Info Breadth Gaze Percentage	Satisficer	.774	20	<.001
	Maximizer	.885	25	.009
TV Info Breadth Gaze Percentage	Satisficer	.820	20	.002
	Maximizer	.792	25	<.001
WMachine Info Breadth Gaze	Satisficer	.820	20	.002
	Maximizer	.792	25	<.001
Refrigerator Info Breadth Gaze	Satisficer	.818	20	.002
	Maximizer	.907	25	.026

a. Lilliefors Significance Correction

Upon further examination, several cases stand out as the cause of this distribution. As shown in ***Figure 28***, several participants (e.g., #23, #25, #40) only considered a relatively small proportion of the information presented when making their decisions.

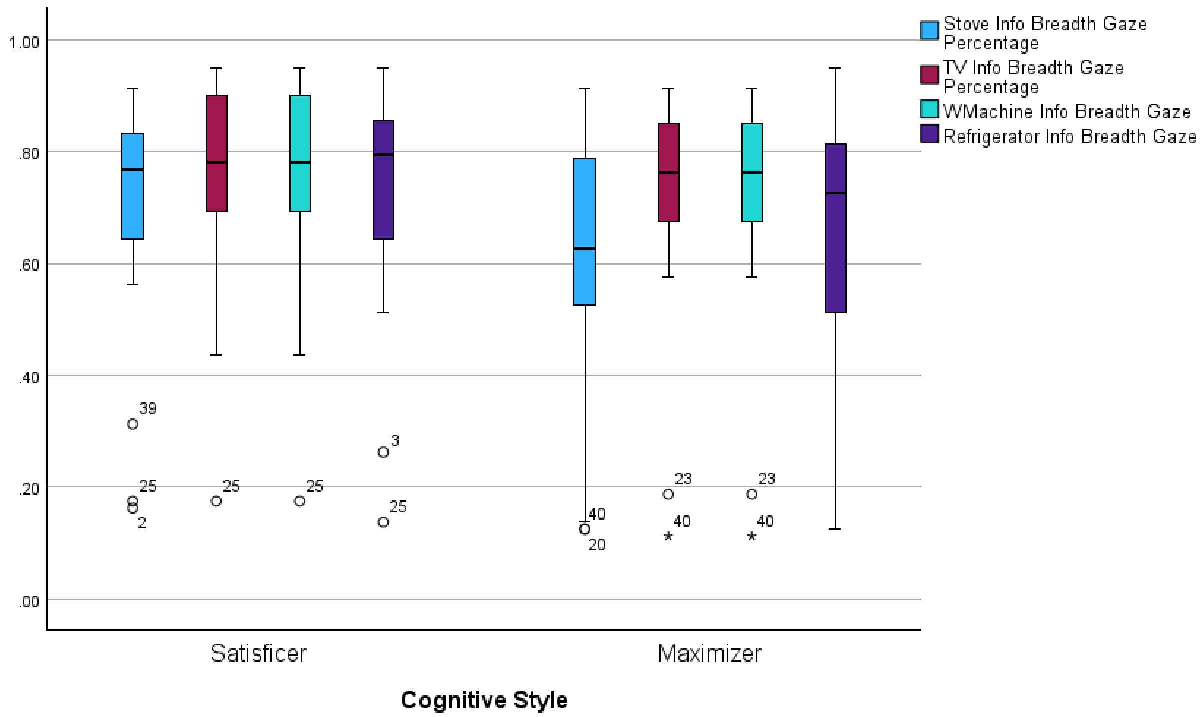

Figure 28. Breadth Gaze Data Boxplot by Task and Cognitive Style

5.2.2.5.2 Deliberation

The second composite of VPC is deliberation, which is calculated as the total fixation duration for attended product-relevant information. ***Table 47*** provides a breakdown of deliberation by age and cognitive style. Similar to the breadth, the results are interesting and counter intuitive. While younger adults seem to have spent more time on average deliberately processing product-relevant information before making their decisions, it seems that maximizers, counter intuitively, spent on average less time deliberating product-relevant information before making their decisions.

Table 47. Mean Gaze Deliberation by Age Group and Cognitive Style

				Stove Info Deliberation Gaze Mean	TV Info Deliberation Gaze Mean	WMachine Info Deliberation Gaze Mean	Refrigerator Info Deliberation Gaze Mean
Chronological Age Group	Younger Adults	Cognitive Style	Satisficer	.35	.60	.34	.55
			Maximizer	.22	.49	.21	.46
			Total	**.27**	**.53**	**.26**	**.49**
	Older Adults	Cognitive Style	Satisficer	.16	.39	.21	.42
			Maximizer	.15	.43	.17	.34
			Total	**.16**	**.41**	**.19**	**.39**
	Total	Cognitive Style	Satisficer	.28	.53	.29	.50
			Maximizer	.21	.48	.20	.44
			Total	**.24**	**.50**	**.24**	**.47**

Table 47 provides a breakdown of the tests of normality for deliberation gaze data by age group. The results indicate that all data are negatively skewed, meaning that most of the data is grouped together around the relatively high median with few exceptions. This shows that in each group, some participants deliberated information for a relatively shorter period of time compared to their group.

Table 48. Tests of Normality for Gaze Deliberation by Age Group

		Shapiro-Wilk		
	Chronological Age Group	Statistic	df	Sig.
Stove Info Deliberation Gaze Percentage	Younger Adults	.980	34	.762
	Older Adults	.913	11	.266
TV Info Deliberation Gaze Percentage	Younger Adults	.936	34	.047
	Older Adults	.957	11	.739
WMachine Info Deliberation Gaze	Younger Adults	.974	34	.584
	Older Adults	.916	11	.287
Refrigerator Info Deliberation Gaze	Younger Adults	.959	34	.228
	Older Adults	.960	11	.778

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Upon further examination, no specific cases stand out as the cause of this distribution. As shown in ***Figure 29***, deliberation was typically lower in general for the stove (i.e., training) and washing machine (i.e., order bias) tasks. There were no consistent outliers.

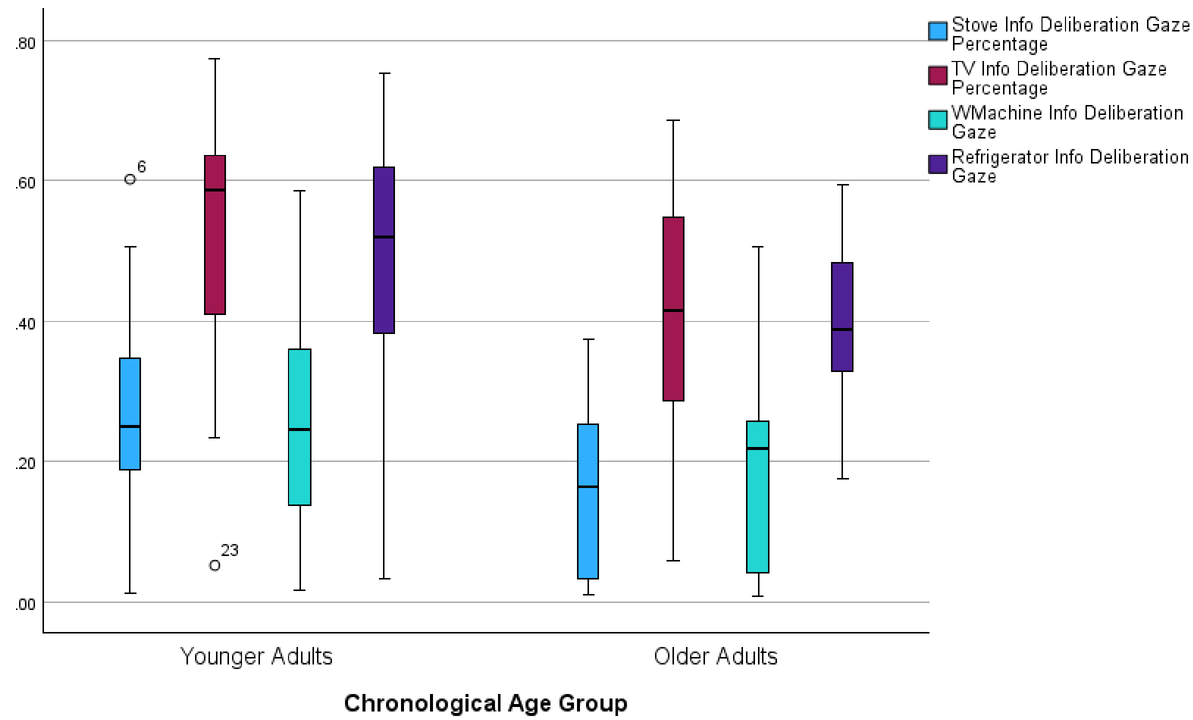

Figure 29. Gaze Deliberation by Task and Age Group

Table 49 provides a breakdown of the tests of normality for deliberation gaze data by cognitive style. The results indicate that all data are negatively skewed, meaning that most of the data is grouped together around the relatively high median with few exceptions. This shows that in each group, some participants deliberated information for a relatively shorter period of time compared to their group.

Table 49. Tests of Normality for Gaze Deliberation by Cognitive Style

		Shapiro-Wilk		
	Cognitive Style	Statistic	df	Sig.
Stove Info Deliberation Gaze Percentage	Satisficer	.977	20	.892
	Maximizer	.966	25	.548
TV Info Deliberation Gaze Percentage	Satisficer	.901	20	.043
	Maximizer	.933	25	.102
WMachine Info Deliberation Gaze	Satisficer	.960	20	.554
	Maximizer	.951	25	.270
Refrigerator Info Deliberation Gaze	Satisficer	.977	20	.885
	Maximizer	.982	25	.915

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Upon further examination, no specific cases stand out as the cause of this distribution. As shown in ***Figure 30***, deliberation was typically lower in general for the stove (i.e., training) and washing machine (i.e., order bias) tasks. There were no consistent outliers.

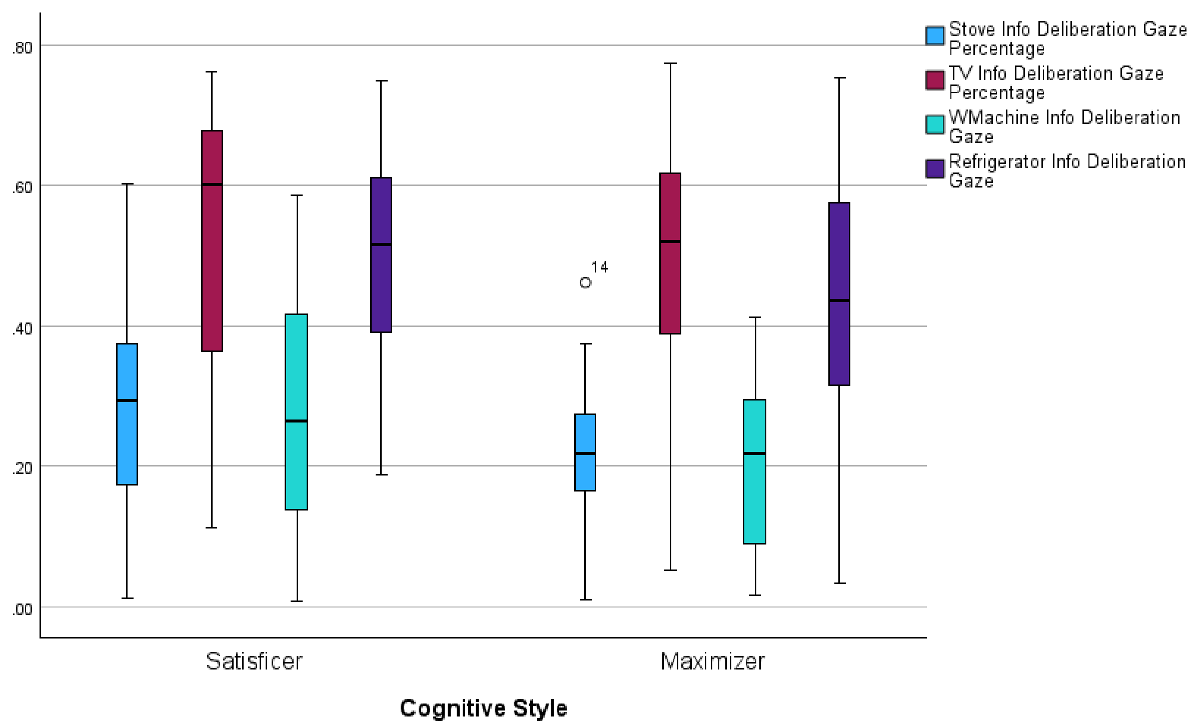

Figure 30. Gaze Deliberation by Task and Cognitive Style

5.3 Bootstrapping

There are some limitations in the data that necessitate the use of bootstrapping techniques in the hypothesis testing that follows. First, given the challenges in participant recruitment and data loss due to technical and physiological issues related to the eye-tracking procedures, the resulting sample size is small. As shown in ***Table 43***, all four cells contain fewer than 30 participants, which is considered the minimum for robust parametric analyses given the power analysis discussed earlier. In addition, as discussed in ***Section 5.2***, several variables exhibit violations of normality assumptions. This issue is exacerbated by the small sample size. ANOVA/MANOVA are not viable options and are not appropriate for hypotheses testing under these conditions.

To address these limitations, subsequent hypothesis testing will employ bootstrapping at 10,000 samples with a 95% Confidence Interval (CI) in combination with non-parametric Partial Least Squares Structural Equation Modeling (PLS-SEM), allowing for more robust estimation of standard errors and confidence intervals despite these data constraints (Field 2024; Mooney et al. 1993).

To perform this analysis and to test the hypotheses and the model in a robust manner, the data was augmented using two different statistical approaches to meet the minimum sample size requirements before the bootstrapping technique is used (Fox 2017; John 1981; Ma et al. 2024; Mokhtar et al. 2023; Mooney et al. 1993). In the first method (Approach A), the data was augmented using bootstrap resampling such that each factorial cell meets the minimum number of 30 observations, resulting in 120 records per task, and an overall sample size of 480 records for all four experimental tasks. In the second method (Approach B), the data was bootstrapped such that the factorial cell with the smallest sample size (i.e., Older Maximizers at s = 4) was resampled to meet the minimum required number of 30 observations, and each of the remaining cells were resampled such that it maintains the same distribution ratio of sample size compared to the factorial cell with the smallest sample size in the original raw dataset. This created a dataset with 330 records for each of the experimental tasks, and a total sample size of 1320 for all four tasks. ***Table 50*** provides a summary of the sample size for the two data augmentation approaches. Both data augmentation methods address the sample size limitation while preserving group characteristics (Baroudi and Orlikowski 1989; Nakhwan and Duangsoithong 2022).

Table 50. Sample size per task for the two Bootstrapping Approaches

Bootstrapping Technique		Approach A*			Approach B**		
		Cognitive Style			Cognitive Style		
		Satisficer	Maximizer	**Total**	Satisficer	Maximizer	**Total**
Chronological Age	Younger Adults	30	30	60	98	150	248
	Older Adults	30	30	60	52	30	82
	Total	60	60	**120**	150	180	**330**

*Augmenting the data using resampling so that each factorial cell meets the minimum requirement of 30 samples
**Augmenting the data using resampling so that each factorial cell meets the minimum requirement of 30 samples while preserving the original distribution ratio of sample size across factorial cells

5.4 Hypotheses Testing

A PLS-SEM model was created in SmartPLS 4 for each of the two augmented datasets. The model included three reflective constructs (i.e., Cognitive Style, Perceived Decision Quality, Perceived Decision Effort), one formative composite construct (i.e., VPC), and three objective measures (i.e., Age, Decision Quality, Decision Effort). To test the hypotheses, each model was calculated using a one-tailed percentile bootstrapping of 10,000 subsamples at a p value of 0.05, and a 95% confidence level was used to assess the significance of the path coefficients. The measurement model demonstrated acceptable reliability and validity. All factor loadings exceeded 0.70, composite reliability (CR) values were above 0.70, and average variance extracted (AVE) exceeded 0.50, indicating good convergent validity. Discriminant validity was confirmed using the Heterotrait-Monotrait (HTMT) criterion, with all values below 0.85. For formative constructs, multicollinearity was assessed using Variance Inflation Factor (VIF). All VIF values were below 3.3, indicating no critical multicollinearity concerns. The outer weights of formative indicators were evaluated through bootstrapping to confirm their significance and relevance. ***Figure 31*** shows the PLS-SEM model results for augmented Approach A, while ***Figure 32*** shows the results for Approach B. The hypotheses testing results are discussed below.

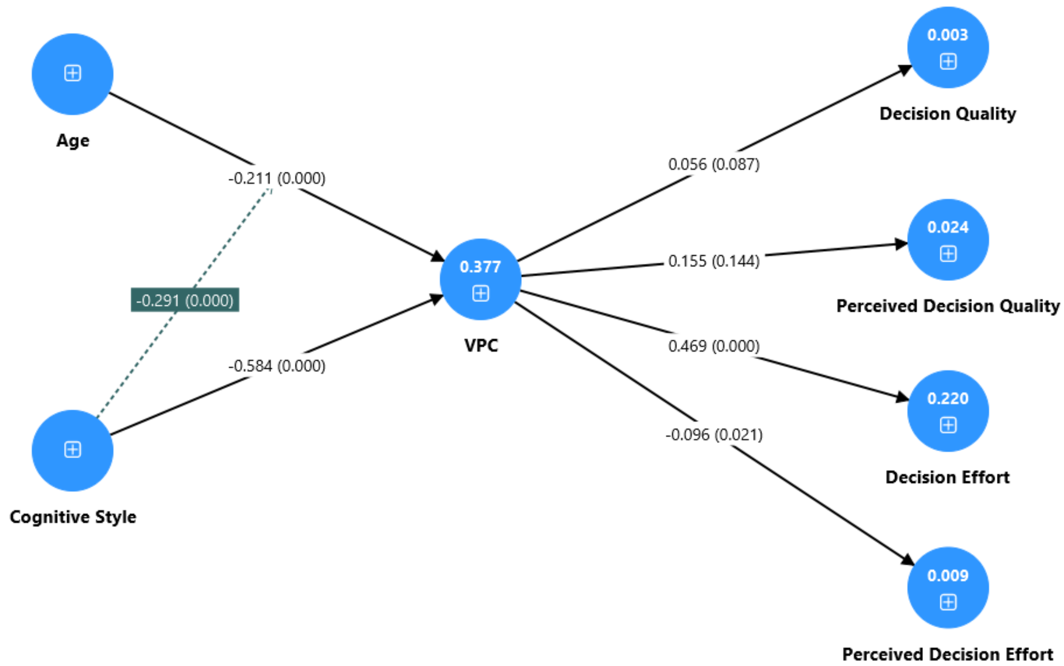

Figure 31. SmartPLS 4 PLS-SEM Model Results for Augmented Approach A

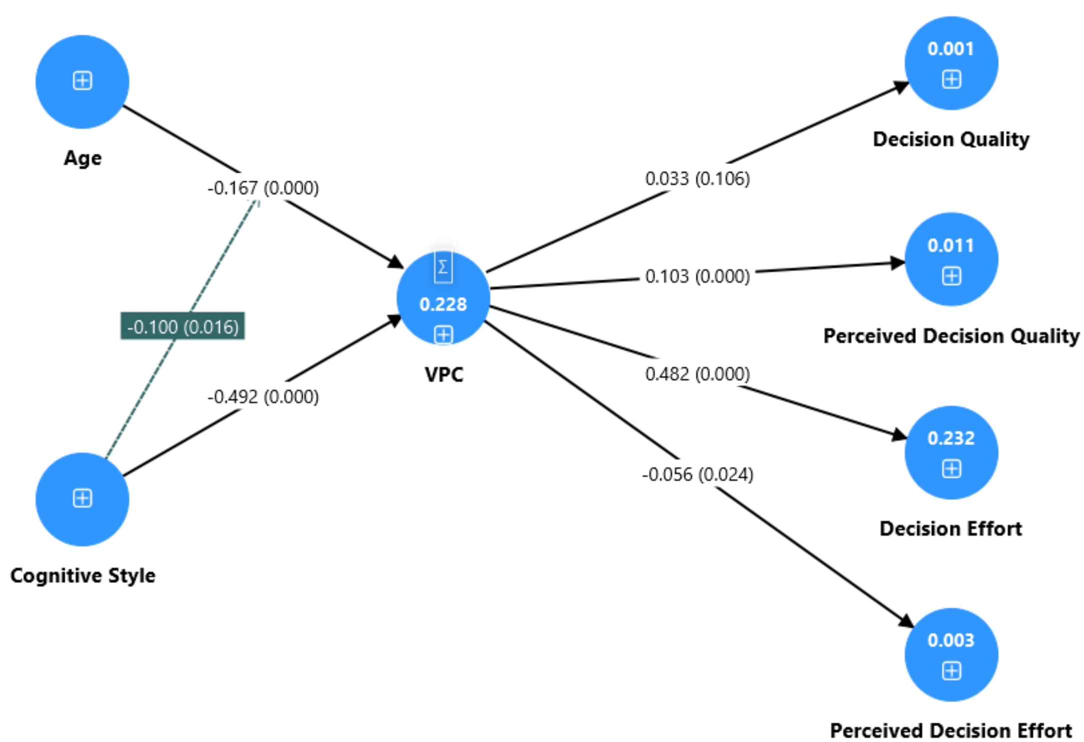

Figure 32. SmartPLS 4 PLS-SEM Model Results for Augmented Approach B

5.4.1 Individual Differences and VPC

As hypothesized, age had a significant negative effect on VPC for both augmented approaches. The path coefficients and p-values for each analysis are (β = -0.211, $p < .00$) for Approach A and (β = -0.167, $p < .00$) for Approach B. This provides strong support for H1.

Surprisingly, the results for H2 were counter intuitive as they were significant but in the opposite of the hypothesized direction. Cognitive style had a significant negative effect on VPC for both augmented approaches. The path coefficients and *p* values for each analysis are (β = -0.584, $p < .00$) for Approach A and (β = -0.492, $p < .00$) for Approach B. This does not support H2.

Despite this result, cognitive style was found to negatively moderate the relationship between age and VPC in both models as hypothesized. Cognitive style had a significant negative moderating effect on the relationship between age and VPC for both augmented approaches. The path coefficients and *p* values for each analysis are (β = -0.291, $p < .00$) for Approach A and (β = -0.100, $p = .016$) for Approach B. This provides strong support for H3.

Looking at the R^2 values overall, these relationships explained 37.7% of the variance for VPC using Approach A and 22.8% using Approach B.

5.4.2 VPC and Decision Outcomes

VPC had a marginal positive impact on decision quality using Approach A (β = 0.056, $p = .087$) with a *p* value approaching significance and an R^2 of only 0.3%. VPC had marginal to no impact on decision quality in the model using Approach B (β = 0.033, $p = .106$). Thus, hypothesis H4 is only marginally supported.

VPC had had no effect on perceived decision quality for Approach A, the path coefficients and *p* values are (β = 0.155, $p = .144$). For Approach B, the relationship was positive and statistically significant as hypothesized (β = 0.103, $p < .00$) with an R^2 of 1.1%. This provides partial support for H5.

VPC had a strong significant positive effect on decision effort for both models. The path coefficients and *p* values are (β = 0.469, $p < .00$) for Approach A with an R^2 of 22%, and (β = 0.482, $p < .00$) for Approach B with an R^2 of 23.2%. This provides strong support for H6.

Finally, the relationship between VPC and perceived decision effort was also found to be counter intuitive as they were significant but in the opposite of the hypothesized direction. VPC had a significant negative effect on VPC for both augmented approaches. The path coefficients and *p* values for each analysis are (β = -0.096, p = .021) with an R^2 of 0.9% for Approach A and (β = -0.056, p = .024) with an R^2 of 0.3% for Approach B. This does not support H7.

6 Discussion

The hypothesis testing analysis results are summarized in ***Table 51***.

Table 51. Summary of Hypotheses Testing

Hypothesis	Independent Variable	Dependant Variable	Results for Approach A	Results for Approach B
H1	Age	VPC	Supported	Supported
H2	Cognitive Style	VPC	Significant but opposite direction	Significant but opposite direction
H3	Age * Cognitive Style	VPC	Supported	Supported
H4	VPC	Decision Quality	Marginal support	Not supported
H5	VPC	Perceived Decision Quality	Not supported	Supported
H6	VPC	Decision Effort	Supported	Supported
H7	VPC	Perceived Decision Effort	Significant but opposite direction	Significant but opposite direction

6.1 Main Findings Discussion

The findings of this study provided mixed support for the proposed hypotheses. In line with H1, older adults exhibited significantly lower Visual Perceptual Comprehensiveness (VPC) compared to younger adults. This indicates that compared to younger adults, older adults generally attended to less product-relevant information and spent less time gazing at their attended information. This finding aligns with prior research on age-related declines in attentional control and information processing, suggesting that visual information acquisition may become less efficient with age.

In contrast to H2, cognitive style was significantly related to VPC, but in the opposite direction than hypothesized, with Maximizers exhibiting lower VPC than Satisficers. One possible explanation for this is that maximizers perform better in analytic decision-making tasks, suggesting focused, deliberate processing that may come at the expense of broader attention (Misuraca, R. et al. 2015). Another possible explanation is the measurement items for cognitive style. While the items showed sufficient reliability, the inter-correlation matrix for the construct items shown earlier in ***Table 23*** shows that some items are negatively correlated to each other, which is unusual for a reflective construct and not consistent with other studies using this scale (Karimi et al. 2015; Love 2009). A further post-hoc factor analysis of cognitive style items was conducted to investigate this further, with the scree plot shown in ***Figure 33***. The results indicate that the 13 items for cognitive style loaded on, not one but, 5 distinct factors. This can be explained by the large item set for the measurement scale coupled with the small sample size, whereas a much larger sample size is required for factor stability (Hair et al. 2014). Another post-hoc analysis indicated that maximizing has the strongest negative impact on the "Breadth" composite of VPC. This pattern may help explain why the relationship between cognitive style and VPC observed in H2 was in the opposite direction than hypothesized. Maximizers may focus more narrowly but more intently on key information, resulting in lower overall VPC scores despite more effortful or deliberate processing.

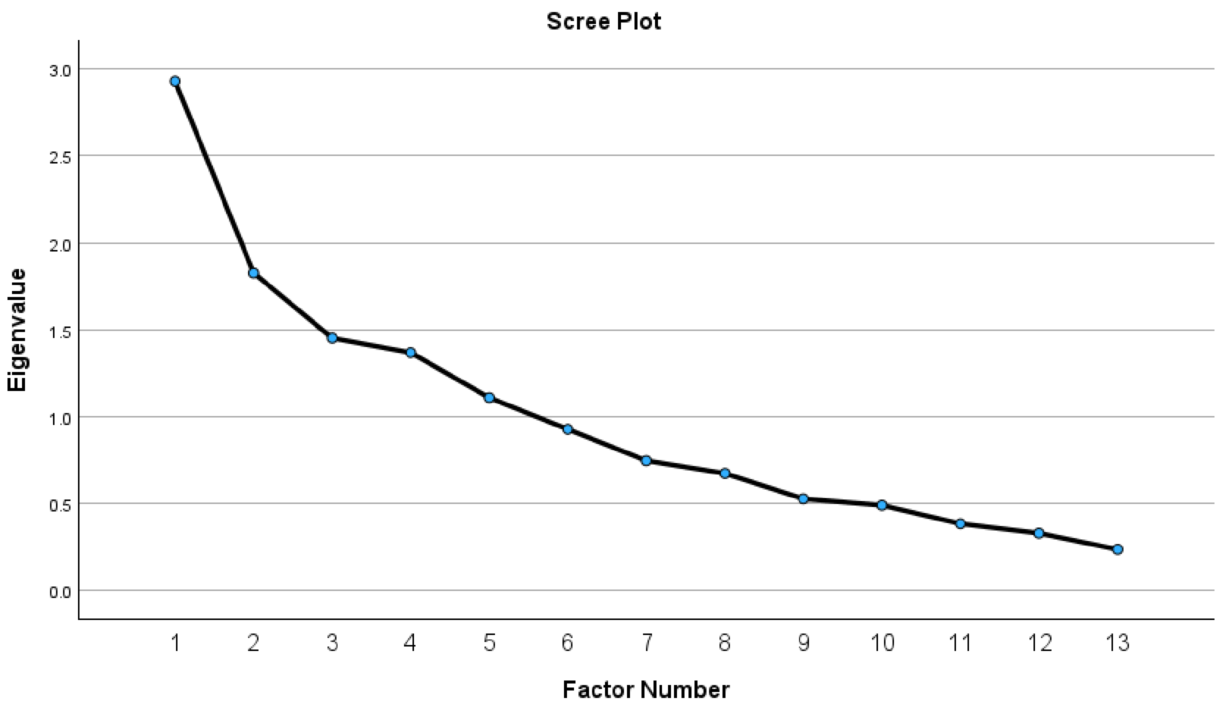

Figure 33. Scree Plot for Cognitive Style Items Factors

The interaction between age group and cognitive style (H3) was strongly negative and significant as hypothesized, suggesting that maximizing moderated the effect of age on VPC, reducing its negative impact. This supports that older adults who exhibit maximizing tendencies are better able to offset age-related declines in visual processing by engaging in more focused or effortful strategies. These findings align with the theoretical view that decision strategies can act as compensatory mechanisms in aging populations (Hess et al. 2009).

In terms of decision outcomes, the results for H4 and H5 were limited. VPC had only a marginally significant effect on objective decision quality under one data augmentation approach and no effect under the other. These findings suggest that more comprehensive visual attention does not necessarily lead to better decisions in this context, possibly because decision quality is influenced by additional unmeasured factors such as system quality or product knowledge. For perceived decision quality (H5), the results were mixed—non-significant under Approach A but statistically significant under Approach B. This partial support may reflect the subjective nature of perception-based outcomes, which can be influenced by response biases or self-confidence rather than visual processing patterns alone.

The findings for H6 were strong and consistent. VPC was significantly and positively associated with objective decision effort (decision time) in both models, providing support for the hypothesis. This reinforces the conceptual assumption that broader, more deliberate, and more focused visual attention requires more cognitive and temporal resources. This result also serves as a useful internal validation of the VPC construct.

However, the results for H7 ran counter to expectations. Rather than being positively associated with perceived decision effort, VPC was negatively associated with it, and significantly so in both augmented models. This suggests that participants who engaged in more extensive visual processing did not perceive themselves as exerting more effort. One possible explanation is that participants who process information more comprehensively may experience greater fluency or confidence, reducing their subjective sense of effort. This dissociation between objective behaviour (decision time) and subjective experience (perceived effort) is not uncommon in decision-making research and highlights the importance of measuring both behavioral and perceptual dimensions separately (Kahneman 2011). Another explanation could be a sense of cognitive flow or perceived enjoyment, where participants who were more intensely immersed in the task or generally enjoy e-commerce shopping experience may have not felt the passage of time or effort typically associated with purely utilitarian IS as opposed to mixed utilitarian-hedonistic systems such as e-commerce (Agrawal and Karahanna 2000; Barta et al. 2023; Burns 2006; Cowart and Goldsmith 2007).

Together, these findings provide a nuanced picture. While VPC appears to play a significant role in how individuals invest effort into decision-making tasks (as seen in H1, H3, and H6), its connection to outcomes such as decision quality and perceived effort is less clear and may depend on additional mediators or moderators not captured in the current model.

6.2 Cognitive Bias & Multigroup Task Analysis

6.2.1 Training (Stove) and Control (No Bias/Refrigerator) Tasks

To examine whether structural relationships varied by task type, a Partial Least Squares Multigroup Analysis (PLS-MGA) was conducted using SmartPLS 4, comparing the training task (Stove) and the control/no bias task (Refrigerator) across the two augmented datasets (i.e., Approach A, Approach B). Each model included the same constructs and paths, and bootstrapping was conducted using 10,000 resamples and one-tailed testing with 95% confidence intervals to evaluate significance. ***Table 52*** provides a summary of the results.

Table 52. PLS-MGA Path Coefficients and Significance by Task and Approach (Stove vs. Refrigerator)

Path	Refrigerator (A)	Stove (A)	Refrigerator (B)	Stove (B)	Notes
Age → VPC	–0.023 (p = .410)	–0.423 (p = .047)	–0.054 (p = .176)	–0.381 (p < .001)	Stronger age effect in Stove (training)
Cognitive Style → VPC	–0.688 (p < .001)	–0.536 (p = .002)	–0.558 (p = .001)	–0.484 (p < .001)	Strong negative effect across both tasks
Cog. Style × Age → VPC	–0.355 (p = .001)	–0.295 (p = .022)	0.009 (p = .465)	–0.189 (p = .004)	Moderation stronger in Stove (B), both significant in A
VPC → Decision Effort	0.763 (p < .001)	0.365 (p = .109)	0.705 (p < .001)	0.358 (p < .001)	Strong effect in Refrigerator; weaker but sig. in Stove (B)
VPC → Decision Quality	0.061 (p = .236)	–0.048 (p = .388)	0.070 (p = .092)	0.076 (p = .082)	Non-significant across all models
VPC → Perceived Effort	0.133 (p = .141)	–0.405 (p < .001)	–0.087 (p = .212)	–0.172 (p = .001)	Strong negative effect in Stove (training)
VPC → Perceived Quality	–0.163 (p = .133)	0.338 (p < .001)	0.163 (p = .053)	0.265 (p < .001)	Positive in Stove, sig. in both models (B stronger)

In both approaches, the age to VPC path was significantly stronger in the Stove (training) task than in the Refrigerator (control) task. In Approach A, the effect was significant for Stove (β = –0.423, p = .047) but not for Refrigerator (β = –0.023, p = .410). In Approach B, this pattern persisted, with the effect highly significant for Stove (β = –0.381, p < .001) and again non-significant for Refrigerator (β = –0.054, p = .176). This suggests that age-related declines in visual comprehensiveness were more pronounced in the training context, potentially due to unfamiliarity with the task or lower engagement.

The negative effect of cognitive style on VPC was consistent and significant across all conditions and models, with path coefficients ranging from –0.484 to –0.688 (p < .01 in all cases). This reinforces the earlier counter-intuitive findings that maximizers exhibited lower VPC scores compared to satisficers, regardless of task type.

For the interaction between age and cognitive style, moderation effects were significant across both tasks in Approach A, but only in the Stove task in Approach B. In Approach A, the interaction was significant for both Stove ($\beta = -0.295$, $p = .022$) and Refrigerator ($\beta = -0.355$, $p = .001$). In Approach B, the interaction was significant only in the Stove condition ($\beta = -0.189$, $p = .004$), and non-significant in the Refrigerator condition ($\beta = 0.009$, $p = .465$). This suggests that maximizers were better able to compensate for age-related declines in VPC, especially during the training task where strategic behavior may have been more variable. This was not the case for the no-bias condition where alternatives were randomized.

The relationship between VPC and decision effort (i.e., time) was strong and significant in the Refrigerator (control) condition across both approaches (A: $\beta = 0.763$, $p < .001$; B: $\beta = 0.705$, $p < .001$). In contrast, the effect in the Stove (training) condition was weaker: it was non-significant in Approach A ($\beta = 0.365$, $p = .109$), but reached significance in Approach B ($\beta = 0.358$, $p < .001$). This suggests that VPC consistently contributes to increased decision effort in familiar or neutral decision contexts but may have a more limited role during early or instructional phases.

The effect of VPC on decision quality was non-significant across all models, with coefficients near zero. This result further supports earlier findings that visual processing alone may not directly improve decision performance, especially when task demands are complex or decisions are difficult under randomized conditions.

A notable pattern emerged for VPC and perceived decision effort. In both approaches, VPC had a strong negative effect in the Stove task (A: $\beta = -0.405$, $p < .001$; B: $\beta = -0.172$, $p = .001$), but not in the Refrigerator task. This counterintuitive result indicates that participants who processed information more thoroughly during training perceived the decision as less effortful, possibly due to cognitive flow or enjoyment especially early in the study with the training task.

Finally, VPC positively predicted perceived decision quality in the Stove task, significantly so in both approaches (A: $\beta = 0.338$, $p < .001$; B: $\beta = 0.265$, $p < .001$). In contrast, the effect was negative or marginal in the Refrigerator condition. These findings suggest that during training, participants with more comprehensive visual processing felt more confident in their decisions, even if this did not translate into objectively higher decision quality.

The PLS-MGA results for the Stove (training) and Refrigerator (control) tasks highlight meaningful differences in how individual differences and visual processing interact across task types. Age and Cognitive Style effects on VPC were more pronounced in the training task, suggesting that older adults and maximizers may behave differently when first encountering a decision context. The perceptual outcomes also varied: participants in the Stove condition who showed higher VPC reported less effort and higher perceived decision quality, even though objective performance did not improve, indicating a possible fluency effect during training. By contrast, in the more neutral Refrigerator task, VPC mainly predicted longer decision times without affecting perceptions. These findings suggest that task novelty and familiarity may moderate how cognitive traits and visual attention shape decision outcomes.

6.2.2 Vividness (TV) and Order (Washing Machine) Bias Tasks

To assess whether the structural relationships varied by task type, a Partial Least Squares Multigroup Analysis (PLS-MGA) was conducted using SmartPLS 4, comparing the vividness bias task (TV) and the order bias task (Washing Machine) for each of the two augmented datasets. Each model included the same constructs and paths, and bootstrapping was conducted using 10,000 resamples and one-tailed testing with 95% confidence intervals to examine significance within and across groups. ***Table 53*** provides a summary of the results.

Table 53. PLS-MGA Path Coefficients and Significance by Task and Approach (TV vs. Washing Machine)

Path	TV (A)	WM (A)	TV (B)	WM (B)	Notes
Age → VPC	–0.109 (p = .084)	–0.177 (p = .017)	–0.050 (p = .248)	–0.149 (p = .017)	Stronger effect in WM across both approaches
Cognitive Style → VPC	–0.614 (p < .001)	–0.613 (p < .001)	–0.530 (p < .001)	–0.640 (p < .001)	Strong negative effect in all models
Cog. Style × Age → VPC	–0.042 (p = .337)	–0.267 (p = .045)	–0.015 (p = .419)	–0.202 (p = .019)	Significant only in WM task
VPC → Decision Effort	0.771 (p < .001)	0.532 (p = .001)	0.593 (p < .001)	0.537 (p < .001)	Strong and consistent effect across models
VPC → Decision Quality	0.357 (p < .001)	0.124 (p = .086)	0.034 (p = .219)	0.111 (p = .041)	Significant in TV (A) and WM (B)
VPC → Perceived Effort	–0.234 (p = .003)	0.174 (p = .090)	–0.184 (p = .124)	0.186 (p = .150)	Significant only in TV (A)
VPC → Perceived Quality	–0.104 (p = .226)	0.294 (p = .036)	–0.081 (p = .178)	0.145 (p = .158)	Only significant in WM (A)

The results revealed several notable differences between the two task conditions. First, the path from Age to VPC was significant in the Washing Machine condition (β = –0.177, p = .017), but only marginally significant in the TV condition (β = –0.109, p = .084), suggesting that age had a stronger negative influence on visual perceptual comprehensiveness in the order bias task. This indicates that older adults may be less influenced by the bottom-up vividness of alternatives and more influenced by the top-down ability to retain information in working memory (Czaja et al. 2006).

The path from Cognitive Style to VPC was significant and similarly strong in both tasks (TV: β = –0.614, Washing Machine: β = –0.613; both p < .001), indicating that the counter-intuitive inverse relationship between maximizing tendencies and VPC was robust across task types.

The moderation effect of Cognitive Style on the Age to VPC path was significant in the Washing Machine (order bias) task (β = –0.267, p = .045) but not in the TV (vividness) task (β = –0.042, p = .337), suggesting that maximizing tendencies more strongly buffered the negative impact of age in the order bias condition than in the vividness condition.

The path from VPC to Decision Effort was strong and significant in both tasks (TV: β = 0.771, p < .001; Washing Machine: β = 0.532, p = .001), but substantially stronger in the TV condition, indicating that comprehensiveness of visual processing more heavily influenced time investment during vividness-based decisions.

Interestingly, the path from VPC to Decision Quality was significant in the TV task ($\beta = 0.357$, $p < .001$), but not in the Washing Machine task ($\beta = 0.124$, $p = .086$), suggesting that visual comprehensiveness may play a greater role in improving outcomes when vividness bias is at play.

The relationship between VPC and Perceived Decision Effort revealed a reversed effect: significantly negative in the TV task ($\beta = –0.234$, $p = .003$), and marginally positive (but non-significant) in the Washing Machine task ($\beta = 0.174$, $p = .090$). This suggests that under vivid conditions, those who process information more visually comprehensively may feel that the task required less effort, possibly due to fluency or confidence effects.

Finally, VPC had a significant positive effect on Perceived Decision Quality in the Washing Machine task ($\beta = 0.294$, p = .036), but a non-significant and negative relationship in the TV task ($\beta = –0.104$, $p = .226$), highlighting a divergent role of VPC in shaping perceived decision outcomes across bias conditions.

Overall, these findings suggest that task type moderates the influence of VPC on both behavioral and perceptual decision outcomes, with stronger and sometimes reversed effects depending on the bias being induced. This highlights the importance of contextual task characteristics in shaping how visual attention processes impact decision-making.

7 Conclusion

This study set out to investigate how individual differences, particularly age and cognitive style, influence visual information processing in e-commerce decision-making and how this processing relates to decision outcomes. To address this, a novel construct, Visual Perceptual Comprehensiveness (VPC), was developed and validated using PLS-SEM and eye-tracking data across multiple decision tasks.

As outlined in Chapter 1, the study pursued three core research objectives:

1. To explore the impact of individual differences (age, cognitive style) on objective and perceived decision outcomes of quality and effort.
2. To develop a visual decision processing construct (VPC) and objectively investigate how it influences susceptibility to harmful biases and how it impacts objective and perceived decision quality and effort.
3. To validate VPC as an objective measure of bias susceptibility and investigate how these relationships vary across different task contexts (e.g., bias-inducing vs. neutral tasks).

These objectives have been met in several important ways:

First, the study confirmed that older adults tend to exhibit lower VPC, suggesting age-related declines in the ability to engage in focused and comprehensive visual attention during online shopping decisions.

Second, while the relationship between cognitive style (maximizing vs. satisficing) and VPC was in the opposite direction than hypothesized, the finding was consistent across models, offering new insights: Maximizers may engage in more selective but intense information processing, rather than broad scanning.

Third, results demonstrated that VPC is meaningfully associated with decision effort, particularly objective decision time, affirming that visually engaged users tend to invest more cognitive effort.

Finally, through PLS Multigroup Analysis, the study showed that task context matters. Some effects varied across bias-inducing vs. neutral tasks (e.g., vividness, order bias), highlighting that VPC's role is influenced by situational characteristics.

The study thus contributes to the growing literature in NeuroIS and e-commerce decision making by proposing a quantifiable, eye-tracking-based construct (VPC) that captures complex user attention patterns. Methodologically, it also demonstrated the value of combining objective gaze behavior with psychometric modeling through SmartPLS 4. This research bridges a significant gap in understanding how older adults and different decision-makers visually process online shopping information, and how this processing influences real and perceived outcomes.

The theoretical, methodological, and practical contributions of this study are discussed next. Followed by acknowledgements of the limitations of this study accompanied by relevant suggestions for future research.

7.1 Contributions

This research makes several significant theoretical, methodological, and practical contributions to the literature on decision-making in digital commerce contexts, particularly with respect to age, cognitive style, and visual information processing.

7.1.1 Theoretical Contributions

First, the study introduces and operationalizes the construct of Visual Perceptual Comprehensiveness (VPC), derived from objective eye-tracking data. By integrating breadth and deliberation of gaze behavior, this construct offers a novel lens for understanding how users interact with digital decision environments. While the relationships between VPC and decision quality were mixed, the construct proved consistently predictive of decision effort, and its interaction with individual differences (age and cognitive style) yielded several theoretically meaningful insights.

Second, the study contributes to the growing body of literature on individual differences in digital decision-making by examining how chronological age and cognitive style (satisficing vs. maximizing) influence visual information processing. The finding that older adults exhibit lower VPC aligns with cognitive aging theories and reinforces the importance of accommodating age-related changes in decision interfaces. In contrast, the inverse relationship between maximizing and VPC offers new perspectives on how decision strategies may shape, and at times constrain, visual attention patterns.

Third, the inclusion of task-specific bias conditions (i.e., vividness bias, order bias, no bias, training) adds ecological validity to the experimental design. The multigroup analyses revealed that task context significantly moderates key relationships, highlighting the importance of accounting for decision task characteristics and decision features when modeling behavior in applied settings.

7.1.2 Methodological Contributions

Methodologically, this study makes several contributions. First, the study introduces a novel algorithm designed to control for several confounding variables and procedurally generate realistic alternatives for increased ecological validity. The algorithm uses real market data to generate a list of realistic alternatives to control for task difficulty and varying personal preferences and affluence between participants. To the best of my knowledge, this algorithm is the first of its kind in the decision-making literature and adds significant value to future research studies.

Second, the study demonstrates the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) to model both formative and reflective constructs using multimodal data, including psychometric scales, behavioral measures, and eye-tracking outputs. The integration of formative modeling for VPC and the use of PLS-Multigroup Analysis (PLS-MGA) provide a robust and flexible analytical framework suitable for complex, small-sample studies.

Third, the study utilizes two approaches for data augmentation aimed to address limitations in sample size while preserving original group characteristics. To the best of my knowledge, this is the first use of such bootstrapping techniques aimed at addressing sample size limitations associated with NeuroIS research.

Finally, the research also validates an experimental framework for integrating cognitive bias manipulations with real-time physiological measures. This framework can be adapted for future research in interface design, cognitive training, and aging and technology.

7.1.3 Practical Contributions

From a practical standpoint, the findings have implications for the design of e-commerce interfaces, particularly those targeted toward older adults or individuals with differing cognitive styles. For instance, maximizing users may benefit from tools that reduce information overload or structure choices more clearly. Further, older adults could be advised through intervention methods about the benefits of maximizing, and how it doesn’t impact their perceptions of decision effort but improves the quality of decisions, nonetheless. Similarly, interface adaptations that support visual focus and reduce cognitive effort could improve decision experience and efficiency, particularly for older users.

The research also underscores the importance of early task design (e.g., training content) in shaping user expectations and confidence. Findings from the Stove (training) task indicate that comprehensiveness in early decisions can significantly affect users' perceived effort and decision satisfaction, with potential implications for onboarding and instructional design in online systems.

7.2 Limitations and Future Research

Despite the study's contributions, several limitations should be acknowledged, as with any research study.

7.2.1 Sample Size and Generalizability

The study employed a relatively small sample size, which, although manageable with the bootstrapping and data augmentation approaches and with the analysis within the PLS-SEM framework, limits the generalizability of the findings. The small sample size also constrained the complexity of the models and increased susceptibility to Type II errors. In particular, the cognitive style scale showed some irregularities in inter-item correlations, likely exacerbated by the limited sample size. Larger samples are necessary to ensure factor stability and better capture potential subgroup differences. Future research can focus more on recruitment and securing data for the experiment using mobile research infrastructure such as the MUXL.

7.2.2 Age Operationalization

This study employed a simple chronological conceptualization of aging and was limited to two of the four age groups. As discussed earlier, age is a composite construct and several conceptualizations of aging could be explored, such as cognitive age. Future research can explore other conceptions of the aging human within the framework of e-commerce decision making, especially as related to gaze behaviours and decision outcomes. Future research can examine different conceptualizations of age, such as normal vs. pathological aging or cognitive age.

7.2.3 Measurement of Cognitive Style

As noted, post hoc analyses indicated that the cognitive style scale loaded on multiple factors, which may reflect measurement noise or multidimensionality not accounted for in the original model. This issue highlights the need for scale refinement or item reduction, particularly in small-sample physiological studies where scale reliability directly impacts structural model stability. Future research can examine and validate the cognitive style scale in the context of e-commerce with a larger sample size in varying nomological networks.

7.2.4 Construct Validity of VPC

While VPC was conceptually grounded and analytically derived through both PCA and PLS modeling, the construct remains exploratory. Its predictive validity was strong for decision effort but limited for decision quality and perceptions of decision effort, and its association with cognitive biases was not strong. Additional research is needed to refine the operationalization of VPC, potentially by incorporating dynamic or temporal gaze metrics, or including additional attentional constructs such as quality adjusted weighted averages of fixated information or consistency with personal rankings and attribute preferences.

7.2.5 Operationalization of Decision Effort

This study utilized a straightforward operationalization of decision effort through decision time. While this is commonly used in the literature, other methods of operationalizing decision effort are also utilized in research, particularly in NeuroIS studies. These objective measures of decision effort include Pupil Dilation and Electroencephalography (EEG). Under equiluminant and equidistant conditions, pupils dilate as function of the ANS response to cognitive effort and strain (Duchowski et al. 2018; Kahneman 2011; Kahneman and Beatty 1966; Piquado et al. 2010). For EEG, parietal oscillations in the Alpha band (i.e., 8 Hz to 13 Hz) are associated with low cognitive effort, while prefrontal-cortex oscillations in the Theat band (i.e., 4 Hz to 8 Hz) indicate high load and strain (Cavanagh and Frank 2014; Kahana 2006; Williams et al. 2019). Future research can explore the relationship between VPC and these direct physiological measures of cognitive load and decision effort.

7.2.6 Task-Specific Confounds

Although the study controlled for complexity across tasks through algorithmic design, differences in task framing and presentation order may still have introduced confounds. For example, the vividness and order bias conditions may have unintentionally varied in cognitive load or emotional salience. Similarly, the training task may have elicited behavior not representative of later decisions. Further, the collection of independent variable data, such as cognitive style, was consistently done at the beginning of the experimental session and was not counterbalanced between participants. Some of these effects were partially mitigated through multigroup analysis but cannot be entirely ruled out.

7.2.7 Qualitative Methods

This study did not utilize qualitative methods. One relevant method that could be utilized in this research is Retrospective Think-Aloud (RTA) as a qualitative method to delve deeper into the cognitive processes of participants as they recall and explain their fourth and final decision of the experiment while watching a gaze replay on the screen. Such interviews can provide deep insights into the decision-making process of participants. For example, thematic analysis (Creswell and Creswell 2018; Detlor 2003) of RTA interviews could reveal deeper and more meaningful insights on the relationship between the constructs in the research model. It could be particularly useful in understanding the counter-intuitive finding regarding maximizing and VPC. Future research can examine this in more depth.

7.2.8 Bias-Product Confounding Effect

This study assigned specific cognitive biases to specific products without counterbalancing. While this approach substantially reduced the complexity of the experimental design, it may have introduced potential bias–product confounding effects. Future experimental research could address this by randomly assigning different cognitive biases to different products to control for such confounding.

In addition, the manner in which VPC was prepared and calculated prior to inclusion in the PLS model, by aggregating across tasks to produce a single composite score per participant, precluded the use of statistical models designed to account for correlated residuals in repeated-measures data (e.g., repeated measures ANOVA, linear mixed models, or GLMM). This aggregation ensured independence of observations for PLS-SEM, but it also meant that within-subject variability and residual correlation could not be explicitly modeled. Future research could retain the repeated-measures structure and apply appropriate longitudinal or mixed-model approaches to account for these correlations.

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9 Appendices

Appendix I: Major Heuristics and their associated Cognitive Biases

Table 54: Heuristics and Biases mentioned in the discussion

Heuristic	Relevant Bias	Definition	References
Availability	Order*	Primacy Effect*: Primal alternatives in a set receive more attention compared to later ones	(Arnott 2006; Bazerman and Moore 2009; Orquin and Loose 2013)
		Recency Effect: Latest perceived alternatives in a set receive more attention because they are more readily available in working memory	
	Vividness*	Visually salient alternatives attract and receive more attention	(Arnott 2006; Bazerman and Moore 2009; Fleischmann et al. 2014; Kahneman et al. 1982; Orquin and Loose 2013)
	Imaginability	Easily imaginable events can be misjudged as more probable	(Arnott 2006; Bazerman and Moore 2009; Kahneman 2011; Tversky and Kahneman 1974)
Representativeness	Base Rate	Case-specific information tends to be used in isolation from base rate data	(Arnott 2006; Bazerman and Moore 2009; Kahneman et al. 1982)
	Sample Size	The size of the sample related to a piece of evidence tends to be ignored	(Arnott 2006; Bazerman and Moore 2009; Kahneman et al. 1982)
	Misconception of Chance	Independent events tend to be judged as dependent when presented in a sequence	(Arnott 2006; Bazerman and Moore 2009; Kahneman et al. 1982)
	Conjunction	Probabilities of subsets tend to be overestimated relative to sets when conjunctions are more stereotypical and descriptively representative	(Arnott 2006; Bazerman and Moore 2009; Kahneman 2011; Kahneman et al. 1982)
Confirmation	Confirmation	Confirmatory evidence tends to be sought when disconfirmatory evidence can be more useful and critical	(Arnott 2006; Bazerman and Moore 2009; Kahneman 2011; Kahneman et al. 1982)
	Anchoring	An initial data point, even a random one, is used as a basis for adjustment. Adjustments tend to be insufficient	(Arnott 2006; Bazerman and Moore 2009; Kahneman 2011; Kahneman et al. 1982)
	Overconfidence	Ability and skill are often overestimated by decision-makers	(Arnott 2006; Bazerman and Moore 2009; Kahneman et al. 1982)
	Hindsight	Predictability of outcomes is often overestimated in retrospect	(Arnott 2006; Bazerman and Moore 2009; Kahneman et al. 1982)

**Biases that are the focus of this study*

Appendix II: Decision Strategies and Heuristics

Table 55: Decision Strategies and Heuristics, sorted from most to least impactful and effortful, adapted from (Bettman et al. 1990; Chu and Spires 2000; Johnson and Payne 1985; Payne et al. 1993; Tan et al. 2010; Todd and Benbasat 1992, 1994a, 1994b)

Decision Strategy	Description	C*	II**
Weighted Additive (WADD)	The decision-maker assigns a weight for each attribute, rates alternatives on each attribute, sums the products of the weights and attribute ratings, and selects the alternative with the highest total score.	C	N
Equal Weighted Additive (EQW)	Similar to the WADD, the decision-maker examines all attributes and alternatives to identify a total score. However, to simplify the decision process, all attributes are assigned equal weights.	C	N
Elimination by Aspect (EBA)	The decision-maker determines the most important attribute and sets a threshold. All alternatives not meeting the threshold are eliminated. The process is repeated with the next most important attribute until only one alternative remains and is selected.	N	Y
Satisficing (SAT)	The decision-maker examines alternatives one at a time. Each attribute is compared to a pre-defined threshold. The first alternative that exceeds all attribute thresholds is selected.	N	Y
Lexicographic (LEX)	The decision-maker determines the most important attribute. The alternative with the highest rating is selected unless there are ties. For tied alternatives, the process is repeated to evaluate the ratings for the next most important attribute.	N	Y
Majority of Confirming Dimensions (MCD)	The decision-maker compares two alternatives at a time and the alternative with the most winning attribute ratings is retained.	N	Y
Random Choice (RC)	The decision-maker selects one alternative at random with minimal effort and consideration.	-	Y

*Compensatory (C) vs. Non-Compensatory (N) strategy

** Information Ignored (Y=Yes, N=No) when utilizing this strategy Furthermore, the sum of EIPs is positively related to task complexity factors such as the number of alternatives, number of attributes, alternative similarity, and information quality (Payne et al. 1993). Meaning that the more information presented in the decision task, the more cognitive effort is required. Cognitive effort is also complemented by the decision time, which is another objective indicator of cognitive effort involved in a decision (Rydzewska et al. 2024; Tan et al. 2010; Tanius et al. 2009).

Appendix III: Elementary Information Processes

Table 56: Elementary Information Processes (EIP's) adapted from (Johnson and Payne 1985; Payne et al. 1993)

Elementary Information Processes	Description
READ	Read an alternative's value on an attribute and encode into working memory
COMPARE	Compare two alternatives on an attribute
DIFFERENCE	Calculate the size of the difference of the two alternatives for an attribute
ADD	Add the values of an attribute in working memory
PRODUCT	Weight one value by another (multiply)
ELIMINATE	Remove an alternative or attribute from consideration
MOVE	Go to next alternative or attribute
CHOOSE	Announce preferred alternative and stop process

Appendix IV: Adult Cognitive Abilities

Table 57: Adult Cognitive Abilities, categorized as Fluid and Crystalized. These can be measured using the 60 item Weschler Adult Intelligence Scale – IV (Climie and Rostad 2011; Czaja et al. 2006; Tams, Grover, et al. 2014)

Ability Category	Description	Cognitive Ability	Definition
Fluid Abilities	A group of cognitive abilities that enable individuals to learn and perform new tasks efficiently and effectively. These abilities decline with aging.	Attention* *(i.e., Selective, Divided)*	Individual's cognitive ability to clearly perceive stimuli to process and respond efficiently and effectively
		Working Memory Capacity*	Individual's mental ability to preserve new information necessary to complete an active task
		Spatial Reasoning	Individual's ability to conceive relative locations and create a mental representation of a physical system
		Inductive Reasoning	Individual's ability to make generalizations and inferences based on representations and data through induction
		Perceptual Speed	Individual's ability to process information quickly
Crystalized Abilities	A group of cognitive abilities that reflect longer term attributes and variety of abilities, skills, and wisdom that individuals accumulate in their lifetime of education and experiences. These abilities are enhanced with aging.	Verbal Abilities	Individual's vocabulary knowledge and abstract verbal reasoning
		Knowledge and Experience Transfer	Individual's ability to apply their existing knowledge to new situations and tasks
		Discrete Knowledge Structure	Individual's collective repository of general information collected from culture and a lifetime of situations that enables them to link disparate pieces together to make better inferences and judgements

**Abilities that are relevant for this study. These are not measured directly but assumed to decline with Age based on the mounting evidence from the literature as discussed in Section 2.5.2*

Appendix V: DSS Features of Major E-Commerce Websites

A review of the top 25 most-visited B2C and C2C e-commerce websites (Alexa 2018) was performed to identify the predominant features of RAs available to consumers[6]. The following features were examined: Multi-attribute, whether the RA enables the user to set thresholds or preferences for multiple product attributes simultaneously or a single attribute at a time (i.e., LEX); attribute levels, whether the RA enables the user to select multiple values for each attribute, so the user can perform compensatory evaluations; product specific, whether the RA's attribute selection dialogue dynamically adjusts to accommodate product specific attributes (e.g., LCD for TVs, propane for grills) or is static and limited to generic attributes (e.g., price); And CM, whether the website provides a comparison matrix to its users to afford simpler evaluation across a few alternatives.

Table 58: Review of the DSS features provided by the top 25 most-visited e-commerce websites (Alexa 2018)

#	Company	Website	Product Categories	B2C	C2C	Multi-Attribute	Attribute Levels	Product Specific
1	Amazon US	amazon.com	Multiple	Yes	Yes	Yes	Partial	Yes
2	Netflix	netflix.com	Digital Media	Yes	No	No	No	No
3	eBay	ebay.com	Multiple	No	Yes	Yes	Yes	Yes
4	Amazon UK	amazon.co.uk	Multiple	Yes	Yes	Yes	Partial	Yes
5	Etsy	etsy.com	Multiple	No	Yes	Yes	Partial	No
6	Steam	store.steampowered.com	Software and Technology	Yes	Yes	Yes	Yes	No
7	Walmart	walmart.com	Multiple	Yes	No	Yes	Partial	Yes
8	IKEA	ikea.com	Home Improvement	Yes	No	Yes	No	No
9	BestBuy	bestbuy.com	Electronics and Technology	Yes	No	Yes	Yes	Yes
10	Target	target.com	Multiple	Yes	No	Yes	Yes	Yes
11	Nike	nike.com	Apparel and Technology	Yes	No	Yes	No	No
12	Home Depot	homedepot.com	Multiple	Yes	No	Yes	Partial	Yes

[6] Accessed February 24th, 2018

13	Cambridge University	cambridge.org	Books and Print	Yes	Yes	-	-	-
14	Wiley	wiley.com	Books and Print	Yes	No	-	-	-
15	Humble	www.humblebundle.com	Software and Technology	Yes	Yes	Yes	Partial	No
16	Newegg	newegg.com	Multiple	Yes	No	Yes	Partial	Yes
17	H&M	www.hm.com	Apparel	Yes	No	No	No	No
18	GROUPON	www.groupon.com	Multiple	No	Yes	Yes	No	No
19	Nordstrom	nordstrom.com	Multiple	Yes	No	Yes	Partial	Yes
20	TicketMaster	ticketmaster.com	Venue Tickets	Yes	-	-	-	-
21	Macys	macys.com	Multiple	Yes	No	Yes	Yes	Yes
22	B&H	bhphotovideo.com	Electronics and Technology	Yes	No	Yes	Yes	Yes
23	BodyBuilding	bodybuilding.com	Fitness Supplements	Yes	No	Yes	Partial	Yes
24	Costco Wholesale	costco.com	Multiple	Yes	No	Yes	Yes	Yes
25	Lowe's	lowes.com	Multiple	Yes	No	Yes	Yes	Yes

The review reveals many interesting things. Only a few websites feature CMs (e.g., BestBuy) while DSS is predominantly offered in the form of RAs. Three websites do not feature RAs or CMs (i.e., Netflix, Cambridge, Wiley) and only offer category-based browsing and search functions. For the remaining websites, most RAs provided are multi-attribute capable (i.e., 22 RAs). Most interestingly, RAs were found to vary greatly in terms of affordances and features. Eight RAs were found to be very simple and restrict screening to only generic product attributes (e.g., price, delivery time), while 14 RAs afforded product-specific attribute screening. Additionally, only eight RAs were found to be capable of screening attributes based on multiple levels and multiple attributes. Nine RAs were found to partially support this feature, while five RAs were only found to be restrictive in terms of filtering by only one attribute value at a time.

Appendix VI: Vividness Bias Inducing Tactics in E-Commerce

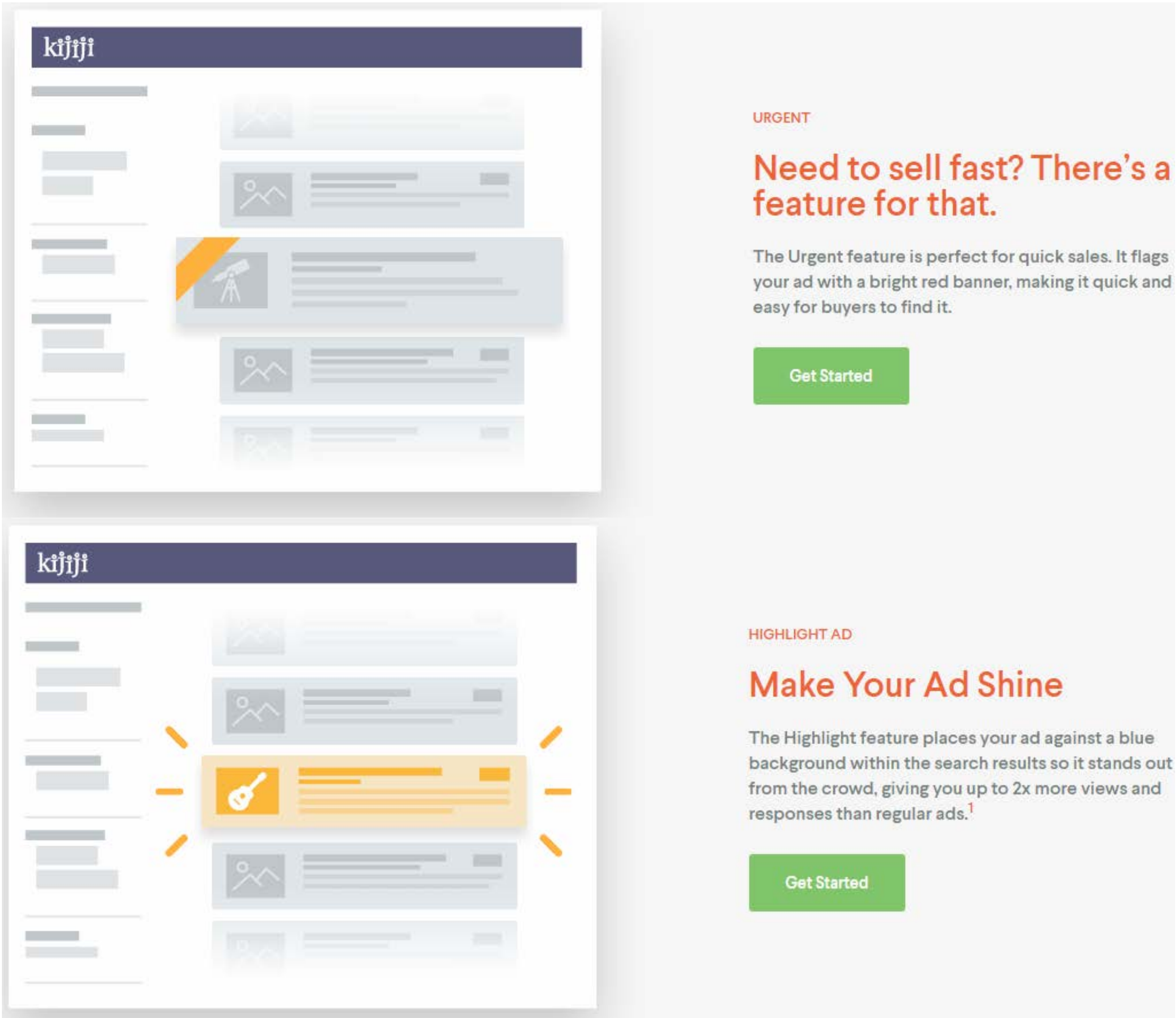


Figure 34: Vividness Bias Inducing Features Available at Kijiji for a Fee

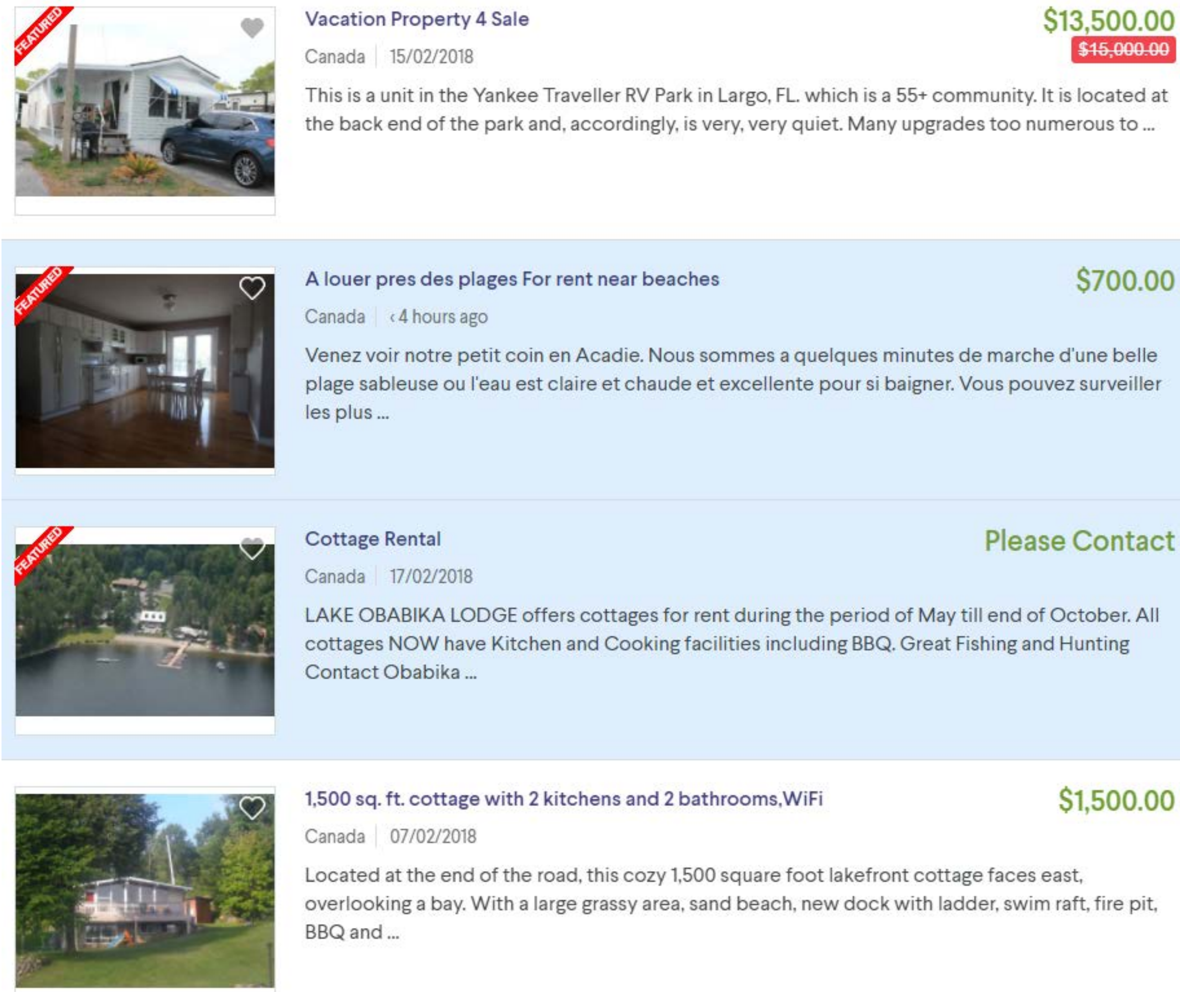


Figure 35: Example from Kijiji showing Vividness Inducing Tactics (i.e., tags, background) in Practice

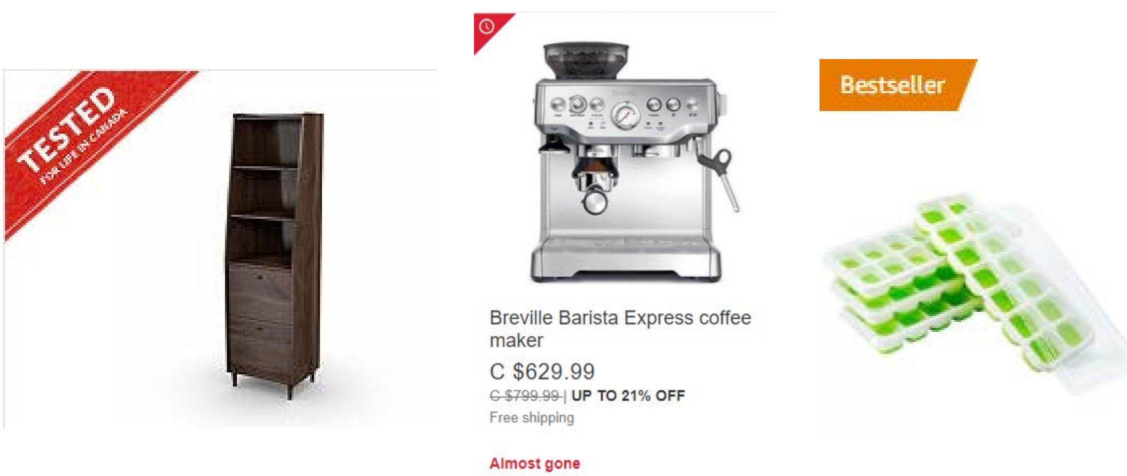


Figure 36: Examples of Vividness Inducing Tactics from Canadian Tire, eBay and Amazon

Appendix VII: Order Bias Inducing Tactics in E-Commerce

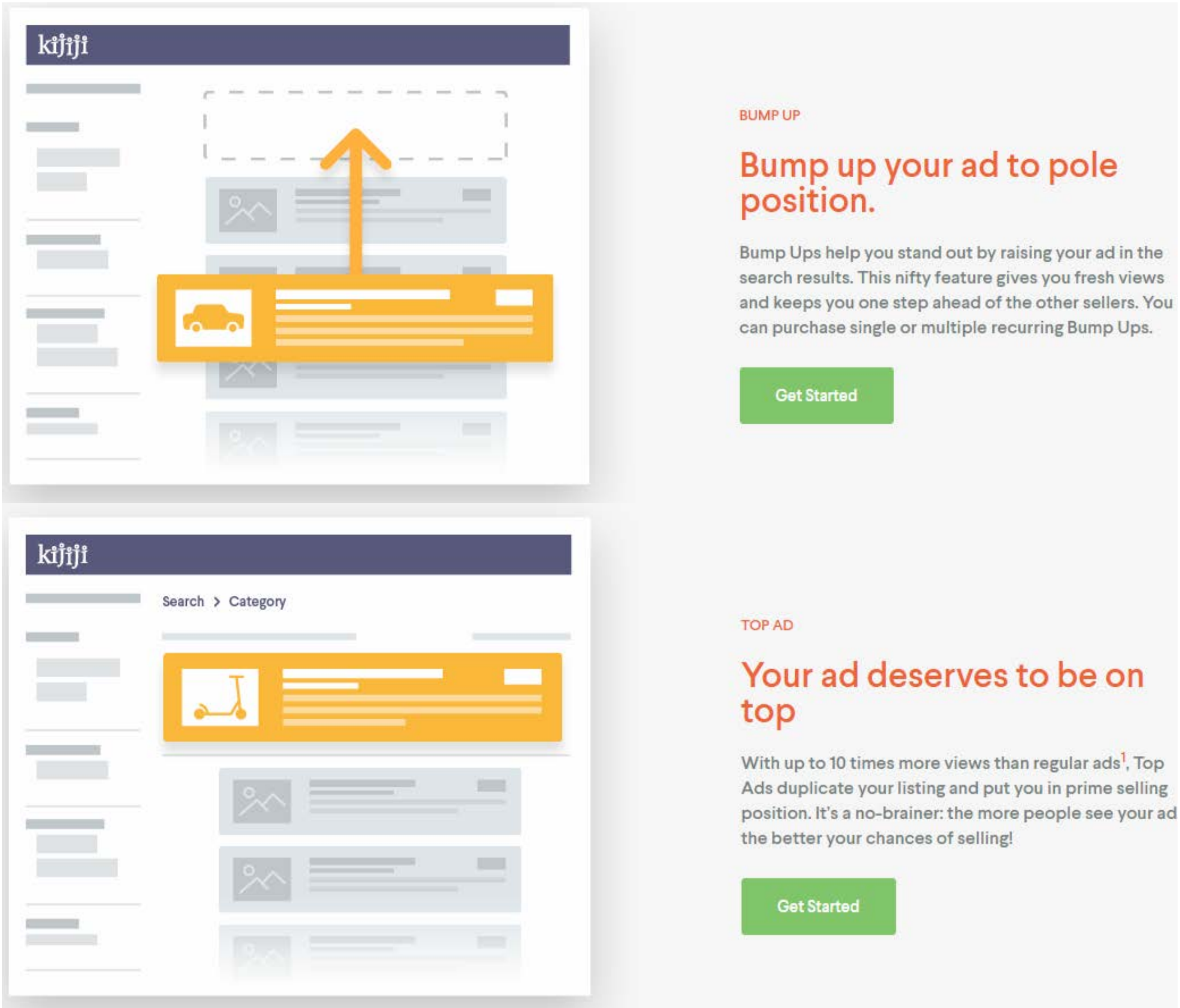


Figure 37: Order Bias Inducing Features Available on Kijiji for a Fee

Appendix VIII: Experimental Procedures & Lab Environment

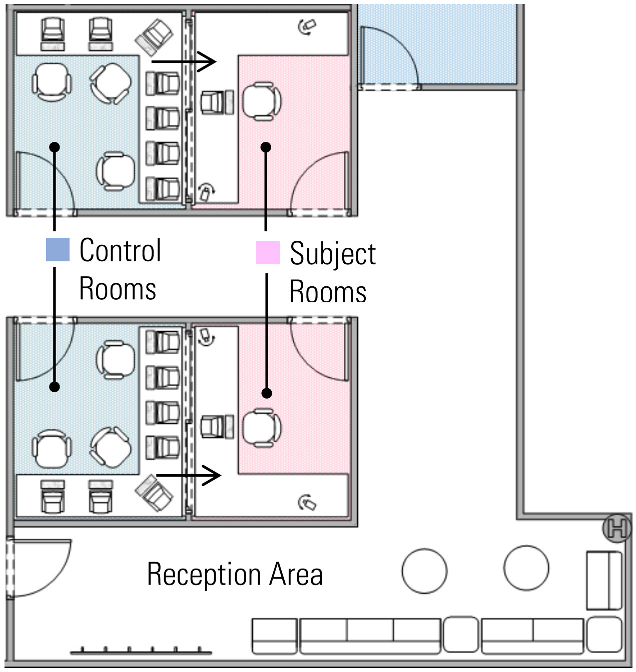


Figure 38. MDTRC Floorplan of Evidence-Based Decision Making Labs of MDTRC at Ron Joyce Centre where the study took place

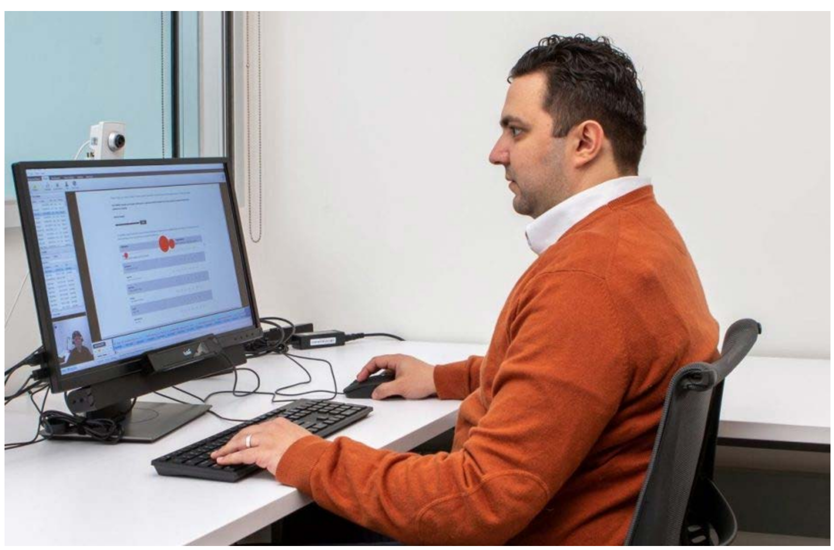


Figure 39. Dissertation Author, Nour El Shamy, reviewing the RTA interview of a participant in MDTRC Lab B

Appendix IX: Product Pictures Used in this Study

Table 59: List of Product Pictures Used in this Study

Stove	TV*	Refrigerator	Washing Machine
			
			
			
			
			
			
			
			
			
			

*The first three pictures were used as manipulations to induce the Vividness Bias

Appendix X: Alternatives Generation Algorithm with Example

The following algorithm was developed for this study to generate a standardized alternative set across participants and tasks for this proposed study. The algorithm was mainly developed from scratch, but the logic, rationale, and some of the equations are adapted from seminal work with similar research designs (Häubl and Trifts 2000; Tan et al. 2010, 2012; Wang and Benbasat 2007, 2009; Xu et al. 2014). It is currently a work-in-progress and some fine tuning is still underway.

Participant attribute importance ratings will be collected for each product category at the beginning of each task. These values will be used to weight the importance of the attributes and calculate a fit score for every possible unique combination of attribute values comprising an alternative. All product attributes are ordinal or categorical, and the desirability of each attribute is assumed to increase or decrease monotonically as a function of the attribute value. For example, a better (i.e., lower) price, a bigger screen, a better resolution, a longer warranty, higher energy savings, a smart TV, and a higher quality sound system are always better. Given the number of attributes and levels per attribute, there are 2,700 possible unique alternatives for each product category (i.e., 5^2 x 3^3 x 2^2). The fit score for each alternative is calculated following Häubl and Trifts (2000), Wang and Benbasat (2009), and Tan et al. (2010) based on the formula:

$$\boldsymbol{F_j = \sum_{r=1}^{7} 1 - \left(W_r \times G_{jr} \right)}$$

$$\boldsymbol{0 \leq F_j \leq 1}$$

Equation 3: Fit Score Formula for Alternative *j* with *r* Attributes

where ***j*** is the sequential number of each potential unique alternative (i.e., ***1 ≤ j ≤ 2,700***), ***W*** is the ***importance weight*** assigned by the participant to attribute ***r*** divided by the total weights assigned to all attributes. ***G*** is the ***attribute gap***, representing the difference between the value of attribute ***r*** for an alternative ***j*** and the maximum possible value (i.e., optimum value) for attribute ***r***, adjusted for the number of total ranks for attribute ***r***. These two factors are calculated based on the following formulae:

$$\boldsymbol{W_r = \frac{Participant_x\, W_r}{Participant_x \sum_{r=1}^{7} W_r}}$$

$$\boldsymbol{0 < W_r < 1}$$

Equation 4: Importance Weight Formula for Attribute r for Participant *x*

$$\boldsymbol{G_{jr} = \frac{Rank_r - 1}{Number\ of\ Ranks_r - 1}}$$

$$0 \leq \boldsymbol{G_{jr}} \leq 1$$

Equation 5: Attribute Gap Formula for Attribute *r* for Alternative *j*

For example, ***Participant 1*** is performing the TV decision task. She has selected $1,250 as her median budget for buying a TV and has rated the importance of each of the 7 TV attributes in the preference elicitation dialogue (see ***Figure 6***) as follows: price 7; dimension 5; resolution 3; warranty 4; energy 3; smart 5; sound 8. Using the price dimension fit line (see ***Figure 7***), the DSS calculates the reasonable median range of TV dimensions for that budget to be 50”. The choice set population for this task based on the participant’s preferences will be generated from the attribute levels shown in ***Table 60***.

Table 60: Example of Participant 1 Showing TV Attribute Data Used to Generate Alternatives Based on Participant 1's Input and Preferences

r	**Attribute**	**Weight $_r$**	**Possible TV Attributes and their Corresponding Values**					
1	**Price**	7	**Rank**	1	2	3	4	5
			Value	\$ 749.99	\$ 999.99	\$ 1,249.99	\$ 1,499.99	\$ 1,749.99
			$\boldsymbol{G_1}$	$\frac{1-1}{5-1}=0$	$\frac{2-1}{5-1}=0.25$	$\frac{3-1}{5-1}=0.5$	$\frac{4-1}{5-1}=0.75$	$\frac{5-1}{5-1}=1$
2	**Dimensions**	5	**Rank**	1	2	3	4	5
			Value	60"	55"	50"	45"	40"
			$\boldsymbol{G_2}$	$\frac{1-1}{5-1}=0$	$\frac{2-1}{5-1}=0.25$	$\frac{3-1}{5-1}=0.5$	$\frac{4-1}{5-1}=0.75$	$\frac{5-1}{5-1}=1$
3	**Resolution**	3	**Rank**	1	2	3		
			Value	2160p (4K/Ultra HD)	1080p (Full HD)	720p (HD)		
			$\boldsymbol{G_3}$	$\frac{1-1}{3-1}=0$	$\frac{2-1}{3-1}=0.5$	$\frac{3-1}{3-1}=1$		
4	**Warranty**	4	**Rank**	1	2	3		
			Value	3 Years	2 Years	1 Year		
			$\boldsymbol{G_4}$	$\frac{1-1}{3-1}=0$	$\frac{2-1}{3-1}=0.5$	$\frac{3-1}{3-1}=1$		
5	**Energy Saving**	3	**Rank**	1	2	3		
			Value	High Savings	Medium Savings	Low Savings		
			$\boldsymbol{G_5}$	$\frac{1-1}{3-1}=0$	$\frac{2-1}{3-1}=0.5$	$\frac{3-1}{3-1}=1$		
6	**Smart**	5	**Rank**	1	2			
			Value	Yes	No			
			$\boldsymbol{G_6}$	$\frac{1-1}{3-1}=0$	$\frac{2-1}{3-1}=0.5$			
7	**Sound System**	8	**Rank**	1	2			
			Value	Mini-Theatre	Hi-Fi			
			$\boldsymbol{G_7}$	$\frac{1-1}{3-1}=0$	$\frac{2-1}{3-1}=0.5$			

A full factorial set of alternatives is generated for all possible combinations of attribute levels available for ***Participant 1***, and a fit score for each alternative is calculated according to her preferences. A sample of the possible alternatives and their corresponding fit scores is illustrated in ***Table 61***.

Table 61: Example of Participant 1 Showing a Sample of Generated Alternatives and their Corresponding Fit Scores Based on Attribute Combinations and Participant Preferences

j	Variable	Price	Dimension	Resolution	Warranty	Energy Saving	Smart	Sound System	Fit Score
1	Value	$ 749.99	60”	2160p (4K/Ultra HD)	3 Years	High Savings	Yes	Mini-Theatre	**1**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	0	0	0	0	0	0	0	
15	Value	$ 749.99	60”	2160p (4K/Ultra HD)	2 Years	High Savings	Yes	Hi-Fi	**0.9**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	0	0	0	0.5	0	0	0.5	
649	Value	$ 999.99	55”	2160p (4K/Ultra HD)	3 Years	High Savings	Yes	Mini-Theatre	**0.914**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	0.25	0.25	0	0	0	0	0	
1081	Value	$ 1,249.99	60”	2160p (4K/Ultra HD)	3 Years	High Savings	Yes	Mini-Theatre	**0.9**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	0.5	0	0	0	0	0	0	
1278	Value	$ 1,249.99	55”	720p (HD)	2 Years	Medium Savings	Yes	Hi-Fi	**0.45**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	0.5	0.25	1	0.5	0.5	0	1	
1734	Value	$ 1,499.99	55”	2160p (4K/Ultra HD)	3 Years	Low Savings	Yes	Hi-Fi	**0.5**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	0.75	0.25	0	0	1	0	1	
2700	Value	$ 1,749.99	40”	720p (HD)	1 Year	Low Savings	No	Hi-Fi	**0**
	W_1	7 / 35	5 / 35	3 / 35	4 / 35	3 / 35	5 / 35	8 / 35	
	G_1	1	1	1	1	1	1	1	

Consumers rarely find products that match their exact preferences or are superior in every way to their alternatives (Wang and Benbasat 2009). The list of results is generated in such a way that ensures that no alternative dominates the others in the result list, and that the participant should make trade-offs and deliberate to find the best alternative in the set. To achieve this, the full set of results are grouped into bins of fit scores ranging from 0.84 to 0.60 in 0.3 increments. This range was selected after thorough analysis and testing because higher and lower cutoff scores were found to include alternatives that are either completely dominating or dominated. A pretest phase included a Monte Carlo simulation of numerous result lists to ensure that there are no significant differences between them. Thus, a final result list is constructed by randomly selecting ***10 alternatives*** from these bins of scores. The result list must satisfy the following criteria: no alternative dominates the others with regards to all attribute values; the full range of each attribute must be represented across alternatives; alternatives vary in terms of fit scores such that the top fit score is not shared between two or more alternatives; alternative fit score variations are standardized across participants and tasks. These criteria ensure that the results are sufficiently complex and realistic enough to require deliberation and not overwhelming enough to induce satisficing. Two samples of potential final results possible for ***Participant 1*** based on his inputs are shown in ***Table 62***.

Table 62: Two Samples of Possible Results List Generated for Participant 1

Sample	*j*	Price	Dimension	Resolution	Warranty	Energy Saving	Smart	Sound System	Fit Score
1	1	$999.99	55"	1080p (Full HD)	3 Years	Medium Saving	Smart TV	Mini-Theater	0.829
	2	$999.99	60"	1080p (Full HD)	1 Year	High Saving	Smart TV	Mini-Theater	0.793
	3	$999.99	60"	720p (HD)	2 Years	High Saving	Smart TV	Mini-Theater	0.807
	4	$749.99	55"	1080p (Full HD)	1 Year	Medium Saving	Smart TV	Mini-Theater	0.764
	5	$749.99	60"	2160p (4K/Ultra HD)	3 Years	Low Saving	Standard TV	Mini-Theater	0.771
	6	$1,499.99	55"	2160p (4K/Ultra HD)	3 Years	Low Saving	Smart TV	Mini-Theater	0.729
	7	$1,249.99	60"	1080p (Full HD)	3 Years	High Saving	Standard TV	Mini-Theater	0.714
	8	$1,749.99	50"	1080p (Full HD)	3 Years	High Saving	Smart TV	Mini-Theater	0.686
	9	$749.99	40"	1080p (Full HD)	1 Year	Medium Saving	Smart TV	Mini-Theater	0.657
	10	$1,249.99	45"	720p (HD)	2 Years	Medium Saving	Smart TV	Mini-Theater	0.607
2	1	$749.99	60"	720p (HD)	3 Years	Low Saving	Smart TV	Mini-Theater	0.829
	2	$1,249.99	55"	2160p (4K/Ultra HD)	2 Years	High Saving	Smart TV	Mini-Theater	0.807
	3	$999.99	40"	2160p (4K/Ultra HD)	3 Years	High Saving	Smart TV	Mini-Theater	0.807
	4	$749.99	55"	2160p (4K/Ultra HD)	1 Year	Low Saving	Smart TV	Mini-Theater	0.764
	5	$749.99	55"	1080p (Full HD)	3 Years	High Saving	Standard TV	Mini-Theater	0.779
	6	$999.99	55"	2160p (4K/Ultra HD)	3 Years	Medium Saving	Standard TV	Mini-Theater	0.729
	7	$1,249.99	60"	2160p (4K/Ultra HD)	3 Years	Medium Saving	Standard TV	Mini-Theater	0.714
	8	$1,749.99	55"	2160p (4K/Ultra HD)	2 Years	Medium Saving	Smart TV	Mini-Theater	0.664
	9	$999.99	60"	720p (HD)	3 Years	Low Saving	Standard TV	Mini-Theater	0.636
	10	$999.99	55"	720p (HD)	3 Years	High Saving	Smart TV	Hi-Fi	0.6

Appendix XI: Ocular Metrics

Table 63: Ocular Metrics used for descriptive statistics measurements including those of the VPC indicators

Eye Tracking Metric	Description	Reference
Total Fixations	Number of overall fixations. More overall fixations indicate a more deliberative process. It can also mean a less efficient decision process.	(Duchowski 2007; Goldberg and Kotval 1999)
Fixation per AOI	More fixations in an AOI indicate that it is more salient, more important, or more attended to compared to other areas.	(Duchowski 2007)
Fixation per AOI adjusted for Text Length	When working with text, the fixation count can be adjusted to the text length by dividing the number of fixations by the number of words in the text.	(Sharafi et al. 2015)
Repeat Fixation	More repeat fixations can be indicative of exhaustive decision processes or poor information quality.	(Duchowski 2007; Horstmann et al. 2009; Sharafi et al. 2015)
Fixation Duration	Longer durations are indicative of more deliberative processing	(Duchowski 2007; Huang and Kuo 2011; Just and Carpenter 1976)
Fixation Duration per AOI	Longer durations indicate that the AOI is more engaging or requires more deliberation compared to other areas.	(Duchowski 2007; Sharafi et al. 2015)
% of Participants Fixating on an AOI	Saliency of information or relative importance in a given task.	(Poole and Ball 2006)

Appendix XII: Adult Cognitive Abilities

Table 64: Adult Cognitive Abilities, categorized as Fluid and Crystalized. These can be measured using the 60 item Weschler Adult Intelligence Scale – IV (Climie and Rostad 2011; Czaja et al. 2006; Tams, Grover, et al. 2014)

Ability Category	Description	Cognitive Ability	Definition
Fluid Abilities	A group of cognitive abilities that enable individuals to learn and perform new tasks efficiently and effectively. These abilities decline with aging.	Attention* *(i.e., Selective, Divided)*	Individual's cognitive ability to clearly perceive stimuli to process and respond efficiently and effectively
		Working Memory Capacity*	Individual's mental ability to preserve new information necessary to complete an active task
		Spatial Reasoning	Individual's ability to conceive relative locations and create a mental representation of a physical system
		Inductive Reasoning	Individual's ability to make generalizations and inferences based on representations and data through induction
		Perceptual Speed	Individual's ability to process information quickly
Crystalized Abilities	A group of cognitive abilities that reflect longer term attributes and variety of abilities, skills, and wisdom that individuals accumulate in their lifetime of education and experiences. These abilities are enhanced with aging.	Verbal Abilities	Individual's vocabulary knowledge and abstract verbal reasoning
		Knowledge and Experience Transfer	Individual's ability to apply their existing knowledge to new situations and tasks
		Discrete Knowledge Structure	Individual's collective repository of general information collected from culture and a lifetime of situations that enables them to link disparate pieces together to make better inferences and judgements

Appendix XIII: Control Variables

Table 65: Control variables in this study

Construct	Description	Reference
Gender (i.e., male, female, other)	Gender differences have been observed in e-commerce contexts.	(Cyr et al. 2007; Djamasbi and Loiacono 2008; Hassanein and Head 2007)
Cognitive Age (i.e., decade scale)	An alternate conceptualization of Age as an attitude and state of mind for each individual.	(Ghasemaghaei et al. 2014; Hong et al. 2013; Kwon 2016; Tams, Grover, et al. 2014)
Cognitive Load (i.e., pupil dilation)	Dilation of the pupil provides a live measure of cognitive load, which can be used to differentiate inattentive wandering from deliberative attention.	(Kahneman 1973, 2011; Kahneman and Beatty 1966; Piquado et al. 2010)
Product Knowledge	Prior knowledge about the product and its attributes, which can impact decision process behaviour and confound the results.	(Li et al. 2016; Tan et al. 2010; Xiao and Benbasat 2007, 2014; Xu et al. 2014)
Decision Effort (i.e., decision time)	An alternate objective measure of effort, indicated by the duration of the decision from the onset of the decision task to the final click of confirming the selected choice.	(Lilien et al. 2004; Tan et al. 2010; Xiao and Benbasat 2007)
Perceived Decision Quality	A subjective alternative measure of decision quality.	(Tan et al. 2010; Xiao and Benbasat 2007)
Perceived System Quality	A subjective measure of decision process focusing on the user's perceptions of the ability of the DSS to support the decision-making process.	(Tan et al. 2010)

Appendix XIV: Verbal Screening Questionnaire

Verbal Screener Questionnaire

A Study of Decision-Making in E-Commerce

Thank you for you interest in participating in our study.

We are going to use some simple technology to track eye movements during the study. Do you mind if I ask you some questions about your eye health?

1. Do you wear contacts or eyeglasses in order to read the computer screen?

[YES] CONTINUE
[NO] Skip to 3

2. Are your glasses for

[Reading Only] CONTINUE
[Seeing Distant Objects Only] CONTINUE
[Both! (Do you wear bifocals, trifocals, layered lenses, or regression lenses?)] TERMINATE

3. Can you read a computer screen and surf the web without difficulty (with your contacts and/or eye glasses on)?

[YES] CONTINUE
[NO] TERMINATE

4. Do you have cataracts?

[YES] TERMINATE
[NO] CONTINUE

5. Do you have any eye implants?

[YES] TERMINATE
[NO] CONTINUE

6. Do you have Glaucoma?

[YES] TERMINATE
[NO] CONTINUE

7. Do you use a screen reader, screen magnifier, or other assistive technology to use the computer or surf the web?

[YES] TERMINATE
[NO] CONTINUE

8. Are either of your pupils permanently dilated?

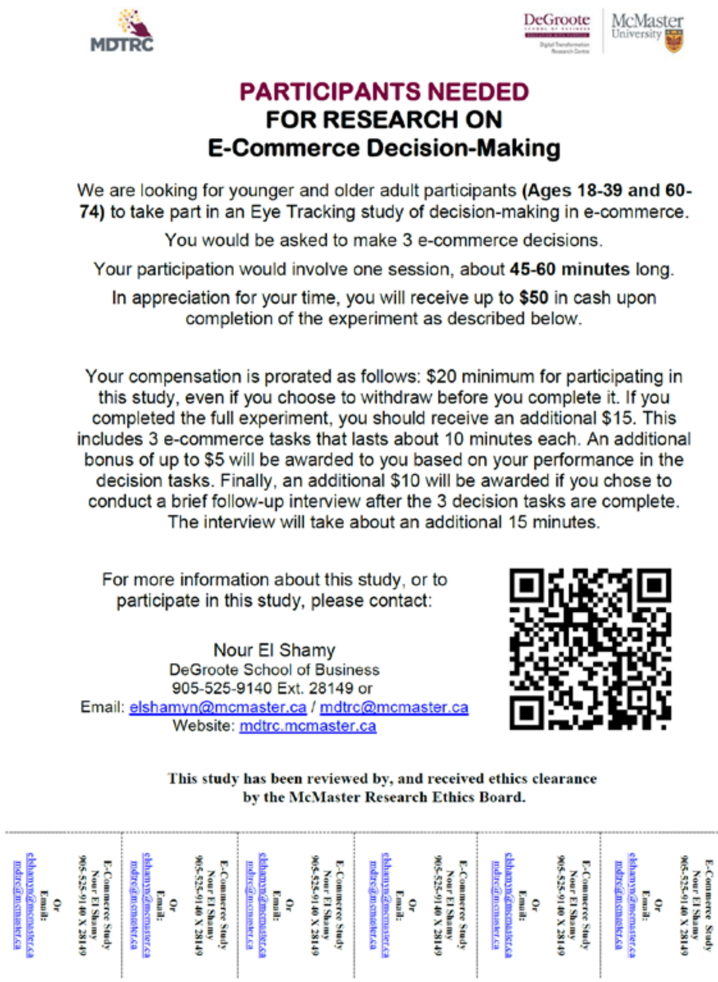
[YES] TERMINATE
[NO] CONTINUE

Appendix XV: Sample of the Recruitment Material

Older adults comprise the fastest growing segment of both the population and e-commerce users. With many older adults being particularly at risk the during pandemic, online shopping has evolved to become a necessity for many. However, the natural process of aging and its associated cognitive and physiological changes puts older adults at a disadvantage and makes them more susceptible to harmful decision biases, which are detrimental to their decisions and experience. This study examines how age interplays with other individual difference factors to impact the quality of e-commerce decisions using a combination of psychometric and neurophysiological methods. The main objective is to devise interventions that ultimately help older adults make higher quality decisions and improve their e-commerce experience.

Figure 40. The Study Page on the MDTRC website

Figure 41. Study Ad Posted in the Free Coffee News Newspaper Circulated around the Community



MDTRC

DeGroote | McMaster University

PARTICIPANTS NEEDED
FOR RESEARCH ON
E-Commerce Decision-Making

We are looking for younger and older adult participants **(Ages 18-39 and 60-74)** to take part in an Eye Tracking study of decision-making in e-commerce.

You would be asked to make 3 e-commerce decisions.

Your participation would involve one session, about **45-60 minutes** long.

In appreciation for your time, you will receive up to **$50** in cash upon completion of the experiment as described below.

Your compensation is prorated as follows: $20 minimum for participating in this study, even if you choose to withdraw before you complete it. If you completed the full experiment, you should receive an additional $15. This includes 3 e-commerce tasks that lasts about 10 minutes each. An additional bonus of up to $5 will be awarded to you based on your performance in the decision tasks. Finally, an additional $10 will be awarded if you chose to conduct a brief follow-up interview after the 3 decision tasks are complete. The interview will take about an additional 15 minutes.

For more information about this study, or to participate in this study, please contact:

Nour El Shamy
DeGroote School of Business
905-525-9140 Ext. 28149 or
Email: elshamyn@mcmaster.ca / mdtrc@mcmaster.ca
Website: mdtrc.mcmaster.ca

This study has been reviewed by, and received ethics clearance by the McMaster Research Ethics Board.

E-Commerce Study
Nour El Shamy
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Figure 42. Study Tear-out Poster Posted across the Hamilton/Halton Region Community

Appendix XVI: Mobile User Experience Lab (MUXL)

McMaster Mobile User Experience Lab (MUXL), shown in ***Figure 43***, is a research initiative launched by the McMaster Digital Transformation Research Centre (MDTRC) at the DeGroote School of Business. It was conceived and developed as a direct response to the methodological and equity-related challenges encountered during the data collection phase of the present thesis research.

Figure 43. Dissertation Author, Nour El Shamy, with the MUXL at Ron Joyce Centre, DeGroote School of Business, McMaster University (March 26th, 2023)

Although this study was not conducted using MUXL infrastructure, the recruitment difficulties, accessibility barriers, and data loss faced—particularly in trying to include older adults in lab-based, eye-tracking experiments—motivated the conceptualization and realization of MUXL.

9.1.1 Origins and Motivation

The thesis research required in-lab participation for older adults, but challenges emerged at every stage:

- Low response rates to recruitment campaigns.
- Logistical and mobility constraints for older participants.
- High exclusion rates due to ocular conditions incompatible with eye-tracking calibration.
- Costly and inefficient recruitment with compromised data quality.

These issues were not unique to this project but are common in NeuroIS and UX research involving equity-deserving groups. The experience underscored the need for mobile, accessible research environments to reach participants where they are rather than requiring them to travel to research facilities, with the added bonus of enhanced ecological validity.

9.1.2 MUXL Description

In response, the MDTRC research team proposed and built the Mobile User Experience Lab (MUXL), a fully equipped, retrofitted mobile recreational vehicle (RV) capable of supporting high-quality NeuroIS data collection in the field. MUXL includes:

- An electromagnetically shielded and soundproof participant room.
- Mobile equipment for eye-tracking, EEG, and physiological sensing.
- Multiple power systems (battery, solar, generator) enabling remote operation.
- Plans for full accessibility via an external lift for participants with mobility issues.

9.1.3 Purpose and Future Applications

MUXL is designed to bring rigorous, lab-quality user experience research to underserved populations, including older adults, people with disabilities, and residents of remote communities. It enables researchers to address Equity, Diversity, and Inclusion (EDI) challenges in a meaningful way, while also supporting ecologically valid data collection in situ.

The lessons learned during this thesis informed both the conceptual design and operational requirements of MUXL. Future work will apply these insights to evaluate how mobile NeuroIS labs and in-the-field research can expand the reach and relevance of UX and IS research, particularly among vulnerable or excluded user groups.

9.1.4 Acknowledgements

The author is proud to have contributed to the inspiration and early documentation of the MUXL project. The author acknowledges the contributions of the research infrastructure granting agencies and the broader research team’s efforts in securing funding, designing the infrastructure, and materializing the vision.