[Inner endpaper]

HEC MONTRÉAL

Master's Thesis

Evaluating the Impact of Product Recommendations in the Context of E-Commerce Choice Overload: A Neuro-Adaptive Development and Approach

par / by
Bella Tadson

Sylvain Sénécal
HEC Montréal
Codirecteur de recherche / Research codirector

Pierre-Majorique Léger
HEC Montréal
Codirecteur de recherche / Research codirector

Sciences de la gestion / Managerial Sciences
(Spécialisation Expérience Utilisateur / User Experience Specialization)

Mémoire présenté en vue de l'obtention
du grade de maîtrise ès sciences en gestion
(M. Sc.)
Thesis presented in fulfillment of the requirements
for the degree of master of science
(M. Sc.)

December 2023

Résumé

L’environnement actuel du commerce électronique expose de plus en plus les consommateurs à un phénomène appelé « surcharge de choix », faisant référence à un nombre surchargeant de choix de produits qui entravent le traitement cognitif. Les méthodes actuellement employées, visant à lutter contre cette surcharge de choix et à faciliter la prise de décision, grâce à des recommandations de produits, sont remises en question par des résultats empiriques contradictoires.

Ce mémoire par articles répond d’abord à un appel à la recherche en introduisant une nouvelle méthode d'évaluation plus fiable pour comprendre l’effet des recommandations sur les résultats décisionnels en contexte de surcharge de choix, et procède ensuite à l'application de cette nouvelle approche dans une étude expérimentale quantitative.

Tout d'abord, nous mobilisons une méthodologie DSR (Design Science Research) pour développer une interface neuro-adaptative, en tirant parti des neurosciences cognitives et de la technologie BCI (Brain-Computer Interface). Les résultats de cette recherche englobent le système neuro-adaptif qui répond aux exigences de conception définis au préalable, ainsi qu’une théorie de conception prescriptive, qui peut dorénavant servir à guider le développement d'artefacts similaires dans le domaine des systèmes d'information (SI).

Les résultats de l’expérimentation subséquente (n=55) révèlent que la présentation des recommandations de produits augmente la perception de surcharge de choix, mais procure des retombées bénéfiques quant à la prise de décision. De plus, l'approche neuro-adaptative que nous avons proposée, qui consiste à n'afficher des recommandations qu'en cas de détection d'une surcharge de choix via un signal neurophysiologique EEG en temps réel, procure des résultats comparables et parfois même supérieurs aux stratégies actuelles, où les recommandations sont affichées systématiquement à tous les utilisateurs, sans personnalisation en fonction de la surcharge de choix. Les avantages de ces recommandations neuro-adaptives sont particulièrement révélés chez certaines catégories d'utilisateurs : ceux possédant de bas niveaux d'expertise et d'implication, ainsi que chez ceux ayant des degrés élevés de besoin de cognition et de réactance.

Cette recherche dévoile le potentiel d'utilisation de la technologie neuro-adaptative pour répondre aux différents besoins d'évaluation dans un contexte de commerce électronique et ouvre la porte à des solutions alternatives aux recommandations systématiques actuelles qui manquent de finesse.

Mots clés : commerce électronique, recommandations, interface cerveau-ordinateur, interface neuro-adaptive, surcharge de choix, charge cognitive, prise de décision, design science research

Méthodes de recherche : design science research, expérimentation, mesures neurophysiologiques, recherche quantitative

Abstract

The current e-commerce landscape increasingly exposes consumers to a phenomenon called choice overload, referring to an overwhelming number of decision alternatives that impede cognitive processing. Currently employed methods of combating choice overload and facilitating decision-making through the display of product recommendations are being challenged by contradicting empirical findings.

This article-based thesis addresses a call for research by developing a novel, more reliable evaluation tool to understand the interplay between recommendations and decisional outcomes, and then proceeds to the application of this new approach in a quantitative experimental study.

First, we delve into a DSR (Design Science Research) methodology to create a neuro-adaptive interface, leveraging cognitive neuroscience and BCI (Brain-Computer Interface) technology. The results of this endeavour comprise the fulfillment of sought-out design requirements by the system and a prescriptive design theory, which provides guidance for the development of similar artifacts in the field of IS (Information Systems).

The findings of the subsequent experiment (n=55) reveal that presenting product recommendations increases the perception of choice overload, but provides beneficial decisional outcomes. Moreover, our proposed neuro-adaptive approach, consisting of displaying recommendations only upon detecting choice overload through a real-time neurophysiological EEG signal, performs similarly optimally and, at times, surpasses current strategies, consisting of providing recommendations to all users systematically, without accounting for choice overload. The advantages of these neuro-adaptive recommendations are particularly highlighted among certain categories of users: those with low product involvement and expertise, as well as individuals with high need for cognition and reactance scores.

This research underscores the great potential of applying neuro-adaptive technology to accommodate for various e-commerce evaluation needs and opens avenues for alternative solutions to current systematic recommendations that lack nuance.

Keywords: e-commerce, recommendations, brain-computer interface, neuro-adaptive interface, choice overload, cognitive load, decision-making, design science research

Research methods: design science research, experiment, neurophysiological measures, quantitative research

Table of contents

List of tables and figures

List of Tables

List of Figures

List of abbreviations and acronyms

BCI: Brain-Computer Interface

MADM-SAW: Multi-Attribute Decision Making – Simple Average Weighting

DSR: Design Science Research

DR: Design Requirement

CL: Cognitive load

CO: Choice overload

DO: Decisional outcomes

EEG: Electroencephalography

DESRIST: Design Science Research in Information Systems and Technology

IS: Information Systems

IT: Information Technology

HTML: Hypertext Markup Language

CSS: Cascading Stylesheet

LSL: Lab Streaming Layer

MVC: Model-View-Controller

Preface

With the authorization of the administrative directors of the Master's of Science in User Experience program, this thesis comprises two articles. The articles are added to the thesis with the written consent of all co-authors.

This research project received approval from HEC's Research Ethics Board (REB) under certificate number 2023-5071, on June 13, 2022. The certificate has been successfully renewed on June 1, 2023. Both documents can be found in **Appendix G**.

The article in Chapter 2 has been submitted and accepted as a conference proceeding for the DESRIST (Design Science Research in Information Systems and Technology) 2023 conference, held in Pretoria, South Africa, between May 31 and June 2, 2023. The project was presented at the conference and received appreciative and insightful feedback. The article in Chapter 3 is envisioned to be dissected and merged with other studies, to be submitted to high impact journals.

Acknowledgements

Where do I begin? This massive project would not have been possible without the blissful orchestration of so many remarkable teams of people!

As the conductors of this magnificent symphony, my most wholehearted thank you to Pierre-Majorique Léger and Sylvain Sénécal! Thank you for entrusting me with such a fascinating project, which symbiosed both of my passions for technology and neuroscience. I am tremendously grateful for your guidance, patience, and the valuable learnings. An extra *massive* thank you for having sent me to the DESRIST conference, which was undoubtedly an awe-inspiring experience of a lifetime! I came out of it inspired, enthused, and while being spared from malaria, I got bit by the research bug. :)

Thank you to Brendan for administrating that unforgettable trip logistically and financially. Speaking of finances, thank you to IVADO for financially supporting this research project. Thank you to the incredible Tech3Lab operations team. David, for arranging the usage of the Faraday cage and the g.tec equipment. Salima, for being so understanding and, along with Xavier, helping us schedule participants for our numerous pre-tests. Thank you to all those who agreed, sometimes more than once, to be our guinea pigs for said pre-tests, especially Karine, Sabrina, Baptiste, Claudie, Jeremy, Kaja, and Ikram. Thank you to Marine and Amine for their tech expertise and of course to François, Jared, and Alex who spent many hours with us perfecting the BCI. An extra thank you to Jared for mentoring me during my first-ever and very memorable research article writing experience. Thank you to Carl and Shang Lin for helping me with statistical analyses.

And of course, thank you to my partner-in-crime, my lab mate Noémie. This project would not have been half as engaging without having someone so diligent and hard-working by my side, with whom to share the ups and downs, and who was just as invested in the project as I was. Our collaboration grew beyond the lab into a supportive friendship, filled with supportive pep-talks and occasional laughter attacks.

Thank you to Annemarie Lesage for, time and again, entrusting me with the role of TA, all whilst generously sprinkling the way with emotional support. Likewise, thank you to Ruxandra Monica Luca for her kindness and the opportunity to expand my TA'ship into the world of Web Analytics. Thank you Constantinos Coursaris for trusting with TA'ing the monstrous, but tremendously rewarding class of Advanced UX Evaluation and, notably, for sharing with me his precious career advice, even during out-of-office hours.

This master's was enthrallingly fulfilling itself, but the juicy cherry on top was the beyond wonderful group of people I've encountered along the way, many of whom became close friends. Thank you, Lan-Chi, Maya, Barbara, Chantel, and Kaja (yes, her again) for being there for me, and the opportunity to share this incredible adventure with you.

Thank you of course to my loyal outside-of-master's friends, Polina, Lisa, Wayne, Samara, and Arthur. Thank you for supporting me, believing in me, and forgiving me for occasionally disappearing from the social realm.

Thank you to Anna, my childhood skating coach, who was incredibly tough, but to whom I'm grateful for putting me through a school of life, teaching me the value of hard work, grit, and time management.

Thank you to my dad Alexander, whose brain is infused with so much knowledge about so many different subjects that it would take a lifetime to account for it, and who, inadvertently, led by example to engrain in me an acute curiosity and instill a passion for learning. Thank you to my mom Raisa, for bringing me into this world.

Last, but most certainly not least, thank you to my partner Lukas, with whom I learn and am (hopefully) becoming a better person every day. Thank you for nobly assuming the role of our household chef, groceries and chocolate supplier, motivator, supporter (both emotional and literal, during my anemic moments), and even occasional proofreader. Having these fewer things to worry about made this degree significantly more manageable. Thank you to your family as well for being so supportive and kind to me.

This journey has come to an end, but I want to hope this is only the beginning. To a lifetime of happy learning and discoveries! :)

To my dad,
one of the most intelligent
people I know.

Chapter 1 – Introduction

1.1 Research Context

Within the last few years, the global e-commerce environment has been growing unprecedentedly, reaching a surge in volumes that was only expected by 2025-2030 (Fabius et al., 2020). Catalyzed by the COVID-19 pandemic (Beckers & Cant, 2023; Collins & Geist, 2023), broader availability of internet services (Bhatti et al., 2022; Köten, 2023), and improved logistical efficiency (Beckers & Cant, 2023; Torres et al., 2022), online shopping has expanded beyond urban, affluent consumers (Beckers et al., 2018; Kirby-Hawkins et al., 2018) and has spread through more diverse sociodemographic realms (Szász et al., 2022), spanning older populations and consumers in emerging economies (Itani & Hollebeek, 2021; Nguyen et al., 2021). While presenting greater opportunity for online merchants to diversify their product offerings to accommodate for this more varied customer base, online shoppers are increasingly confronted with the growing issue known as choice overload.

Choice overload denotes a decision-making process that is too cognitively demanding, due to the overwhelming number of complex alternatives available (Chernev et al., 2015; Iyengar & Lepper, 2000; Schwartz, 2016). In the context of e-commerce, this translates into a consumer's hindered ability to select a product within the abundant assortment of choices offered by the current online market (Collins & Geist, 2023; NielsenIQ, 2019). Stemming from individual limitations in cognitive workload capacity (Malhotra, 1982; Sweller, 1988, 2011), the phenomenon of choice overload has been linked to elevated cognitive load (Deck & Jahedi, 2015; Fehrenbacher & Djamasbi, 2017; Peng et al., 2021), or an undue mental effort (Paas et al., 2003; Reutkaja et al., 2021; Sweller et al., 1998). While a certain level of heightened cognitive load is essential for task completion (Reutkaja et al., 2021), an excessive cognitive load impedes information processing, compromising on decision accuracy and adversely impacting decision-makers' emotional states (Allen et al., 2014; Bigras et al., 2019; Collins & Collins, 2021; Deck & Jahedi, 2015).

In the realm of e-commerce, when online shoppers are faced with choice overload, they have been shown to experience higher levels of frustration (Deng & Poole, 2010; Haynes, 2009; Lee & Lee, 2004), dissatisfaction (Diehl & Poynor, 2010; Huber et al., 2012; Lee & Lee, 2004), regret (Gourville & Soman, 2005; Hassan et al., 2019) and a lack of confidence in their selected option (Calvo et al., 2022; Lee & Lee, 2004; Zhang et al., 2018). Moreover, research reveals that choice overload may impede decision-making to a point that online shoppers may select less optimal products (Arora & Narula, 2018; Calvo et al., 2022; Deck & Jahedi, 2015), or even resort to avoiding the decision altogether, either through delay (Kurien et al., 2014) or abandonment (Iyengar & Lepper, 2000; Kuksov & Villas-Boas, 2009; Özkan & Tolon, 2015) of their purchase.

To mitigate these impeding effects of choice overload, over two thirds of online retailers provide users with personalized product recommendations to aid them in their decision-making (Aljukhadar et al., 2012; Dellaert & Häubl, 2012). However, research surrounding current recommendations systems reveals contradicting findings. Despite some studies yielding positive results from the use of recommendations in online decision-making (Aljukhadar et al., 2012; Dellaert & Häubl, 2012), others have unveiled opposing outcomes, suggesting that recommendations, on the opposite, deterred decision quality (Banker & Khetani, 2019; Chen et al., 2022; Dellaert et al., 2017; Xiao & Benbasat, 2018) and satisfaction (Bollen et al., 2010; Willemsen et al., 2016), and amplified choice overload (Bollen et al., 2010; Willemsen et al., 2011; Willemsen et al., 2016).

This dichotomy in the literature has spurred the idea that displaying personalized recommendations may only be beneficial in instances where consumers are actively experiencing choice overload but prove detrimental in occurrences where users are not subject to this phenomenon (Häubl & Trifts, 2000; Yan et al., 2016). Yet, canonical recommendations systems display this decisional aid systematically, failing to distinguish between the two scenarios. In addition, scholars have underscored the challenges in both testing and developing a viable solution (Aljukhadar et al., 2012; Appiah Kusi et al., 2022; Häubl & Trifts, 2000; Yan et al., 2016). Currently utilized methods of assessing choice overload, either through self-reported measures or neurophysiological tools, only enable its detection during post-hoc analysis, when the user is no longer interacting with the system (Antonenko et al., 2010; Fehrenbacher & Djamasbi, 2017; Reutkaja et al., 2021; Rose, 2005; Zhang et al., 2018; Zhou et al., 2022). Furthermore, an additional layer of difficulty is imposed by individual differences in cognitive workload capacity, preventing researchers from determining a universal threshold of choice overload (Appiah Kusi et al., 2022; Ho et al., 2021; Lurie, 2004; Malhotra, 1982; Sweller, 1988, 2011). Scholars have therefore emphasized the necessity for improved measurement tools to explore the double-edged effects of recommendations (Appiah Kusi et al., 2022; Häubl & Trifts, 2000; Yan et al., 2016), as well as a call for a more nuanced approach to personalize the interactivity and display of recommendations as a means of alleviating choice overload and its adverse impact on decision-making (Chen et al., 2009; Jugovac & Jannach, 2017; Konstan & Riedl, 2012; Patharia & Jain, 2023).

1.2 Study Objectives and Research Questions

From the aforementioned limitations, we identified an opportunity for a meaningful research contribution in the scope of this article-based thesis. We devised an investigation whose objective would be twofold.

First, we address the necessity highlighted by researchers for a more reliable method of evaluating the effects of personalized product recommendations against choice overload (Aljukhadar et al., 2012; Appiah Kusi et al., 2022; Häubl & Trifts, 2000; Yan et al., 2016). Our envisioned solution comprised a system that would allow the detection of excessive cognitive workload, indicative of choice overload (Ariga, 2018; Bawden & Robinson, 2020; Deck & Jahedi, 2015; Fehrenbacher & Djamasbi, 2017; Peng et al., 2021), with reliable neurophysiological tools in real-time, and provide the user with product recommendations accordingly. To achieve this, we applied the Design Science Research (DSR) methodology brought forth by Gregor and Hevner (2013) and Hevner et al. (2004), and developed an original artifact, leveraging cognitive neuroscience and neuro-adaptive technology. A neuro-adaptive interface, also referred to as Brain-Computer Interface (BCI), is a system that continuously monitors an individual's neurophysiological signal, and utilizes it as input to initiate an adaptation of the system in real-time (Andreessen et al., 2021; Krol & Zander, 2017; Wolpaw et al., 2020). Though the application of BCIs has lately extended beyond their original sphere of biomedical engineering (Krol & Zander, 2017; Yangyang Miao et al., 2020), to our knowledge, our research constitutes the first instantiation of this technology in the field of e-commerce. The modality we selected for neurophysiology was electroencephalography (EEG), given its high temporal fidelity, customizability, and common application in BCI systems (Aricò et al., 2018; Fernandez Rojas et al., 2020; Guan et al., 2022; Spuler, 2017). The envisioned contribution was thus twofold. First, creating an artifact to support the problem in e-commerce research regarding the lack of a rigorous means of evaluating the effect of product recommendations on consumers' choice overload. Secondly, contributing to the body of knowledge in IS through our proof-of-concept, which can serve as a prescriptive theory (Hevner et al., 2004; Kuechler & Vaishnavi, 2008a) to successfully implement such an artifact. The first article therefore answers the following research question:

RQ1. *How can we address the aforementioned call to research*[1] *by following a DSR approach while leveraging cognitive neuroscience to develop a real-time neuro-adaptive interface for e-commerce evaluation?*

Second, we proceed to the application of our developed artifact in an investigation aimed to meet the need raised by academics and industry professionals for a more tailored solution to replace currently employed indiscriminate recommendations (Chen et al., 2009; Jugovac & Jannach, 2017; Konstan & Riedl, 2012; Patharia & Jain, 2023). This experiment also comprises our artifact's summative assessment phase brought forth by Gregor and Hevner (2013). Specifically, with the capability of the neuro-adaptive interface to assess choice overload in real-time and, if detected, respond with recommendations, we undertake a quantitative empirical study to evaluate this novel method of displaying recommendations to users. We estimate that this approach could offer a more nuanced experience by providing recommendations to users experiencing choice overload and thereby facilitate their decision-making, while refraining from

[1] This formulation was preserved, based on the original research question from the article. The call for research being referenced is the need for reliable evaluation tools to assess the effects of recommendations in instances of choice overload (Aljukhadar et al., 2012; Appiah Kusi et al., 2022; Häubl & Trifts, 2000; Yan et al., 2016).

offering recommendations to users not experiencing choice overload, and hence avoid hindering their decision-making process. The second article (Chapter 3) thus evaluates decisional outcomes that result from this new dimension of personalization in the display method of recommendations (Blut et al., 2023; Tsekouras et al., 2022) and answers two relevant research questions. The first question aims to reveal the direct effects of our newly proposed recommendations display method:

RQ2. *To what extent does a neuro-adaptive interface which detects cognitive load and provides recommendations accordingly impact users' decision-making in an online shopping experience?*

Additionally, as existing research highlights the mediating role of choice overload in the relationship between recommendations and the outcomes of a decision (Chernev et al., 2015; Scheibehenne et al., 2010), the second research question the article attends to this consideration. Moreover, scholars have advocated for future research to consider individual characteristics when assessing recommendations and their effects in the context of choice overload (Aljukhadar et al., 2017; Appelt et al., 2011; Johnson et al., 2012; Takemura, 2014; Xiao & Benbasat, 2014). However, studies that holistically integrate most influential individual differences in evaluating recommendations systems are scant. This encouraged us to address this second knowledge gap and incorporate this additional research question in our second article:

RQ3. *To what extent consumers' perceptions and individual characteristics influence their decision-making outcomes when provided with recommendations from a neuro-adaptive system?*

1.3 Thesis Structure

Given that both articles of this paper-based thesis fall under the umbrella of a holistic research problem, readers may observe redundancy in the introductory sections of every article, which is nonetheless inevitable and even custom to the iterative approach we employed (Hevner, 2007; Hevner et al., 2004; Peffers et al., 2008).

The first article (Chapter 2), congruent with the DSR methodological structure (Gregor & Hevner, 2013; Hevner et al., 2004), presents the research problem, key concepts relevant to the development of the artifact, and objectives of a solution. Subsequently, it defines design requirements, and closes with a proof-of-concept demonstration and formative evaluation of the artifact.

The second article (Chapter 3) presents the findings derived from a summative evaluation of the constructed artifact, focusing on perceptual and behavioural outcomes. It begins with an introduction of the research problem, an overview of the state of the art surrounding the subject, and presents a conceptual framework for a comprehensive quantitative experiment. It then states the results, discusses theoretical contributions and practical implications, and concludes with limitations and proposed avenues for future research.

Chapter 4 serves as a synthesis of the sections preceding it, and summarizes the main findings from both theoretical and practical perspectives.

The articles of this thesis serve as integral pieces of a large-scale research endeavour of the Tech3Lab. As data collection from the aforementioned experiment comprised neurophysiological tools, namely EEG, eye-tracking and facial emotions recognition, subsequent studies will assess these respective measures to supplement the behavioural and perceptual findings presented in the second article (Chapter 3). Moreover, the novel real-time cognitive load classification index developed for the BCI (Chapter 2) will also be presented in a separate research article. However, both undertakings fall outside of the scope of this thesis.

1.4 Information on Article 1

The first article has been submitted and accepted for publication in the proceedings of the 2023 DESRIST (Design Science Research in Information Systems and Technology) conference. This conference took place between May 31 and June 2, 2023, in Pretoria, South Africa. The project was presented at the conference and received overwhelmingly positive feedback and insightful suggestions for optimization and diversification of the

BCIs applications, which will be applied to further ideation cycles by this study's successors.

Based on the intention of this article to develop a neuro-adaptive artifact, which entails a multi-component and multi-disciplinary complexity, we opted for a DSR methodology. It provided us with rigour and structure in defining our design requirements, while allowing for flexible iteration cycles of various subcomponents of our envisioned solution. Specifically, we adopted the DSR framework by Peffers et al. (2008) (**Figure 1**), based on its widely acknowledged application in IS research (Gregor & Hevner, 2013; van der Merwe et al., 2020). It also aligned with our needs given its cyclical ideation process and the possibility of an entry point directly at the objectives of a solution (Peffers et al., 2008; van der Merwe et al., 2020). This was particularly appropriate for our study since the research questions had already been established (see "Research questions" section of **Table 1**).

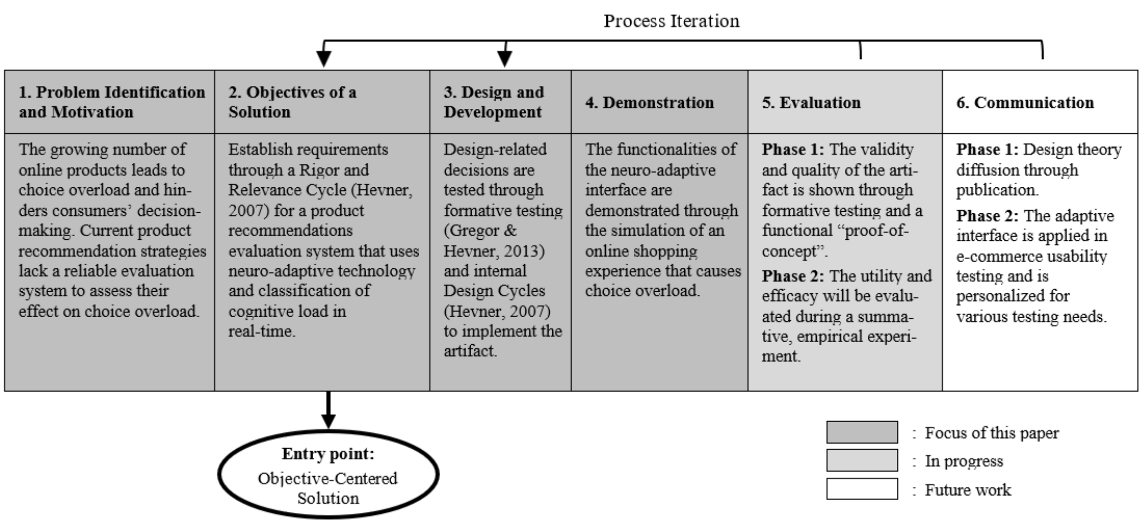


Figure 1. Design Science Research framework by Peffers et al. (2008) adapted for this research.

During our development, as portrayed in **Figure 1**, we cycled through various iteration phases. We engaged in a Rigor Cycle (Hevner, 2007), where we drew upon the existing body of knowledge and currently employed neuro-adaptive systems to ground our system's objectives, a Relevance Cycle (Hevner, 2007; Hevner et al., 2004), where we assessed and refined our design requirements through a series of formative testing sessions, and a Design Cycle (Hevner, 2007), where we alternated between ideating our design-related decisions, implementing them, evaluating outcomes, and refining them until the solution's objectives were met. This resulted in the elaboration of the following design requirements:

1. An interactive prototype of an e-commerce user interface, susceptible of inducing choice overload.
2. A clear, yet non-intrusive display of product recommendations.
3. An accommodation for distinct experimental conditions for summative testing.
4. A means of identifying which products to recommend to the user, based on their personal preferences.
5. A means of informing the system of which products to recommend to every user.
6. Measurement of raw neurophysiological data throughout the experiment.
7. A real-time classification of cognitive load, based on electroencephalographic (EEG) data.
8. Continuous transmission of the cognitive load classification to the user interface.
9. A flexible manipulation of conditions to initiate the presentation of recommendations.
10. An ability to record and extract performance and perceptual measures for post-hoc analyses.

Given that there was no previously available data for manipulation, nor were any operations or methods of addressing the research problem established in prior work, the development of the artifact was categorized as a Type 4 research problem (Gregor & Hevner, 2013; McKenny & Keen, 1974). However, since neuro-adaptive technology has been applied in other fields, the novelty of our research lay in the unique extension of such systems into the field of e-commerce. Hence, based on the knowledge contribution framework (Gregor, 2006; Gregor & Hevner, 2013; Kuechler & Vaishnavi, 2008b), the sought-out solution constitutes an exaptation, accompanied by a prescriptive design theory, which could guide future work in the implementation of neuro-adaptive artifacts in e-commerce.

1.5 Information on Article 2

The second article presents a summative evaluation of the artifact from Article 1 through its practical application in consumer behaviour research. Specifically, it assesses the behavioural (performance) and perceptual impacts of a neuro-adaptive display of product recommendations through a comprehensive quantitative research experiment.

As such, readers may find the contents to be exhaustive for a standard research paper. However, the intention behind this extensive evaluation lies in dissecting the results into subcomponents, to be incorporated with other findings, and subsequently be presented in multi-study research papers, meant for high impact factor publications.

To empirically evaluate our novel approach of providing recommendations neuro-adaptively, based on the occurrence of choice overload, the experiment employs a within-subject study design, with three experimental conditions:

(a) Control, where no recommendations are displayed.
(b) Static, where recommendations are displayed perpetually and systematically, canon to current recommendations strategies.
(c) Neuro-adaptive, where recommendations are displayed only upon detecting choice overload, identified through a real-time assessment of cognitive load.

The article explores the connection between these recommendations conditions and decision-making through the lens of the behavioural decision theory (Simon, 1959), building on two established models: the cost-accuracy framework (Johnson & Payne, 1985; Payne et al., 1993), a theoretical foundation for understanding the mechanisms in play in a decision-making process, and the meta-cognitive decision-making model under information overload (Takemura, 1985, 2014), which complements the former by acknowledging the context of choice overload and the role of individual characteristics, which may influence the decision-making process.

These models have also guided the choice of constructs of interest included in this investigation. Specifically, the article looked at decisional outcomes proposed by Xiao and Benbasat (2007) in their assessment of recommendations systems (choice satisfaction, choice confidence, decision quality, and decision time), the mediating role of choice overload (Chernev et al., 2015; Scheibehenne et al., 2010), and predominant individual characteristics (Aljukhadar et al., 2017; Appelt et al., 2011; Johnson et al., 2012; Takemura, 2014; Xiao & Benbasat, 2014) that have been shown to moderate decision-making and the effects of recommendations (compliance with recommendations, consumer product involvement, product expertise, psychological reactance, and need for cognition).

By incorporating these measures in its conceptual framework, the article aims to deliver empirical evidence to support the beneficial outcomes associated with our proposed method of customizing the display of recommendations based on cognitive load. In doing so, we seek to resolve the conflicting findings pertaining to recommendations and provide conclusive insights into the underlying phenomenon. This could finalize the summative testing phase to assess the effectiveness of our neuro-adaptive artifact, and contribute to the body of knowledge, serving both researchers and industry stakeholders to foster a comprehensive understanding of the impact of recommendations in the dynamic e-commerce decision-making context.

To facilitate readers' comprehension of extensive sections, concise summaries have been incorporated throughout the article:

- **Figure 7**, which illustrates the conceptual framework and included variables.
- **Table 4**, which outlines the hypotheses that compose our conceptual framework.
- **Table 5**, which provides a summary of all assessed constructs and measures.
- **Table 7**, **Table 8**, **Table 9**, and **Table 10**, which specify the results of the mediation analyses.
- **Table 6**, **Table 11**, and **Table 12**, which encapsulate the conclusions related to each hypotheses.
- A general discussion further offers a rapid recapitulation of all findings.

1.6 Contributions and Responsibilities

As this research has been conducted at the Tech3Lab, many collaborators were implicated, bringing various degrees of involvement at different stages of this thesis. The following table summarizes my contributions, based on levels of effort, output, and ideas.

Table 1. Contributions and responsibilities in the realization of this thesis.

Activity	**Contribution**
Research questions	Defining the experimental context, research problem and questions – **70%** • The research problem existed at the start of the project, inherited from a previous study. • Contextualizing the problem and defining the scope of the research. • Honing in on the research questions and formulating the hypotheses and research narrative.
Literature review	Conducting relevant research, writing the literature review and conceptual framework – **100%** Elaborating the conceptual framework – **90%** • Guided by my research supervisors. Identifying constructs and measures – **60%** • Certain constructs and questionnaire items were reproduced based on results obtained by the predecessors of my inherited research problem. • Guided by my research supervisors. Justifying chosen constructs and scales – **100%**
Conception and experimental design	Preparing the ethics request and renewals – **100%** Customizing the participant consent and compensation forms, based on existing templates – **100%** Conceptualizing the experimental design and operational stimuli – **60%**

<table>
<tr>
<td></td>
<td>

Certain stimuli and elements of the experimental design were inherited with my research problem.

Composing the experimental protocol – 100%
Preparing the Faraday cage and processing room for data collection – 25%

The Tech3Lab operations team set up the software and equipment required for the experiment.

Developing the neuro-adaptive system artifact – 60%

Simulink model built by g.tec (the supplier) based on prerequisites provided by Alexander-John Karran.
Real-time cognitive workload classification index was developed in collaboration with Jared Boasen and François Courtemanche.

Initial index proposed by Jared Boasen.
Index adjustments completed in collaboration with Jared Boasen and François Courtemanche.
Adjustment of index for task specificities endorsed by Jared Boasen.
Ideating the classification logic through eight months of iteration cycles.
Adjusting the JSON-based rules engine.

Guiding and supporting the Tech3Lab development team in creating the user interface.

Collaborating with Marine Ménoret on the development of the front-end interface and AngularJS MVC application.
Collaborating with Amine Abdessemed on the implementation of the communication with the WebSocket client.

Creating the database of 360 products and 8 attributes each to be displayed in the user interface.

Implementing the MADM-SAW calculation function and enabling its simple input into the user interface – 100%
</td>
</tr>
<tr>
<td>Pre-tests</td>
<td>Taking charge of the operations during pre-tests – 80%</td>
</tr>
</table>

	• François Courtemanche collaborated during certain pre-test sessions. Soliciting, recruiting, and managing pre-test participants for formative testing (n = 42) – **80%** • The Tech3Lab operations team helped in scheduling participants for pre-test sessions.
Recruitment	Soliciting, recruiting, and managing experiment participants for summative testing (n = 55) – **90%** • Recruitment facilitated by HÉC's research panel.
Data collection	Generating the study questionnaires on Qualtrics – **100%** Taking charge of the operations and moderating the data collection – **100%** • Present during all data collection sessions.

Analysis	Extracting and formatting for analysis participants' performance data from the neuro-adaptive system – **100%**
	
	Extracting and formatting for analysis the data from the Qualtrics questionnaires – **100%**
	
	Conducting statistical analyses – **80%**
	• The Tech3Lab statistician assisted in:
	  o Guiding me in the choice of statistical software and models for analysis.
	  o Normalizing the Leptokurtic distribution of one of my constructs.

Writing the thesis	Writing the articles and thesis – **100%** • Jared Boasen assumed the role of a mentor through his precious guidance in writing my first article (Chapter 2). • My supervisors supported me throughout the rest of my writing process and provided their invaluable feedback to help me improve the quality of my work (Chapters 1, 3, and 4).

References

Aljukhadar, M., Senecal, S., & Daoust, C.-E. (2012). Using Recommendation Agents to Cope with Information Overload. International Journal of Electronic Commerce, 17(2), 41-70. http://www.jstor.org/stable/41739511

Aljukhadar, M., Trifts, V., & Senecal, S. (2017). Consumer self-construal and trust as determinants of the reactance to a recommender advice. Psychology and Marketing, 34, 708-719. https://doi.org/10.1002/mar.21017

Allen, P. M., Edwards, J. A., Snyder, F. J., Makinson, K. A., & Hamby, D. M. (2014). The Effect of Cognitive Load on Decision Making with Graphically Displayed Uncertainty Information [Article]. Risk Analysis: An International Journal, 34(8), 1495-1505. https://doi.org/https://doi.org/10.1111/risa.12161

Andreessen, L. M., Gerjets, P., Meurers, D., & Zander, T. O. (2021). Toward neuroadaptive support technologies for improving digital reading: a passive BCI-based assessment of mental workload imposed by text difficulty and presentation speed during reading [Article]. User Modeling & User-Adapted Interaction, 31(1), 75-104. https://doi.org/10.1007/s11257-020-09273-5

Antonenko, P. P., Paas, F., Grabner, R., & Gog, T. (2010). Using Electroencephalography to Measure Cognitive Load. Educational Psychology Review, 22, 425-438. https://doi.org/https://doi.org/10.1007/s10648-010-9130-y

Appelt, K. C., Milch, K. F., Handgraaf, M. J. J., & Weber, E. U. (2011). The Decision Making Individual Differences Inventory and guidelines for the study of individual differences in judgment and decision-making research. Judgment and Decision Making, 6(3), 252-262. https://doi.org/10.1017/S1930297500001455

Appiah Kusi, G., Azmira Rumki, Z., Hammond Quarcoo, F., Otchere, E., & Fu, G. (2022). The Role of Information Overload on Consumers' Online Shopping Behavior. Journal of Business and Management Studies, 4(4), 162-178. https://doi.org/10.32996/jbms

Aricò, P., Borghini, G., Di Flumeri, G., Sciaraffa, N., & Babiloni, F. (2018). Passive BCI beyond the lab: current trends and future directions. Physiol Meas, 39(8), 08tr02. https://doi.org/10.1088/1361-6579/aad57e

Ariga, A. (2018, 31 Jan.-3 Feb. 2018). Is Choice Overload Replicable? 2018 10th International Conference on Knowledge and Smart Technology (KST), Arora, P., & Narula, S. (2018). Linkages Between Service Quality, Customer Satisfaction and Customer Loyalty: A Literature Review. IUP Journal of Marketing Management, 17(4), 30.

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. Journal of Public Policy & Marketing, 38(4), 500-515. https://doi.org/10.1177/0743915619858057

Bawden, D., & Robinson, L. (2020). Information Overload: An Overview. In Oxford Encyclopedia of Political Decision Making. Oxford: Oxford University Press. https://doi.org/10.1093/acrefore/9780190228637.013.1360

Beckers, J., & Cant, J. (2023). Half a decade in two years: household freight after COVID-19. Transport Reviews, 1-22. https://doi.org/10.1080/01441647.2023.2266859

Beckers, J., Cárdenas, I., & Verhetsel, A. (2018). Identifying the geography of online shopping adoption in Belgium. Journal of Retailing and Consumer Services, 45, 33-41. https://doi.org/https://doi.org/10.1016/j.jretconser.2018.08.006

Bhatti, H. Y., Bint E. Riaz, M., Nauman, S., & Ashfaq, M. (2022). Browsing or buying: A serial mediation analysis of consumer’s online purchase intentions in times of COVID-19 pandemic [Original Research]. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.1008983

Bigras, É., Léger, P.-M., & Sénécal, S. (2019). Recommendation Agent Adoption: How Recommendation Presentation Influences Employees’ Perceptions, Behaviors, and Decision Quality. Applied Sciences, 9(20), 4244. https://www.mdpi.com/2076-3417/9/20/4244

Blut, M., Ghiassaleh, A., & Wang, C. (2023). Testing the performance of online recommendation agents: A meta-analysis. Journal of Retailing. https://doi.org/https://doi.org/10.1016/j.jretai.2023.08.001

Bollen, D., Knijnenburg, B. P., Willemsen, M. C., & Graus, M. (2010). Understanding choice overload in recommender systems Proceedings of the fourth ACM conference on Recommender systems, Barcelona, Spain. https://doi.org/10.1145/1864708.1864724

Calvo, L., Christel, I., Terrado, M., Cucchietti, F., & Pérez-Montoro, M. (2022). Users' Cognitive Load: A Key Aspect to Successfully Communicate Visual Climate Information [Article]. Bulletin of the American Meteorological Society, 103(1), E1-E16. https://doi.org/10.1175/BAMS-D-20-0166.1

Chen, S., Qiu, H., Zhao, S., Han, Y., He, W., Siponen, M., Mou, J., & Xiao, H. (2022). When more is less: The other side of artificial intelligence recommendation. Journal of Management Science and Engineering, 7(2), 213-232. https://doi.org/https://doi.org/10.1016/j.jmse.2021.08.001

Chen, Y.-C., Shang, R.-A., & Kao, C.-Y. (2009). The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment. Electron. Commer. Res. Appl., 8(11), 48-58.

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. Journal of Consumer Psychology, 25(2), 333-358. https://doi.org/10.1016/j.jcps.2014.08.002

Collins, D., & Geist, M. (2023). Chapter 1: Introduction to Research Handbook on Digital Trade

In Research Handbook on Digital Trade (pp. 1-7). Edward Elgar Publishing. https://doi.org/10.4337/9781800884953.00006

Collins, L., & Collins, D. (2021). Managing the Cognitive Loads Associated with Judgment and Decision-Making in a Group of Adventure Sports Coaches: A Mixed-Method Investigation. Journal of Adventure Education and Outdoor Learning, 21(1), 1-16.
http://proxy2.hec.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1292642&lang=fr&site=ehost-live

http://dx.doi.org/10.1080/14729679.2019.1686041

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments [Article]. European Economic Review, 78, 97-119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Dellaert, B. G., Baker, T., & Johnson, E. J. (2017). Partitioning sorted sets: overcoming choice overload while maintaining decision quality. Columbia Business School Research Paper(18-2).

Dellaert, B. G. C., & Häubl, G. (2012). Searching in Choice Mode: Consumer Decision Processes in Product Search with Recommendations. Journal of Marketing Research, 49(2), 277-288. https://doi.org/10.1509/jmr.09.0481

Deng, L., & Poole, M. S. (2010). Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order. MIS Quarterly, 34(4), 711-730. https://doi.org/10.2307/25750702

Diehl, K., & Poynor, C. (2010). Great Expectations?! Assortment Size, Expectations, and Satisfaction. Journal of Marketing Research, 47(2), 312-322. https://doi.org/10.1509/jmkr.47.2.312

Fabius, V., Kohli, S., & Timelin, B. M. V., Sofia (2020, July 30, 2020). How COVID-19 is changing consumer behavior-now and forever. McKinsey & Company. https://www.mckinsey.com/industries/retail/our-insights/how-covid-19-is-changing-consumer-behavior-now-and-forever

Fehrenbacher, D. D., & Djamasbi, S. (2017). Information systems and task demand: An exploratory pupillometry study of computerized decision making [Article]. Decision Support Systems, 97, 1-11. https://doi.org/10.1016/j.dss.2017.02.007

Fernandez Rojas, R., Debie, E., Fidock, J., Barlow, M., Kasmarik, K., Anavatti, S., Garratt, M., & Abbass, H. (2020). Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments. Frontiers in Neuroscience, 14, 40. https://doi.org/10.3389/fnins.2020.00040

Gourville, J. T., & Soman, D. (2005). Overchoice and Assortment Type: When and Why Variety Backfires. Marketing Science, 24(3), 382-395. https://doi.org/10.1287/mksc.1040.0109

Gregor, S. (2006). The Nature of Theory in Information Systems. MIS Quarterly, 30(3), 611-642. https://doi.org/10.2307/25148742

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. MIS Quarterly, 37(2), 337-355. https://doi.org/10.25300/misq/2013/37.2.01

Guan, K., Zhang, Z., Chai, X., Tian, Z., Liu, T., & Niu, H. (2022). EEG Based Dynamic Functional Connectivity Analysis in Mental Workload Tasks With Different Types of Information. IEEE Trans Neural Syst Rehabil Eng, 30, 632-642. https://doi.org/10.1109/TNSRE.2022.3156546

Hassan, L. M., Shiu, E., & McGowan, M. (2019). Relieving the regret for maximizers. European Journal of Marketing, 54(2), 282-304. https://doi.org/10.1108/EJM-03-2018-0200

Häubl, G., & Trifts, V. (2000). Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. Marketing Science, 19(1), 4-21. https://doi.org/10.1287/mksc.19.1.4.15178

Haynes, G. A. (2009). Testing the boundaries of the choice overload phenomenon: The effect of number of options and time pressure on decision difficulty and satisfaction. Psychology & Marketing, 26(3), 204-212. https://doi.org/https://doi.org/10.1002/mar.20269

Hevner, A. (2007). A Three Cycle View of Design Science Research. Scandinavian Journal of Information Systems, 19.

Hevner, A., Park, J., & March, S. T. (2004). Design Science in Information Systems Research. MIS Quarterly, 28(1), 75-105.

Ho, E. H., Hagmann, D., & Loewenstein, G. (2021). Measuring Information Preferences. Management Science, 67(1), 126-145. https://doi.org/10.1287/mnsc.2019.3543

Huber, F., Köcher, S., Vogel, J., & Meyer, F. (2012). Dazing Diversity: Investigating the Determinants and Consequences of Decision Paralysis. Psychology & Marketing, 29(6), 467-478. https://doi.org/https://doi.org/10.1002/mar.20535

Itani, O. S., & Hollebeek, L. D. (2021). Consumers' health-locus-of-control and social distancing in pandemic-based e-tailing services. Journal of Services Marketing, 35(8), 1073-1091. https://doi.org/10.1108/JSM-10-2020-0410

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: can one desire too much of a good thing? J Pers Soc Psychol, 79(6), 995-1006. https://doi.org/10.1037//0022-3514.79.6.995

Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. Management Science, 31(4), 395-414.

Johnson, E. J., Shu, S. B., Dellaert, B. G. C., Fox, C., Goldstein, D. G., Häubl, G., Larrick, R. P., Payne, J. W., Peters, E., Schkade, D., Wansink, B., & Weber, E. U. (2012). Beyond nudges: Tools of a choice architecture. Marketing Letters: A Journal of Research in Marketing, 23(2), 487-504. https://doi.org/10.1007/s11002-012-9186-1

Jugovac, M., & Jannach, D. (2017). Interacting with Recommenders—Overview and Research Directions. ACM Trans. Interact. Intell. Syst., 7(3), Article 10. https://doi.org/10.1145/3001837

Kirby-Hawkins, E., Birkin, M., & Clarke, G. (2018). An investigation into the geography of corporate e-commerce sales in the UK grocery market. Environment and Planning B: Urban Analytics and City Science, 46(6), 1148-1164. https://doi.org/10.1177/2399808318755147

Konstan, J. A., & Riedl, J. (2012). Recommender systems: from algorithms to user experience. User Modeling and User-Adapted Interaction, 22(1), 101-123. https://doi.org/10.1007/s11257-011-9112-x

Köten, E. E. (2023). The impact of internet platform usage on firms' exports: New evidence for Turkish firms. The World Economy, n/a(n/a). https://doi.org/https://doi.org/10.1111/twec.13483

Krol, L. R., & Zander, T. O. (2017). Passive BCI-Based Neuroadaptive Systems. Graz Brain-Computer Interface Conference 2017,

Kuechler, W., & Vaishnavi, V. (2008a). The emergence of design research in information systems in North America. Journal of Design Research, 7, 1. https://doi.org/10.1504/JDR.2008.019897

Kuechler, W., & Vaishnavi, V. (2008b). On theory development in design science research: anatomy of a research project. EJIS, 17, 489-504.

Kuksov, D., & Villas-Boas, J. M. (2009). When More Alternatives Lead to Less Choice. Marketing Science, 29(3), 507-524. https://doi.org/10.1287/mksc.1090.0535

Kurien, R., Paila, A. R., & Nagendra, A. (2014). Application of Paralysis Analysis Syndrome in Customer Decision Making. Procedia Economics and Finance, 11, 323-334. https://doi.org/https://doi.org/10.1016/S2212-5671(14)00200-7

Lee, B.-K., & Lee, W.-N. (2004). The effect of information overload on consumer choice quality in an on-line environment [https://doi.org/10.1002/mar.20000]. Psychology & Marketing, 21(3), 159-183. https://doi.org/https://doi.org/10.1002/mar.20000

Lurie, N. H. (2004). Decision Making in Information-Rich Environments: The Role of Information Structure. Journal of Consumer Research, 30(4), 473-486. https://doi.org/10.1086/380283

Malhotra, N. K. (1982). Information load and consumer decision making. Journal of Consumer Research, 8(4), 419-430.

McKenny, J. L., & Keen, P. G. W. (1974, May 1974). How Managers' Minds Work. Harvard Business Review, 79-90.

Nguyen, J., Le, Q. V., & Ha, J. T. (2021). Impacts of Health and Safety Concerns on E-Commerce and Service Reconfiguration During the COVID-19 Pandemic: Insights from an Emerging Economy. Service Science, 13(4), 227-242. https://doi.org/10.1287/serv.2021.0279

NielsenIQ. (2019). Bursting with new products, there's never been a better time for breakthrough innovation NielsenIQ. https://nielseniq.com/global/en/insights/analysis/2019/bursting-with-new-products-theres-never-been-a-better-time-for-breakthrough-innovation/

Özkan, E., & Tolon, M. (2015). The Effects of Information Overload on Consumer Confusion: An Examination on User Generated Content. Bogazici Journal, 29, 27-51. https://doi.org/10.21773/boun.29.1.2

Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. Educational Psychologist, 38(1), 63-71. https://doi.org/10.1207/S15326985EP3801_8

Patharia, I., & Jain, T. (2023). Antecedents of Electronic Shopping Cart Abandonment during Online Purchase Process. Business Perspectives and Research, 22785337221148810. https://doi.org/10.1177/22785337221148810

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). The adaptive decision maker [doi:10.1017/CBO9781139173933]. Cambridge University Press. https://doi.org/10.1017/CBO9781139173933

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A Design Science Research Methodology for Information Systems Research. Journal of Management Information Systems, 24, 45. https://doi.org/10.2753/MIS0742-1222240302

Peng, M., Xu, Z., & Huang, H. (2021). How Does Information Overload Affect Consumers' Online Decision Process? An Event-Related Potentials Study. Front Neuroscience, 15. https://doi.org/10.3389/fnins.2021.695852

Reutkaja, E. I., S. S , Fasolo, B., & R., M. (2021). Cognitive and Affective Consequences of Information and Choice Overload. In R. Viale (Ed.), Routledge Handbook of Bounded Rationality (pp. pp. 625-636).

Rose, J. M. (2005). Decision Aids and Experiential Learning [Article]. Behavioral Research in Accounting, 17, 175-189. https://doi.org/10.2308/bria.2005.17.1.175

Scheibehenne, B., Greifeneder, R., & Todd, P. (2010). Can There Ever be Too Many Options? A Meta-analytic Review of Choice Overload. Journal of Consumer Research, 37, 409-425. https://doi.org/10.1086/651235

Schwartz, B. (2016). The Paradox of Choice: Why More Is Less (E. Press, Ed. 2nd ed.).

Simon, H. A. (1959). Theories of Decision-Making in Economics and Behavioral Science. The American Economic Review, 49(3), 253-283. http://www.jstor.org/stable/1809901

Spuler, M. (2017). A high-speed brain-computer interface (BCI) using dry EEG electrodes. PLoS ONE, 12(2), e0172400. https://doi.org/10.1371/journal.pone.0172400

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285. https://doi.org/https://doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2011). CHAPTER TWO - Cognitive Load Theory. In J. P. Mestre & B. H. Ross (Eds.), Psychology of Learning and Motivation (Vol. 55, pp. 37-76). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. (1998). Cognitive Architecture and Instructional Design. Educational Psychology Review, 10, 251. https://doi.org/https://doi.org/10.1023/a:1022193728205

Szász, L., Bálint, C., Csíki, O., Nagy, B. Z., Rácz, B.-G., Csala, D., & Harris, L. C. (2022). The impact of COVID-19 on the evolution of online retail: The pandemic as a window of opportunity. Journal of Retailing and Consumer Services, 69, 103089. https://doi.org/https://doi.org/10.1016/j.jretconser.2022.103089

Takemura, K. (1985). Ishikettei sutorateji jikko ni okeru meta ninchi katei moderu [Metacognition process model in the implementation of decision-making strategy]. Doshisha Psychological Review, 32, pp 16-22.

Takemura, K. (2014). Behavioral Decision Theories that Explain Decision-Making Processes. In K. Takemura (Ed.), Behavioral Decision Theory: Psychological and Mathematical Descriptions of Human Choice Behavior (pp. 143-164). Springer Japan. https://doi.org/10.1007/978-4-431-54580-4_12

Torres, F., Gendreau, M., & Rei, W. (2022). Crowdshipping: An open VRP variant with stochastic destinations. Transportation Research Part C: Emerging Technologies, 140, 103677. https://doi.org/https://doi.org/10.1016/j.trc.2022.103677

Tsekouras, D., Li, T., & Benbasat, I. (2022). Scratch my back and I'll scratch yours: The impact of user effort and recommendation agent effort on perceived recommendation agent quality. Information & Management, 59(1), 103571. https://doi.org/https://doi.org/10.1016/j.im.2021.103571

van der Merwe, A., Gerber, A., & Smuts, H. (2020). Guidelines for Conducting Design Science Research in Information Systems. In ICT Education (pp. 163-178). https://doi.org/10.1007/978-3-030-35629-3_11

Willemsen, M., Knijnenburg, B., Graus, M., Velter-Bremmers, L., & Fu, K. (2011). Using latent features diversification to reduce choice difficulty in recommendation lists. CEUR Workshop Proceedings,

Willemsen, M. C., Graus, M. P., & Knijnenburg, B. P. (2016). Understanding the role of latent feature diversification on choice difficulty and satisfaction. User Modeling and User-Adapted Interaction, 26(4), 347-389. https://doi.org/10.1007/s11257-016-9178-6

Wolpaw, J. R., Millán, J. d. R., & Ramsey, N. F. (2020). Chapter 2 - Brain-computer interfaces: Definitions and principles. In N. F. Ramsey & J. d. R. Millán (Eds.), Handbook of Clinical Neurology (Vol. 168, pp. 15-23). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-444-63934-9.00002-0

Xiao, B., & Benbasat, I. (2007). E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact. MIS Quarterly, 31(1), 137-209. https://doi.org/10.2307/25148784

Xiao, B., & Benbasat, I. (2014). Research on the Use, Characteristics, and Impact of e-Commerce Product Recommendation Agents: A Review and Update for 2007–2012. In F. J. Martínez-López (Ed.), Handbook of Strategic e-Business Management (pp. 403-431). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-39747-9_18

Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. Decision Support Systems, 110, 46-57. https://doi.org/https://doi.org/10.1016/j.dss.2018.03.005

Yan, Q., Zhang, L., Li, Y., Wu, S., Sun, T., Wang, L., & Chen, H. (2016). Effects of product portfolios and recommendation timing in the efficiency of personalized recommendation. Journal of Consumer Behaviour, 15(6), 516-526. https://doi.org/https://doi.org/10.1002/cb.1588

Yangyang Miao, m. c., Shugeng Chen, t. c., Xinru Zhang, z. c., Jing Jin, j. g. c., Ren Xu, x. g. a., Ian Daly, i. d. e. a. u., Jie Jia, s. c., Xingyu Wang, x. e. e. c., Andrzej

Cichocki, a. c. r. j., & Tzyy-Ping Jung, t. u. e. (2020). BCI-Based Rehabilitation on the Stroke in Sequela Stage. Neural Plasticity, 2020. https://doi.org/10.1155/2020/8882764

Zhang, H., Zhao, L., & Gupta, S. (2018). The role of online product recommendations on customer decision making and loyalty in social shopping communities. International Journal of Information Management, 38, 150-166. https://doi.org/10.1016/j.ijinfomgt.2017.07.006

Zhou, Y., Huang, S., Xu, Z., Wang, P., Wu, X., & Zhang, D. (2022). Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review. IEEE Transactions on Cognitive and Developmental Systems, 14(3), 799-818. https://doi.org/10.1109/TCDS.2021.3090217

Chapter 2 – Article 1

Neuro-Adaptive Interface System to Evaluate Product Recommendations in the Context of E-Commerce[2]

Bella Tadson, Jared Boasen, François Courtemanche, Noémie Beauchemin, Alexander-John Karran, Pierre-Majorique Léger, Sylvain Sénécal

Tech3Lab, HEC Montréal, Montréal, Canada
Faculty of Health Sciences, Hokkaido University, Sapporo, Japan

Abstract

Personalized product recommendations are widely used by online retailers to combat choice overload, a phenomenon where excessive product information adversely increases the cognitive workload of the consumer, thereby degrading their decision quality and shopping experience. However, scientific evidence on the benefits of personalized recommendations remains inconsistent, giving rise to the idea that their effects may be muted unless the consumer is actually experiencing choice overload. The ability to test this idea is thus an important goal for marketing researchers, but challenging to achieve using conventional approaches. To overcome this challenge, the present study followed a design science approach while leveraging cognitive neuroscience to develop a real-time neuro-adaptive interface for e-commerce tasks. The function of the neuro-adaptive interface was to induce choice overload and permit comparisons of cognitive load and decision quality associated with personalized recommendations, which were presented according to the following three conditions: (a) not presented (control), (b) perpetually

[2] The proceeding was published at the DESRIST 2023 conference. Exceptionally, this chapter follows the IEEE citation style, which was imposed by the conference proceedings guidelines.

Tadson, B., Boasen, J., Courtemanche, F., Beauchemin, N., Karran, A.-J., Léger, P.-M., & Sénécal, S. (2023). Neuro-Adaptive Interface System to Evaluate Product Recommendations in the Context of E-Commerce. Design Science Research for a New Society: Society 5.0, Pretoria, South Africa.

presented, or (c) presented only when a real-time neurophysiological index indicated that cognitive workload was high. Formative testing cycles produced a neuro-adaptive system in which the personalization of recommendations and neuro-adaptivity function as intended. The artifact is now ready for use in summative testing regarding the effects of personalized recommendations on cognitive workload and decision quality.

Keywords: Neuro-adaptive interface, digital technologies, e-commerce, choice overload, cognitive load, decision-making, design science.

2.1 Introduction

Personalized product recommendation systems are being increasingly used in e-commerce. A 2019 Forrester report approximated that 67% of large-scale online retailers employed recommendation systems [1] to aid users in decision-making and combat choice overload, a phenomenon where consumers are unable to analyze and compare excessive quantities of products and product information [2-4]. Choice overload has been recognized to adversely increase cognitive workload [5-8], and thereby degrade purchase decision quality [9-12], or lead consumers to delay [13] or abandon their purchase [2, 4, 14]. However, e-commerce interfaces that offer personalized recommendations generally do so without considering whether a consumer is experiencing choice overload. Coincidentally, empirical research based on such interfaces has yielded inconsistent results regarding the benefits of personalized recommendations against choice overload [15-19]. This has given rise to the idea that the effects of personalized recommendations may be muted or counterproductive unless the consumer is in fact experiencing choice overload. Correspondingly, there has a been a call from e-commerce researchers for the development of a more robust system to evaluate the effects of personalized product recommendations [15, 18].

Answering this call to research requires the development of a system that detects the occurrence of choice overload in real-time and provides personalized product recommendations accordingly. However, to our knowledge, no such system exists, and commonly-used retrospective self-reported measures [15-17, 20-22] are not appropriate. To develop the needed system, we applied the design science research (DSR) approach, as it has demonstrated effectiveness for e-commerce interface de-sign for both industrial and academic purposes [23-26]. We classified our development as a Type 4 research problem, which is characterized by an absence of relevant data available for manipulation, combined with yet unknown operations and methods to address the research problem [27, 28]. One viable approach to measure choice overload in real-time is to target cognitive workload using neurophysiology such as Electroencephalography (EEG). With its high temporal resolution, EEG provides the capability to measure brain activity continuously, and is also an established tool to measure cognitive workload [29-33]. Moreover, recent advances in cognitive neuro-science technology have now made it possible to analyze EEG-derived brain activity in real-time, thereby permitting the development of interfaces that adapt according to changes in a brain activity index (i.e., neuro-adaptive interface) [34-38].

Thus, we asked the following research question: *How can we address the aforementioned call to research by following a DSR approach while leveraging cognitive neuroscience to develop a real-time neuro-adaptive interface for e-commerce evaluation?* Specifically, we sought to design a system with a neuro-adaptive interface that could induce choice overload and permit neuropsychophysiological comparisons of cognitive load to assess the effects associated with personalized recommendations on choice overload and decision quality. The system presented recommendations according to the following three conditions: (a) not presented (control), (b) perpetually presented, or (c) presented only when a real-time neurophysiological index indicated that cognitive workload was high. This study demonstrates the applicability of DSR to neuro-adaptive system design and contributes a novel artifact to the field of e-commerce which answers the call to design a more rigorous means of evaluating the effects of personalized product recommendations against choice overload.

2.2 Foundations and Related Work

2.2.1 Choice Overload and Decision-Making

Choice overload is a form of information overload that occurs when a user is confronted with excessive quantities of information used to support decision-making [5-8]. Consequently, choice overload degrades decision quality, defined as the extent to which a purchase decision is objectively or subjectively optimal in relation to other product options [39]. The relationship between choice overload and decision quality is non-linear. As illustrated in **Figure 2**, decision quality (accuracy) is thought to improve with information quantity up to a certain point, but then deteriorates thereafter with the onset of choice overload (information overload) [11]. As decision quality decreases, negative emotions and impulsive behaviour increase [7, 40, 41]. Consequently, users express less satisfaction with their shopping experience [42], and less confidence in their selections compared with those who did not experience choice overload [12, 17, 42]. Thus, assessing the decision-making process through the lens of decision quality, decision-making behaviour, and psychological measures of satisfaction and confidence are crucial to understanding choice overload and the effectiveness of strategies against it.

Many researchers attempted to predict the exact quantity of information required to induce choice overload [41, 43, 44]. Recently, a few studies have demonstrated that presenting as few as 24 products [2, 45] and 9 attributes [45] at a time is sufficient for inducing choice overload. However, it is also recognized that the threshold for choice overload differs between individuals as a function of level of expertise and cognitive workload capacity [7, 10, 42-44]. In other words, there is no universal threshold of information quantity which will induce choice overload. Therein likely lies a predominant reason why strategies against choice overload such as personalized product recommendations have yielded inconsistent results regarding their effects [15-19], as it is not clear when precisely a given user might be overloaded and thus needs the recommendations. For this reason, studies on choice overload might benefit from targeting measures of cognitive workload.

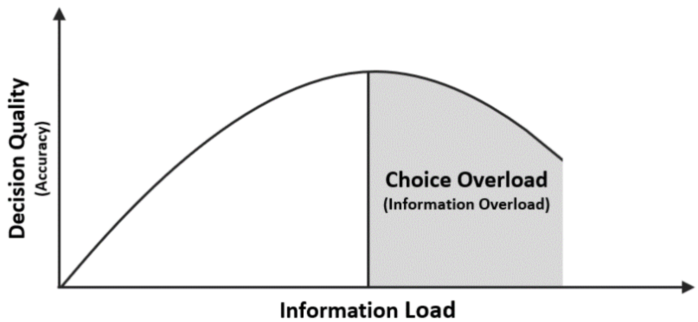


Figure 2. Relationship between choice overload and decision quality. Based on [11].

2.2.2 EEG and Neuro-Adaptive Systems

EEG is a well-established neurophysiological modality which has been used to index cognitive workload [29-33]. A notable recent study used an EEG and event-related potentials to identify cognitive overload and link it with poor decision quality [46]. However, if using personalized product recommendations to counteract choice overload, it is important to not merely know whether choice overload occurred, but also to identify when it is happening in real-time to present recommendations to users at the appropriate time, both achievable using an EEG-based solution.

Recent advances in data processing technology have now made it possible to process neurophysiological data such as EEG in real-time [47-49]. This has given rise to a new technology known as neuro-adaptive systems [34-36]. A neuro-adaptive system is one that continuously evaluates the neurophysiological activity of its user, processing an index of cognitive or affective state in real time. Then, when changes in the cognitive or affective state index are detected, the system adapts, often via visual changes on the interface [34-36]. Due to its high temporal fidelity, portability, and customizability, EEG remains a predominant modality for neuro-adaptive applications [50].

Having originated in the field of biomedical engineering, neuro-adaptive systems have recently broadened their application into other fields. For example, some re-search teams attempted to establish remote communication and control systems between a user and a device [51-53]. Other instances vary from applying neuro-adaptive systems to support learning [37] and reading [34] in education, to maintaining vigilance and attention for air traffic control [38]. While some neuro-adaptive systems have relied upon cognitive indices of user attention and engagement [46, 54], others have targeted cognitive load [34, 37]. However, the application of such systems in the field of e-commerce, albeit relevant and of high potential, remains scant. Consequently, we sought to leverage this neuro-adaptive technology to capture consumers' state of choice overload in real-time via a neurophysiological index of high cognitive workload, which when detected, would cause an e-commerce interface to adapt and display personalized product recommendations.

2.2.3 Personalized Product Recommendations

The personalization of product recommendations is a strategy widely employed across the e-commerce industry. Most global e-commerce sites, including market leaders like Amazon [55], use an algorithm called collaborative filtering [56-58]. Though many variations of it exist, the most common ones are user-based, where individual product preferences are compared to those of other similar users to predict potential purchases, or product-based, where recommended items are similar to those previously liked or visited by a user [57, 59]. Another emerging trend has recently been to add a social component to the computation, such as social tags prediction, based on blogs and online communities [60] or social network graph algorithms, centered on recommendations from friends and other peers [61].

While sophisticated and effective, the algorithmic computational approaches employed by the industry to create personalized product recommendations are not practical for e-commerce research. This is because the historical product viewing or purchasing behaviour required to use industrial algorithms is nearly impossible to acquire for experimental participants within a typical data collection timescale. Instead, a simpler, more expedient method is required which nevertheless yields effective personalization. One commonly employed method is the Multi-Attribute Decision-Making (MADM) method [62], particularly the Simple Additive Weighting (SAW) approach. MADM-SAW permits comparison between large groups of products, taking into consideration the importance an individual places on each product attribute simultaneously [63]. MADM-

SAW has been shown to facilitate optimal decision-making in the contexts of education [64, 65] and internships [66], media consumption [67], and e-commerce [68].

2.2.4 Application to Design Science Research

The multicomponent and multidisciplinary complexity of a neuro-adaptive system artifact calls for a structured definition of requirements, as well as flexible iteration cycles of subcomponents of the solution, making the DSR framework the optimal approach. More specifically, given that current neuro-adaptive systems based on users' cognitive load exist in other fields, our research to extend and refine its application into the realm of e-commerce thereby constituted an exaptation solution, according to the knowledge contribution framework [28]. The envisioned contribution was thus twofold. First, creating an artifact to support the problem in e-commerce research regarding the lack of a rigorous means of evaluating the effect of product recommendations on consumers' choice overload. Secondly, contributing to the body of knowledge in IS through our proof-of-concept, which can serve as a prescriptive theory [69, 70] to successfully implement such an artifact.

2.3 Methodology and Research Design

To provide a logical framework for constructing the neuro-adaptive e-commerce system, we followed the DSR framework by Peffers et al. [71]. Following this approach was deemed appropriate given its widely-acknowledged application among DSR models [26, 28], and its cyclic nature that provides for various entry points into the process [26, 71]. **Figure 3** illustrates said DSR approach, adapted to our study.

In Step 1, a literature review was performed regarding the problem at hand: the lack of a robust system to evaluate the effect of personalized product recommendations on choice overload and identify the state of currently deployed solutions. In Step 2, we derived and refined objectives of a system to solve the problem using a Rigor Cycle [72] grounded in the current body of knowledge and methods regarding e-commerce interfaces and recommendation systems. We also performed a Relevance Cycle [72], building upon neuro-adaptive interface artifacts from different fields and drawing upon exploratory testing formerly conducted at our lab. Step 3 comprised internal Design Cycles [72] over 8-months, cycling between design-related decisions, their implementation, evaluation, and refinement, until the objectives of the solution were fulfilled [73]. This and the following steps of the study were integrated in a research certificate ID 5071 approved by the institution's ethics review board (Comité d'éthique de la recherche de HÉC Montréal - CÉR). In Step 4 we demonstrated that the artifact adapts according to cognitive load classifications via real-time testing with a sample of 42 voluntary participants recruited through convenience sampling. All participants were adults aged 18 years old or older, fluent in English, right-handed, neurotypical and not taking any medication for neurological or behavioural disorders. Their consent and confidentiality were ensured through CÉR's protocols. Then in Step 5, the artifact was evaluated based on validity and quality criteria [28]. The "proof-of-concept" demonstrated through simulations revealed that all design requirements (discussed in the following section) were fulfilled, and interface adaptations occurred as intended. The artifact is now ready for the second evaluation phase, in which we intend to execute summative experimental testing [28]. Approximately 50 new participants are expected to be recruited through random sampling and the same inclusion criteria for this phase. In Step 6, the communication of our designed system will be achieved through two phases: 1) publication of the present manuscript, and 2) via implementation of the system throughout usability testing by practicing professionals, potentially with various customizations of on-screen adaptation elements and conditions.

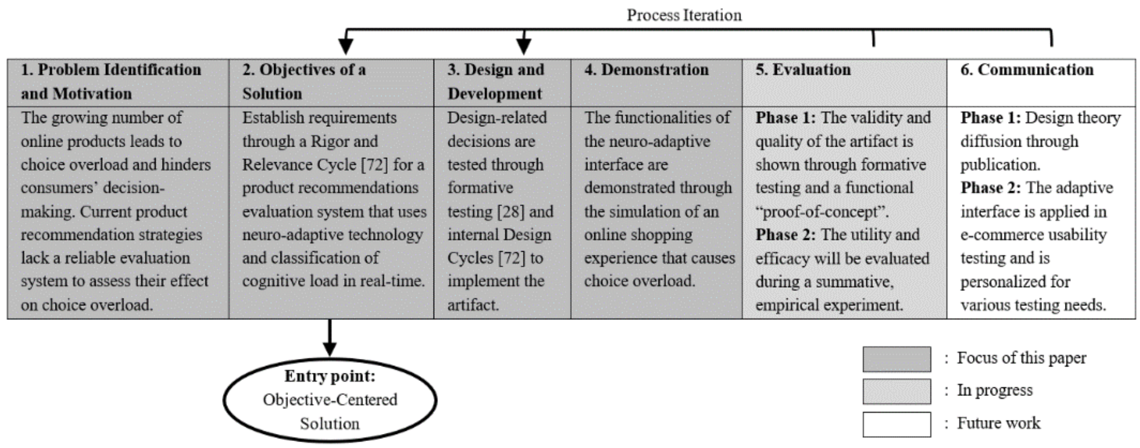


Figure 3. DSR methodology by Peffers et al. [71], adapted for this study.

2.4 Objectives of a Solution

Our overarching objective was to rigorously evaluate the effect of product recommendations on choice overload using neuro-adaptive technology. This technology permitted recommendations to be presented according to real-time EEG measurements of cognitive load. The components of this system were dissected based on Rigor and Relevance Cycles [72], translated into design requirements, and then prioritized according to resource availability and cost-benefit analyses.

First, the system had to comprise an assortment of selectable products and remain complex enough to potentially elicit choice overload (**Table 1**, DR 1). We used laptop computers as products due to their numerous attributes which complexify decision-making [9, 74]. Based on e-commerce research and formative testing, products and their attributes were displayed in a series of product comparison matrices, each with 24 products [2, 45], and 8 attributes per product [45], thereby permitting a trial-based approach for subsequent summative testing.

Next, product recommendations needed to be easily identifiable, yet not obstruct non-recommended products (DR 2). Iterative Relevance Cycles [72, 75] achieved this by highlighting a product row as an indicator of recommendation. The system was furthermore designed to be capable of highlighting (recommending) three product rows out of the 24 on each product matrix trial, with 3 products considered a small enough assortment size [9].

With an interest in comparing the effectiveness of our system to historical all-or-nothing approaches to investigating responses to product recommendations, we addressed the research problem (DR 3) by designing the system to present recommendations according to three conditions: (a) control (i.e., an interface which provides only the list of products and their attributes without any decisional aid in the form of recommendations), (b) static, perpetually presented from the onset of each product selection trial, and (c) neuro-adaptive, presented only when a real-time neurophysiological index has indicated that cognitive workload is high. To maximize the number of trials per participant, a within-subject experimental design was applied to the system, with three product selection trials, each two minutes long, in each evaluation condition to avoid experimental fatigue.

The next requirement was to personalize the recommendations to ensure their trustworthiness and pertinence (DR 4) [20, 21]. This was planned to be achieved by implementing a questionnaire to identify a user's preferences regarding the laptop product device attributes (DR 4.1). Then, the three highest-ranked products to recommend were to be determined using the MADM-SAW calculation method (DR 4.2) [62]. Lastly, the system needed to allow for a manual, but rapid insertion of this information regarding which product recommendations to display, when applicable, on a per user and per trial basis (DR 5).

To achieve the neuro-adaptive recommendations condition (c), the system needed to be capable of recording raw EEG signals (DR 6), which could also serve post-experiment analyses. Then, the system needed to calculate a cognitive load index in real-time based on raw EEG signals (DR 7), and transmit a classifier based on the index to the product recommendation interface (DR 8). Classifier transmission required both a send and receive component which ensured the classifier transmission was properly synchronized. Additionally, the interface required a set of rules on when to present recommendations, i.e., when to trigger the recommendations (DR 9). Given that display conditions required potential adjustment through formative testing, the system design needed to enable a modifiable field to input adaptation triggering rules. Finally, the system needed to support collection of self-reported measures and extraction of behavioural quantitative data for use in post-hoc analyses (DR 10). Self-reported questionnaires were to target choice overload, choice confidence and satisfaction (DR 10.1). Behavioural data would include decision time and product selections and recommendations (when applicable) for each trial (DR 10.2).

Table 2. Overview of design requirements (DR)

Design requirement	Description
User interface	
DR 1: Interactive user interface that displays a matrix of products and attributes to choose from, capable of inducing choice overload.	A difficult-to-process product comparison matrix with 24 laptops [2, 45] (rows) and 8 attributes for each [45] (columns). Images and brand names are removed to avoid bias. To select a product, users may click on the chosen product and click the "Submit" button to confirm their selection.
DR 2: A small number of product recommendations appear clearly, yet without interfering with the decision-making process.	Recommendations appear in form of a highlight of three rows of products. Users are still free to select any product, i.e., to follow the recommendation or not. Three products of 24 are recommended to simplify decision making and reduce choice overload [9].
Experimental design	
DR 3: System permits isolation of recommendation effects for rigorous summative testing.	The artifact presents recommendations according to three conditions: (a) no recommendations (control), product matrix only, (b) static, with recommendations always displayed, and (c) neuro-adaptive, with recommendations being triggered by a real-time EEG index of high cognitive load (signaling choice overload). The system uses a within-subject experimental design, with three product selection trials in each experimental condition.
Personalized recommendations	
DR 4: Personalize product recommendations for each user.	**DR 4.1 –** Gather personal user preferences: determine the relative importance each user allocates to different product attributes through a self-reported questionnaire. **DR 4.2 –** Determine the three highest-ranked products to recommend per trial, when applicable, according to the MADM-SAW method [62].
DR 5: Inform the system of what personalized recommendations to display.	Create a manual input field to inform the system of which products to recommend (obtained in DR 4), when applicable, for each trial and for each user.
Real-time classification of neurophysiological data	
DR 6: Measure raw neurophysiological data throughout the experiment.	Measure and record EEG data for cognitive load classification (DR 7) and post-experimental analyses.
DR 7: Classify raw neurophysiological data as low or high cognitive load.	Calculate an EEG cognitive load index and classify it in real-time in a format readable by the interface.

Neuro-adaptation of the interface	
DR 8: Continuously transmit cognitive load classifiers to the user interface.	Ensure synchronized and continuous transmission and receipt of cognitive load classifiers by the system throughout all trials.
DR 9: Conditions to initiate the presentation of product recommendations.	Enable a modifiable input field for recommendation display rules, based on the continuously received cognitive load classifiers.
Self-reported evaluations/Trial performance data	
DR 10: Enable capture and extraction of trial performance data and self-reported measures for post-hoc analyses.	**DR 10.1** – Behavioural quantitative data: ensure capture and extractability of trial data regarding the classifiers received, products and (when applicable) recommendations displayed, product selected, and decision time. **DR 10.2** – Perceptual quantitative data: enable a pause after each trial to present post-trial questionnaires on choice overload, choice confidence and satisfaction.

2.5 Design and Development

2.5.1 Classification and Transmission of Cognitive Load to the Interface

Real-time processing of neurophysiological activity (DR 6 from **Table 1** above) and classification of cognitive load (DR 7) were designed using Simulink in MATLAB (version R2021b, IBM). The Simulink model was built to sample neurophysiological activity at 250 Hz from a g.tec Research: a 32-channel wireless, gel-based active electrode electroencephalographic (EEG) hardware, installed according to the 32-channel standard montage by g.tec. Real-time processing blocks for channel selection and band-power extraction were incorporated, in addition to Butterworth low-pass and high-pass filtering and a notch filter. A block was added to classify cognitive load as low (0), medium (1), or high (2), based on mean alpha-band power output over six-second intervals. Low and high cognitive workload band power thresholds were calibrated for each individual participant using EEG signals sampled during a 0-Back and a 2-Back task, respectively. The N-Back working memory paradigm is a well-established task for differentiating cognitive workload [76-78]. The raw and processed EEG data, and derived classifications, were set up to be recorded in parallel to permit post-hoc analysis and investigation of our phase 2 evaluation step (**Figure 3**). Cognitive load classifications (0, 1, 2) were continuously transmitted to the interface (DR 8), as they were derived (every six seconds) over the local network via Lab Streaming Layer (LSL). The classification was then communicated to the web interface through a Python-based LSL receiver and a WebSocket client on a web server at the same rate of one classifier every six seconds.

2.5.2 Neuro-Adaptation Logic

Neuro-adaptation was designed such that the interface presented recommendations to users according to primary and secondary cognitive load classification logic. The primary logic consisted of the aforementioned classification of cognitive load sent from Simulink via LSL (transmitted values being 0, 1, or 2). The secondary logic, applied downstream from this using a Python script, converted the output value into a “3” if it satisfied a best out of three condition. In other words, if at least two 2’s were received within the last three classifiers, the script would transform the next value that it would relay to the interface into a “3”. The interface adaptation rules and conditions were implemented through a web application (see 5.4 below).

2.5.3 Product Recommendations

To enable users to attribute personal importance to each of the 8 laptop product criteria (DR 4.1), a 5-point Likert scale (with 1 being “Not important at all” and 5 being “Very important”) was utilized in an online Qualtrics questionnaire. These attribute ratings were then input into an Excel file, which was designed to determine the three highest-ranked products per trial for each user (DR 4.2), according to the MADM-SAW method [62]. The calculation takes into account the total database of 360 fictitious, but plausible laptop products and their attributes which we included in the system, objectively assessing them in accordance with the subjective importance of the attributes reported by each user.

2.5.4 User Testing Interfaces

The front-end (DR 1, DR 2, and DR 3) of the system was developed in HTML and enhanced with CSS formatting, executed on a web browser with a computer operating on Windows 11. A front-end web application was developed in Google’s AngularJS MVC framework, internally called Metamorph, to launch a separate interface for each recommendation presentation condition (control, static and neuro-adaptive) through a link generated on a per participant basis.

For the static and neuro-adaptive condition interfaces, the Metamorph application included a field to integrate the product ID's of the top three laptops for each user and each trial – identified in the previous step – to inform the interface of which products to recommend, when applicable (DR 5).

For the neuro-adaptive condition interface, the application also comprised a rule engine library, that is, a functionality that permitted upload of a set of conditions into the database in form of a JSON file, meant to dictate the rules to display product recommendations (DR 9). These rules use Javascript objects to control the presentation of product recommendations. They were designed such that no recommendations would display the first and last 12 seconds of each trial, to give users the chance to read the entire matrix and react to recommendations if they were presented. Outside of these two time windows, the display of recommendations was triggered when the value received through the WebSocket client was "3" (see 5.2).

Meanwhile, the interface was designed such that users could select only one product with a left mouse click, and then submit their selection by pressing a "Submit" button on the bottom of the screen. After a selection was submitted, the interface presented a transition screen thanking the user and then paused. This pause permitted to present the post-trial questionnaires on choice overload, choice confidence and satisfaction via Qualtrics (DR 10.1). After the questionnaires were completed, the transition screen of the interface was redisplayed and the user was instructed to press a "Continue" button, which initiated the subsequent trial. The transition screen on the last trial displayed a message requesting users to await further instructions and had no "Continue" button.

Lastly, in provision of the second phase of our evaluation (**Figure 3**) (DR 10), a feature was integrated in the application to enable capture and extraction of per-trial post-study behavioural quantitative data. The generatable output is in form of a JSON file, which compiles: a) the different values of classifiers received every six seconds throughout the trial, b) the time users took to complete their product selection, c) the products included in the trial, d) the three products that were recommended (for the static and the neuro-adaptive conditions, when applicable), and e) the product that the user selected.

2.6 Demonstration and Preliminary Evaluations

Daily to weekly iterations were executed over a period of 8 months and included 42 formative testing participants. These formative testing cycles were concluded with proof-of-concept simulations to establish the validity and quality [28] of the system we built, thereby completing the first phase of our evaluation defined in **Figure 3**. A simplified mock-up of the resulting product comparison matrix of the user interface is shown in **Figure 4**, with an example of what a product recommendation looked like. From a technical standpoint, the system now operates consistently and dependably to satisfy sought goals and design requirements defined in previous steps. This development and implementation serve as the main result of our paper. The proof-of-concept demonstration of the artifact working as intended is illustrated in **Figure 5**.

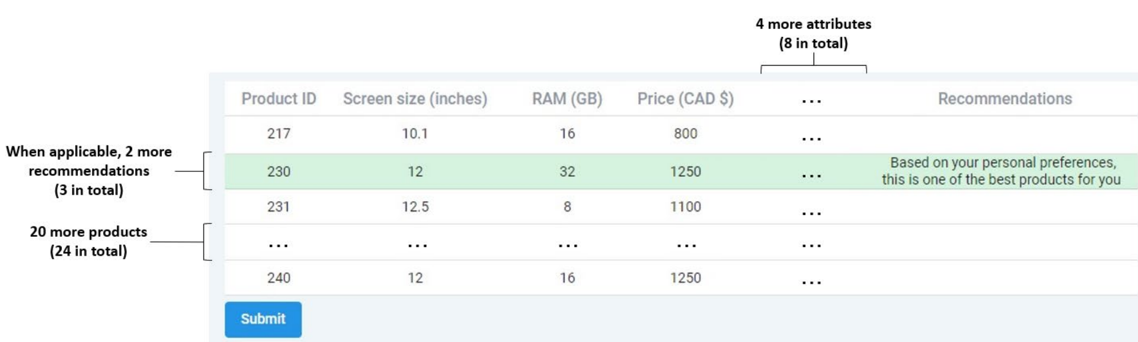


Figure 4. Simplified illustration of the product comparison matrix of the user interface. When applicable, recommendations take the form of a green highlight across the entire product row.

The results of our research carried out during the Rigor Cycle [72] (step 3 in **Figure 3**) suggest a high level of potential utility of the constructed artifact. Given the limited availability of evaluation tools to assess the effectiveness of product recommendations, the value our system can bring outside of the development environment [28, 71] is highly promising. However, the system's utility and efficacy are yet to be evaluated in a second evaluation phase (**Figure 3**) to assess its practical application in summative and empirical research.

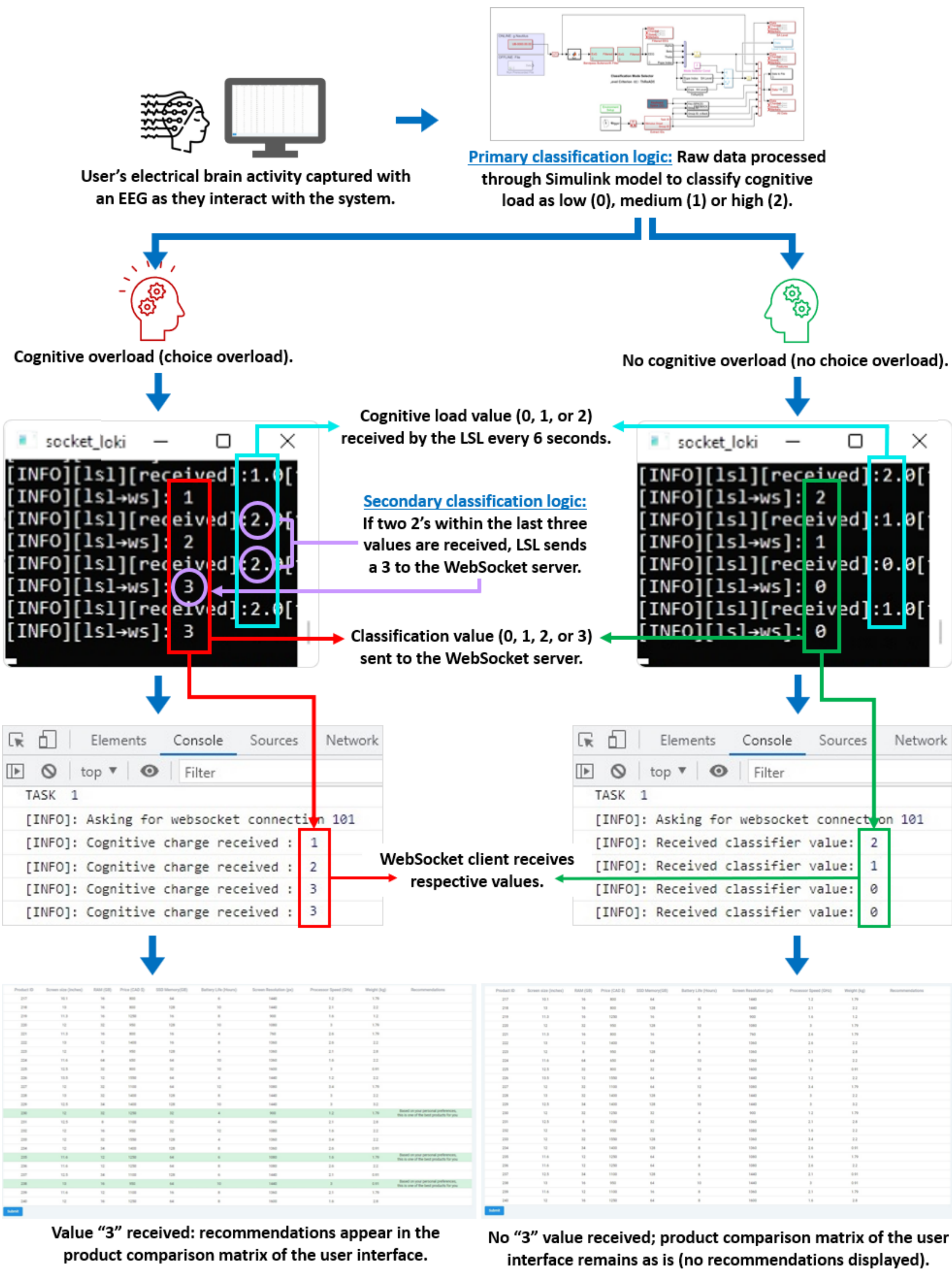


Figure 5. Demonstration of neuro-adaptivity through simulation.

2.7 Discussion

2.7.1 Implications for Design Science

The present study followed a DSR methodology to build a neuro-adaptive system which would permit more rigorous assessment for e-commerce research regarding the effects of personalized product recommendations on choice overload. Formative testing through live simulations revealed that the design requirements of the system [28] functioned as intended. This effectively demonstrated the success of our approach to answer our research question and the call for solutions from e-commerce researchers. The novel application of neuro-adaptive technology in the development of an e-commerce evaluation artifact can now be formalized into a dependable prescriptive (Type V) design theory [69, 70] to guide the choice of functionalities and construction of similar tools. **Table 3** (next page) outlines our acquired design knowledge using the Jones and Gregor framework [79].

2.7.2 Implications for Stakeholders

There are three main advantages of the system. One, whereas past approaches predominantly have relied upon retrospective self-reports of choice overload, the present system permits continuous, real-time assessment of choice overload via an EEG cognitive workload index. Two, the continuous assessment of choice overload via EEG-based cognitive workload permits delivery of personalized recommendations only when choice overload is being experienced by the user, rather than an all or nothing approach. And three, the use of three recommendation conditions and recording of raw EEG along with behavioural and self-reported data permits rigorous evaluation of the hypothesis that personalized product recommendations are most effective against choice overload when it is indeed being experienced at the time of recommendation delivery.

Table 3. Components of a design theory for the evaluation of personalized recommendations in the context of e-commerce, adapted from Jones and Gregor [79].

Type	Component
Purpose and scope	Development of a more robust and reliable evaluation system to assess the effects of personalized product recommendations in an e-commerce context. To efficiently isolate the effect of recommendations, the system includes three recommendations conditions: (a) no recommendations (control), (b) recommendations displayed perpetually, or (c) recommendations triggered by a real-time neurophysiological classification of cognitive workload as high, captured through an EEG.
Constructs	Choice overload, cognitive load, decision quality, decision confidence, satisfaction.
Principles of form and function	A difficult-to-process product comparison matrix with 24 products (rows) and 8 attributes for each (columns). Recommendations appear in form of a highlight of the rows with recommended products.
Artifact mutability	The system is an exaptation of a neuro-adaptive artifact based on cognitive load to apply it to the field of e-commerce evaluation, which constitutes a novel solution that has not yet been explored.
Testable propositions	1. The interface presents a number of products and product attributes that are sufficiently high to induce choice overload. 2. Provided recommendations are personalized. 3. When applicable, personalized recommendations are provided according to a neurophysiological cognitive load index measured in real-time through an EEG.
Justificatory knowledge	The artifact builds on current knowledge from e-commerce user experience, choice overload theory, decision-making theory, cognitive workload theory, real-time neurophysiological processing theory (current neuro-adaptive technology), product recommendations strategies.
Principles of implementation	The tool is intended for use by researchers, as well as industry practitioners in marketing, IS, user experience, etc. to better assess e-commerce strategies to cope with choice overload, in controlled experimental settings, where the users (participants) must be healthy and autonomous adults.

The implications of the present system for stakeholders, particularly marketing and user experience researchers, are manifold. The flexibility of the system permits manipulation of adaptivity elements, conditions, and overall interface design. Not only can the content of the matrices in the e-commerce interface be modified to match different e-commerce contexts, but the HTML-based graphics could be redesigned to model real-world websites while still retaining the neuro-adaptive functionality. Moreover, the brain activity index used for classification can easily be changed, thereby permitting researchers to study responses based on cognitive factors other than cognitive load, such as fatigue or attention. Thus, the present system could potentially be used to investigate behavioural responses to recommendations driven by a multitude of cognitive factors, which could then be leveraged in the industrial domain. Correspondingly, studies using the present system could potentially derive insights about context-dependent information display preferences. The present system could potentially even be used to accurately identify behavioural indices of choice overload, which could then be employed industrially. Ultimately, the present system could drive a change in personalized recommendation strategies, improving their effectiveness along with the experience for consumers.

2.7.3 Limitations and Directions for Future Research

Though overarching objectives have been achieved, there are some limitations to the current iteration of the designed system. First, recommendation conditions were not centralized within the rules agent of the Metamorph application, necessitating the more cumbersome approach of two-step adaptation logic discussed in the Design and Development section (see section 5.2). Additionally, the identification and input of personalized recommendation criteria for each user (DR 4 and DR 5 from **Table 2**) must currently be performed manually using an online Qualtrics questionnaire, Excel spreadsheet, and an input field in the Metamorph application. However, these limitations do not fundamentally impede system function and can thus be addressed in future development cycles. Indeed, the present system functioned smoothly and appropriately, as was demonstrated through formative testing and proof-of-concept simulations.

2.8 Conclusion

This study demonstrates the applicability of DSR to neuro-adaptive interface design to solve Type 4 research problems, and contributes a novel, functional artifact to the field of e-commerce which answers the call to design a more rigorous means of evaluating the effects of personalized product recommendations against choice overload. The system is now ready for summative testing, which should further cement its contribution to the fields of e-commerce and DSR. The present publication marks an important milestone in dissemination of the DSR knowledge gained. Going forward, the system's inherent flexibility should permit improvement of operational efficiency, and context-independent evolution of visual design and adaption based on other cognitive constructs.

References

1 Kodali, S.: ‘The State of Retailing Online 2019’, in Forrester ‘The State of Retailing Online 2019’ (Forrester, 2019, edn.), pp. 25

2 Iyengar, S.S., and Lepper, M.R.: ‘When choice is demotivating: can one desire too much of a good thing?’, J Pers Soc Psychol, 2000, 79, (6), pp. 995-1006

3 Scheibehenne, B., Greifeneder, R., and Todd, P.: ‘Can There Ever be Too Many Options? A Meta-analytic Review of Choice Overload’, Journal of Consumer Research, 2010, 37, pp. 409-425

4 Özkan, E., and Tolon, M.: ‘The Effects of Information Overload on Consumer Confusion: An Examination on User Generated Content’, Bogazici Journal, 2015, 29, pp. 27-51

5 Bawden, D., and Robinson, L.: ‘Information Overload: An Overview’: ‘Oxford Encyclopedia of Political Decision Making’ (Oxford: Oxford University Press, 2020)

6 Fehrenbacher, D.D., and Djamasbi, S.: ‘Information systems and task demand: An exploratory pupillometry study of computerized decision making’, Decision Support Systems, 2017, 97, pp. 1-11

7 Deck, C., and Jahedi, S.: ‘The effect of cognitive load on economic decision making: A survey and new experiments’, European Economic Review, 2015, 78, pp. 97-119

8 Peng, M., Xu, Z., and Huang, H.: ‘How Does Information Overload Affect Consumers' Online Decision Process? An Event-Related Potentials Study’, Front Neurosci, 2021, 15

9 Chernev, A., Böckenholt, U., and Goodman, J.: ‘Choice overload: A conceptual review and meta-analysis’, Journal of Consumer Psychology, 2015, 25, (2), pp. 333-358

10 Chen, Y.-C., Shang, R.-A., and Kao, C.-Y.: ‘The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment’, Electron. Commer. Res. Appl., 2009, 8, (11), pp. 48-58

11 Eppler, M.J., and Mengis, J.: ‘The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines’, The Information Society, 2004, 20, (5), pp. 325-344

12 Calvo, L., Christel, I., Terrado, M., Cucchietti, F., and Pérez-Montoro, M.: 'Users' Cognitive Load: A Key Aspect to Successfully Communicate Visual Climate Information', Bulletin of the American Meteorological Society, 2022, 103, (1), pp. E1-E16

13 Kurien, R., Paila, A.R., and Nagendra, A.: 'Application of Paralysis Analysis Syndrome in Customer Decision Making', Procedia Economics and Finance, 2014, 11, pp. 323-334

14 Deng, L., and Poole, M.S.: 'Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order', MIS Quarterly, 2010, 34, (4), pp. 711-730

15 Aljukhadar, M., Senecal, S., and Daoust, C.-E.: 'Using Recommendation Agents to Cope with Information Overload', International Journal of Electronic Commerce, 2012, 17, (2), pp. 41-70

16 Liang, T.-P., Lai, H.-J., and Ku, Y.-C.: 'Personalized Content Recommendation and User Satisfaction: Theoretical Synthesis and Empirical Findings', Journal of Management Information Systems, 2006, 23, (3), pp. 45-70

17 Zhang, H., Zhao, L., and Gupta, S.: 'The role of online product recommendations on customer decision making and loyalty in social shopping communities', International Journal of Information Management, 2018, 38, pp. 150-166

18 Konstan, J.A., and Riedl, J.: 'Recommender systems: from algorithms to user experience', User Modeling and User-Adapted Interaction, 2012, 22, (1), pp. 101-123

19 Wertenbroch, K., Schrift, R.Y., Alba, J.W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D.R., Matz, S., Nave, G., Parker, J.R., Puntoni, S., Zheng, Y., and Zwebner, Y.: 'Autonomy in consumer choice', Marketing Letters, 2020, 31, (4), pp. 429-439

20 Chen, C.C., Shih, S.-Y., and Lee, M.: 'Who should you follow? Combining learning to rank with social influence for informative friend recommendation', Decision Support Systems, 2016, 90, pp. 33-45

21 Wang, W., and Benbasat, I.: 'Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs', J. of Management Information Systems, 2007, 23, pp. 217-246

22 Rose, J.M., Roberts, F.D., and Rose, A.M.: ‘Affective responses to financial data and multimedia: the effects of information load and cognitive load’, International Journal of Accounting Information Systems, 2004, 5, (1), pp. 5-24

23 Sia, C., Shi, Y., Yan, J., and Chen, H.: ‘Web personalization to build trust in E-commerce: A design science approach’, World Academy of Science, Engineering and Technology, 2010, 64, pp. 325-329

24 Ball, N.L.: ‘Design Science II: The Impact of Design Science on E-Commerce Research and Practice’, Communications of the Association for Information Systems, 2001, 7

25 Karmokar, S., and Singh, H.: ‘Improving the Website Design Process for SMEs: A Design Science Perspective’2012 pp. Pages

26 van der Merwe, A., Gerber, A., and Smuts, H.: ‘Guidelines for Conducting Design Science Research in Information Systems’: ‘ICT Education’ (2020), pp. 163-178

27 McKenny, J.L., and Keen, P.G.W.: ‘How Managers' Minds Work’, in Editor (Ed.)^(Eds.): ‘Book How Managers' Minds Work’ (1974, edn.), pp. 79-90

28 Gregor, S., and Hevner, A.R.: ‘Positioning and Presenting Design Science Research for Maximum Impact’, MIS Quarterly, 2013, 37, (2), pp. 337-355

29 Fernandez Rojas, R., Debie, E., Fidock, J., Barlow, M., Kasmarik, K., Anavatti, S., Garratt, M., and Abbass, H.: ‘Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments’, Front Neurosci, 2020, 14, pp. 40

30 Antonenko, P.P., Paas, F., Grabner, R., and Gog, T.: ‘Using Electroencephalography to Measure Cognitive Load’, Educational Psychology Review, 2010, 22, pp. 425-438

31 Gredin, N.V., Broadbent, D.P., Findon, J.L., Williams, A.M., and Bishop, D.T.: ‘The impact of task load on the integration of explicit contextual priors and visual information during anticipation’, Psychophysiology, 2020, 57, (6), pp. 1-13

32 Guan, K., Zhang, Z., Chai, X., Tian, Z., Liu, T., and Niu, H.: ‘EEG Based Dynamic Functional Connectivity Analysis in Mental Workload Tasks With Different Types of Information’, IEEE Trans Neural Syst Rehabil Eng, 2022, 30, pp. 632-642

33 Al-Samarraie, H., Eldenfria, A., Zaqout, F., and Price, M.L.: ‘How reading in single- and multiple-column types influence our cognitive load: an EEG study’, The Electronic Library, 2019, 37, (4), pp. 593-606

34 Andreessen, L.M., Gerjets, P., Meurers, D., and Zander, T.O.: 'Toward neuroadaptive support technologies for improving digital reading: a passive BCI-based assessment of mental workload imposed by text difficulty and presentation speed during reading', User Modeling & User-Adapted Interaction, 2021, 31, (1), pp. 75-104

35 Krol, L.R., and Zander, T.O.: 'Passive BCI-Based Neuroadaptive Systems', in Editor (Ed.)^(Eds.): 'Book Passive BCI-Based Neuroadaptive Systems' (2017, edn.), pp.

36 Wolpaw, J.R., Millán, J.d.R., and Ramsey, N.F.: 'Chapter 2 - Brain-computer interfaces: Definitions and principles', in Ramsey, N.F., and Millán, J.d.R. (Eds.): 'Handbook of Clinical Neurology' (Elsevier, 2020), pp. 15-23

37 Eldenfria, A., and Al-Samarraie, H.: 'Towards an Online Continuous Adaptation Mechanism (OCAM) for Enhanced Engagement: An EEG Study', International Journal of Human-Computer Interaction, 2019, 35, (20), pp. 1960-1974

38 Di Flumeri, G., De Crescenzio, F., Berberian, B., Ohneiser, O., Kramer, J., Arico, P., Borghini, G., Babiloni, F., Bagassi, S., and Piastra, S.: 'Brain-Computer Interface-Based Adaptive Automation to Prevent Out-Of-The-Loop Phenomenon in Air Traffic Controllers Dealing With Highly Automated Systems', Front Hum Neurosci, 2019, 13, pp. 296

39 Xiao, B., and Benbasat, I.: 'E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact', MIS Quarterly, 2007, 31, (1), pp. 137-209

40 Wheeler, P., and Arunachalam, V.: 'The effects of multimedia on cognitive aspects of decision-making', International Journal of Accounting Information Systems, 2009, 10, (2), pp. 97-116

41 Appiah Kusi, G., Azmira Rumki, Z., Hammond Quarcoo, F., Otchere, E., and Fu, G.: 'The Role of Information Overload on Consumers' Online Shopping Behavior', Journal of Business and Management Studies, 2022, 4, (4), pp. 162-178

42 Lee, B.-K., and Lee, W.-N.: 'The effect of information overload on consumer choice quality in an on-line environment', Psychology & Marketing, 2004, 21, (3), pp. 159-183

43 Ho, E.H., Hagmann, D., and Loewenstein, G.: 'Measuring Information Preferences', Management Science, 2021, 67, (1), pp. 126-145

44 Lurie, N.H.: 'Decision Making in Information-Rich Environments: The Role of Information Structure', Journal of Consumer Research, 2004, 30, (4), pp. 473-486

45 Greifeneder, R., Scheibehenne, B., and Kleber, N.: ‘Less may be more when choosing is difficult: Choice complexity and too much choice’, Acta psychologica, 2009, 133, pp. 45-50

46 Chen, Z., Jin, J., Daly, I., Zuo, C., Wang, X., and Cichocki, A.: ‘Effects of Visual Attention on Tactile P300 BCI’, Computational Intelligence & Neuroscience, 2020, pp. 1-11

47 Khorshidtalab, A., and Salami, M.J.E.: ‘EEG signal classification for real-time brain-computer interface applications: A review’, in Editor (Ed.)^(Eds.): ‘Book EEG signal classification for real-time brain-computer interface applications: A review’ (2011, edn.), pp. 1-7

48 Guarnieri, R., Zhao, M., Taberna, G.A., Ganzetti, M., Swinnen, S.P., and Mantini, D.: ‘RT-NET: real-time reconstruction of neural activity using high-density electroencephalography’, Neuroinformatics, 2021, 19, (2), pp. 251-266

49 Zanetti, R., Arza, A., Aminifar, A., and Atienza, D.: ‘Real-Time EEG-Based Cognitive Workload Monitoring on Wearable Devices’, IEEE Trans Biomed Eng, 2022, 69, (1), pp. 265-277

50 Aricò, P., Borghini, G., Di Flumeri, G., Sciaraffa, N., and Babiloni, F.: ‘Passive BCI beyond the lab: current trends and future directions’, Physiol Meas, 2018, 39, (8), pp. 08tr02

51 Yangyang Miao, m.c., Shugeng Chen, t.c., Xinru Zhang, z.c., Jing Jin, j.g.c., Ren Xu, x.g.a., Ian Daly, i.d.e.a.u., Jie Jia, s.c., Xingyu Wang, x.e.e.c., Andrzej Cichocki, a.c.r.j., and Tzyy-Ping Jung, t.u.e.: ‘BCI-Based Rehabilitation on the Stroke in Sequela Stage’, Neural Plasticity, 2020, 2020

52 Ron-Angevin, R., Garcia, L., Fernández-Rodríguez, Á., Saracco, J., André, J.M., and Lespinet-Najib, V.: ‘Impact of Speller Size on a Visual P300 Brain-Computer Interface (BCI) System under Two Conditions of Constraint for Eye Movement’, Computational Intelligence & Neuroscience, 2019, pp. 1-16

53 Velasco-Álvarez, F., Fernández-Rodríguez, Á., Vizcaíno-Martín, F.-J., Díaz-Estrella, A., and Ron-Angevin, R.: ‘Brain–Computer Interface (BCI) Control of a Virtual Assistant in a Smartphone to Manage Messaging Applications’, Sensors (14248220), 2021, 21, (11), pp. 3716-3716

54 Perry, N.C., Wiggins, M.W., Childs, M., and Fogarty, G.: ‘Can reduced processing decision support interfaces improve the decision-making of less-experienced incident commanders?’, Decision Support Systems, 2012, 52, (2), pp. 497-504

55 Linden, G., Smith, B., and York, J.: ‘Amazon.com Recommendations’, in Editor (Ed.)^(Eds.): ‘Book Amazon.com Recommendations’ (IEEE Computer Society, 2003, edn.), pp. 76-80

56 Sharma, J., Sharma, K., Garg, K., and Sharma, A.K.: ‘Product Recommendation System a Comprehensive Review’, IOP Conference Series: Materials Science and Engineering, 2021, 1022, (1), pp. 12-21

57 Huang, Z., Zeng, D., and Chen, H.: ‘A Comparison of Collaborative-Filtering Recommendation Algorithms for E-commerce’, IEEE Intelligent Systems, 2007, 22, (5), pp. 68-78

58 Sarwar, B., Karypis, G., Konstan, J., and Riedl, J.: ‘Analysis of Recommendation Algorithms for E-Commerce’, in Editor (Ed.)^(Eds.): ‘Book Analysis of Recommendation Algorithms for E-Commerce’ (University of Minnesota, 2000, edn.), pp. 158-167

59 Pandey, S., and Kumar, T.S.: ‘Customization of Recommendation System Using Collaborative Filtering Algorithm on Cloud Using Mahout’, IJRET: International Journal of Research in Engineering and Technology, 2014, 3, (7), pp. 39-43

60 Yuan, Z.-m., Huang, C., Sun, X.-y., Li, X.-x., and Xu, D.-r.: ‘A microblog recommendation algorithm based on social tagging and a temporal interest evolution model’, Frontiers of Information Technology & Electronic Engineering, 2015, 16, (7), pp. 532-540

61 Adabi, A., and de Alfaro, L.: ‘Toward a Social Graph Recommendation Algorithm: Do We Trust Our Friends in Movie Recommendations?’, in Editor (Ed.)^(Eds.): ‘Book Toward a Social Graph Recommendation Algorithm: Do We Trust Our Friends in Movie Recommendations?’ (Springer Berlin Heidelberg, 2012, edn.), pp. 637-647

62 Adriyendi, M.: ‘Multi-Attribute Decision Making Using Simple Additive Weighting and Weighted Product in Food Choice’, International Journal of Information Engineering and Electronic Business, 2015, 7, (6), pp. 8-14

63 Sun, P., Yang, J., and Zhi, Y.: ‘Multi-attribute decision-making method based on Taylor expansion’, International Journal of Distributed Sensor Networks, 2019, 15, (3)

64 Pratiwi, D., Putri, J., and Agushinta R, D.: ‘Decision Support System to Majoring High School Student Using Simple Additive Weighting Method’, International Journal of Computer Trends and Technology, 2014, 10, pp. 153-159

65 Aminudin, N., Huda, M., Kilani, A., Embong, W.H.W., Mohamed, A.M., Basiron, B., Ihwani, S.S., Noor, S.S.M., Jasmi, K.A., and Safar, J.: 'Higher education selection using simple additive weighting', International Journal of Engineering and Technology (UAE), 2018, 7, (2.27), pp. 211-217

66 Santoso, P.A., Wibawa, A.P., and Pujianto, U.: 'Internship recommendation system using simple additive weighting', Bulletin of Social Informatics Theory and Application, 2018, 2, (1), pp. 15-21

67 Hdioud, F., Frikh, B., and Ouhbi, B.: 'Multi-Criteria Recommender Systems based on Multi-Attribute Decision Making'. Proc. International Conference on Information Integration and Web-based Applications & Services2013 pp. Pages

68 Engel, M.M., Utomo, W.H., and Purnomo, H.D.: 'Fuzzy Multi Attribute Decision Making Simple Additive Weighting (MADM SAW) for Information Retrieval (IR) in E Commerce Recommendation', International Journal of Computer Science and Software Engineering, 2017, 6, (6), pp. 136-145

69 Gregor, S.: 'The Nature of Theory in Information Systems', MIS Quarterly, 2006, 30, (3), pp. 611-642

70 Kuechler, W., and Vaishnavi, V.: 'On theory development in design science research: anatomy of a research project', EJIS, 2008, 17, pp. 489-504

71 Peffers, K., Tuunanen, T., Rothenberger, M.A., and Chatterjee, S.: 'A Design Science Research Methodology for Information Systems Research', Journal of Management Information Systems, 2008, 24, pp. 45

72 Hevner, A.: 'A Three Cycle View of Design Science Research', Scandinavian Journal of Information Systems, 2007, 19

73 Simon, H.A.: 'The Sciences of the Artificial' (The MIT Press, 1996. 1996)

74 Okfalisa, O., Rusnedy, H., Iswavigra, D.U., Pranggono, B., Haerani, E.H., and Saktioto, S.: 'Decision Support System for Smartphone Recommendation: The Comparison of Fuzzy Ahp and Fuzzy Anp in Multi-Attribute Decision Making', Sinergi, 2020, 25, (1)

75 Hevner, A., Park, J., and March, S.T.: 'Design Science in Information Systems Research', MIS Quarterly, 2004, 28, (1), pp. 75-105

76 Wang, S., Gwizdka, J., and Chaovalitwongse, W.A.: ‘Using Wireless EEG Signals to Assess Memory Workload in the N-Back Task’, IEEE Transactions on Human-Machine Systems, 2016, 46, (3), pp. 424-435

77 Kirchner, W.K.: ‘Age differences in short-term retention of rapidly changing information’, Journal of Experimental Psychology, 1958, 55, (4), pp. 352-358

78 Karran, A.J., Demazure, T., Leger, P.-M., Labonte-LeMoyne, E., Senecal, S., Fredette, M., and Babin, G.: ‘Toward a Hybrid Passive BCI for the Modulation of Sustained Attention Using EEG and fNIRS’, Frontiers in Human Neuroscience, 2019, 13

79 Jones, D., and Gregor, S.: ‘The Anatomy of a Design Theory’, Journal of the Association for Information Systems, 2007, 8, (5), pp. 312-335

Chapter 3 – Article 2[3]

Evaluating the Decisional Outcomes of Neuro-Adaptive Product Recommendations in an Online Shopping Experience

Bella Tadson, Sylvain Sénécal, Pierre-Majorique Léger, Noémie Beauchemin
Jared Boasen, Alexander-John Karran

Tech3Lab, HEC Montréal, Montréal, Canada

Abstract

In the current e-commerce landscape, consumers are increasingly confronted with choice overload, a phenomenon characterized by an inability to cognitively process an excessive number of decision alternatives. Experiencing choice overload while shopping online has been associated with reduced decision quality, increased frustration, dissatisfaction, lack of confidence, and a proneness to delay or abandon a purchase decision. Incidentally, current methods of facilitating users' decision-making and addressing these detriments by providing product recommendations yield contradictory findings, at times aggravating the experience. This has brought the idea that this form of decisional aid may have adverse effects, unless consumers are, in fact, experiencing choice overload. This empirical study addresses this suggestion by proposing a novel method of displaying recommendations to consumers, based on the detection of choice overload in real-time, leveraging neuro-adaptive technology. To assess the effectiveness of our proposed approach against canon recommendations systems, we employ a within-subject study design (n=55) with three experimental conditions: (a) control (no recommendations), (b) static (recommendations presented perpetually), and (c) neuro-adaptive (recommendations presented only if a real-

[3] The article is expected to be dissected and merged with other studies, to be submitted to high impact factor publications.

time neurophysiological index indicates that cognitive load is high, an indicator of choice overload). The results reveal that both static and neuro-adaptive recommendations increase, rather than alleviate, perceived choice overload. Decisional outcomes, however, with the exception of decision time, benefit from recommendations, especially when they are neuro-adaptive: choice confidence and decision quality are impacted directly, and choice satisfaction and decision time through the mediation of choice overload. Moderating effects of individual characteristics reveal that neuro-adaptive recommendations are particularly advantageous to individuals with low product involvement and low product expertise, as they increase their choice satisfaction and confidence, and individuals with high reactance and high need for cognition, reducing decision times for the former and increasing choice satisfaction for the latter. The study concludes by opening the door to alternative approaches of identifying real-time occurrences of choice overload, using commercially available methods beyond the neuro-adaptive system utilized in this study.

Keywords: E-commerce, recommendations, neuro-adaptive interface, choice overload, cognitive load, decision-making, decisional outcomes, individual characteristics.

3.1 Introduction

Over the last three years, catalyzed by the COVID-19 pandemic (Beckers & Cant, 2023; Collins & Geist, 2023), the growth in global e-commerce has risen to levels that were only anticipated to occur between 2025 and 2030 (Fabius et al., 2020). Previously available only to urban, wealthy populations (Beckers et al., 2018; Kirby-Hawkins et al., 2018), the expanded access to internet services (Bhatti et al., 2022; Köten, 2023), increased health and security concerns (Ghosh, 2022; Itani & Hollebeek, 2021; Nguyen et al., 2021), and improved logistical efficiency (Beckers & Cant, 2023; Torres et al., 2022), have all contributed to the growth of e-commerce beyond its historical geographic and sociodemographic limits (Szász et al., 2022).

Through this continuously expanding e-commerce landscape, consumers are increasingly confronted with a phenomenon described as choice overload. In the context of the digital marketplace, choice overload occurs when the decision-making associated with selecting a product is too cognitively demanding, given the overwhelming amount of information and choices available (Beierle et al., 2020; Chernev et al., 2015; Scheibehenne et al., 2010). On a neurophysiological level, choice overload manifests itself as increased cognitive workload (Ariga, 2018; Bawden & Robinson, 2020; Deck & Jahedi, 2015; Fehrenbacher & Djamasbi, 2017; Peng et al., 2021), or simply put, an excessive mental effort (Drichoutis & Nayga, 2020; Paas et al., 2003; Reutkaja et al., 2021; Sweller et al., 1998).

These cognitive demands associated with choice overload not only negatively impact consumers' decision quality (Arora & Narula, 2018; Calvo et al., 2022; Deck & Jahedi, 2015) but are also linked to higher levels of frustration (Deng & Poole, 2010; Haynes, 2009; Lee & Lee, 2004) and dissatisfaction (Diehl & Poynor, 2010; Huber et al., 2012; Lee & Lee, 2004), as well as a lack of confidence in selected choices (Calvo et al., 2022; Lee & Lee, 2004; Zhang et al., 2018). Moreover, users experiencing choice overload are more susceptible to ultimately delaying (Kurien et al., 2014) or even abandoning (Iyengar & Lepper, 2000; Kuksov & Villas-Boas, 2009; Özkan & Tolon, 2015) their purchase decision altogether, which poses a significant detriment to online retailers as well. As a means of reducing this impeding effect of choice overload, retailers employ recommendation systems, aimed to facilitate the online decision-making process for consumers (Aljukhadar et al., 2012; Dellaert & Häubl, 2012).

However, research regarding the effects of systematically displaying recommendations yields inconsistent results: while some studies demonstrate the beneficial impact of recommendations in online decision-making (Aljukhadar et al., 2012; Dellaert & Häubl, 2012), other findings indicate contradicting results, such as deterred decision quality (Banker & Khetani, 2019; Chen et al., 2022; Dellaert et al., 2017; Xiao & Benbasat, 2018) and, on the opposite, amplified choice overload (Bollen et al., 2010; Willemsen et al., 2011; Willemsen et al., 2016). These inconsistencies have brought forth the idea that displaying recommendations may only be beneficial in instances where users are in fact experiencing choice overload (Häubl & Trifts, 2000; Yan et al., 2016). Additionally, scholars have noted that devising a solution is difficult given the limitations in current evaluation tools; commonly employed assessments of choice overload, either through neurophysiological or self-reported measures, are only completed during post hoc analysis (Antonenko et al., 2010; Fehrenbacher & Djamasbi, 2017; Reutkaja et al., 2021; Rose, 2005; Zhang et al., 2018; Zhou et al., 2022), when the user's interaction with the system no longer takes place. Furthermore, there is no universal threshold for when a consumer might experience choice overload, as it largely depends on individual differences in cognitive workload capacity (Malhotra, 1982; Sweller, 1988, 2011). Researchers have thus emphasized the need for a more nuanced solution against choice overload (Chen et al., 2009; Patharia & Jain, 2023) and improvement in the personalization and interactivity of current recommendations systems (Jugovac & Jannach, 2017; Konstan & Riedl, 2012; Liang et al., 2006; Shen, 2014).

Aiming to fill the research gap addressed in this discourse, we proposed a novel method of tailoring the display of recommendations based on cognitive load, assessed in real-time. For its implementation, we leveraged neuro-adaptive technology, also called Brain-Computer Interfaces (BCI), as such artifacts allow for an ongoing processing of cognitive information in real-time, and a dynamic adaptation of the user experience accordingly (Andreessen et al., 2021; Krol & Zander, 2017; Wolpaw et al., 2020). We opted for a neuro-adaptive system that uses electroencephalography (EEG), an acknowledged neuroscientific tool to assess cognitive load (Al-Samarraie et al., 2019; Fernandez Rojas et al., 2020; Gredin et al., 2020; Guan et al., 2022), to reliably predict the occurrence of choice overload in real-time and, if detected, provide the user with product recommendations (Tadson et al., 2023).

Such an approach would introduce a new dimension of personalization of recommendations (Blut et al., 2023; Tsekouras et al., 2022), as it would allow to both, accommodate users in need of decisional aid and avoid hindering the decision-making of users that are not experiencing choice overload. With this objective in mind, we formulated the following first research question:

RQ1: *To what extent does a neuro-adaptive interface which detects cognitive load and provides recommendations accordingly impact users' decision-making in an online shopping experience?*

To adequately contrast our proposed method of customizing recommendations based on cognitive load with canon recommendations systems, we included three experimental conditions in our within-subjects study design:

(a) control, where no recommendations are presented to participants,

(b) static, where recommendations are presented perpetually and systematically to all participants, and

(c) neuro-adaptive, our novel technique that displays recommendations based on the detection of choice overload through a cognitive workload index.

In this assessment, we included the decisional outcomes outlined in Xiao & Benbasat's (2007) framework, which spans both perceptual measures of choice satisfaction and choice confidence, as well as performance measures of decision quality and decision time.

Additionally, congruent with the metacognitive model of the decision-making process under information overload (Takemura, 1985, 2014), scholars have discussed the relevance of incorporating individual characteristics in research on recommendations and the effects of choice overload (Aljukhadar et al., 2017; Appelt et al., 2011; Johnson et al., 2012; Xiao & Benbasat, 2014). However, studies that comprehensively assess individual differences impacting consumer decision-making are sparse. This shortfall prompted us to devise the second research question below:

RQ2: *To what extent consumers' perceptions and individual characteristics influence their decision-making outcomes when provided with recommendations from a neuro-adaptive system?*

In an attempt to encompass predominant individual characteristics involved in moderating our aforementioned decisional outcomes, we incorporated the following constructs in our evaluation: compliance with recommendations (Melovic et al., 2020; Senecal et al., 2005; Zhang & Xu, 2019), consumer product involvement (Kean Yew & Kamarulzaman, 2020), product expertise (Broniarczyk & Griffin, 2014; Hadar et al., 2013; Senecal & Nantel, 2004), psychological reaction (Kwon & Chung, 2010; Lee & Lee, 2009; Yanping & Yan, 2012) and need for cognition (Petty et al., 2002; Petty et al., 2007; Takemura, 2001, 2014).

The results of this investigation provide empirical support that the neuro-adaptive recommendations we proposed perform just as well as, and occasionally surpass, standard recommendations, particularly when comparing choice satisfaction, choice confidence, and decision quality. Additional advantages of the neuro-adaptive approach are highlighted when taking into account individual characteristics of users, unveiling further benefits and, at times, mitigating certain drawbacks of traditional recommendations.

Our main contribution to the body of knowledge therefore consists of responding to the current research gap, calling for a more personalized and interactive solution to combat the detriments of choice overload in an online decision-making context. We achieved this through a unique instantiation of neuro-adaptive technology in the field of e-commerce, resulting in a novel way of personalizing of the display of recommendations, based on a real-time predictor of choice overload. The investigation also contributes to understanding the discrepancies observed in the research and challenges the conventional dichotomic viewpoint regarding the merits of recommendations, positing instead for more nuanced effects. Lastly, through our proposed conceptual framework, we provide a holistic understanding of the interplay of individual factors and their effects on decisional outcomes, specifically in a context of e-commerce choice overload.

As such, practitioners and researchers alike may now leverage the insights on the promising effects of recommendations adapted to consumers' choice overload, in order to explore means of implementing this dimension of personalization by relying on technology that is commercially available. Moreover, our research underscores the relevance of continuing to devise strategies to entice the adoption of recommendations among consumers, and encourages industry professionals to complement our findings with their own customer research, to guide design and business decisions tailored at consumers with specific characteristics.

3.2 Literature Review

3.2.1 Choice Overload in E-Commerce

3.2.1.1 The E-Commerce Landscape and the Rise of Choice Overload

Accelerated by the COVID-19 pandemic (Beckers & Cant, 2023; Collins & Geist, 2023), e-commerce has been growing unprecedentedly across the international market over the past few decades. Despite the convenience and safety that online shopping offers consumers and the additional stream of revenue it provides retailers with (Szász et al., 2022), the growing adoption of e-commerce has its shortcomings.

With over 30,000 new products added to the global online market every year (NielsenIQ, 2019), choosing items from these wider assortments becomes increasingly challenging. While consumers demonstrate apparent preferences for choice variety and larger product assortments (Iyengar & Lepper, 2000; Khan et al., 2021), their decision-making becomes increasingly hindered by a phenomenon referred to as choice overload (Chernev et al., 2015; Iyengar & Lepper, 2000; Scheibehenne et al., 2010; Schwartz, 2016). Also called overchoice, it denotes an individual's inability to cognitively process an excessive number of decision alternatives (Iyengar & Lepper, 2000; Simon, 1959; Toffler, 1970). It stems from the broader concept of information overload, which pertains to an overwhelming amount of information that exceeds a subject's mental processing capacity (Aljanabi & Al-Hadban, 2023; Eppler & Mengis, 2004; Hu & Krishen, 2019; Lee & Lee, 2004; Roetzel, 2019). However, choice overload specifically addresses the context of decision-making when faced with multiple alternatives (Fasolo et al., 2007; Nagar & Gandotra, 2016; Peng et al., 2021; Reutkaja et al., 2021).

3.2.1.2 The Nuisance Brought by Choice Overload

The impeding influence of choice overload on the outcome of a decision, particularly its quality, has been widely documented. Decision quality is a concept defined as the extent to which a decision is objectively or subjectively optimal in relation to other options (Xiao & Benbasat, 2007). Deck and Jahedi (2015), for example, found that choice overload led to a behaviour that is more risk-averse, impatient in regard to money, and more likely to be subject to the effect of anchoring. Further research concluded that users experiencing choice overload were more susceptible to emotional and impulsive decisions, not always being the optimal, rational choice (Chen et al., 2009). Similarly, Sela et al. (2009) discovered that when faced with choice overload, decision-makers were likely to opt for an alternative that was simpler to justify, despite the availability of an option that was more optimal, but harder to explain. Individuals' inherent sense of skepticism has also shown to be amplified under decision-making complexified by choice overload (Guo & Li, 2022; Hu & Krishen, 2019). Overall, similar to information overload, the accuracy (quality) of a decision increases with the number of available options (Eppler & Mengis, 2004; Reutskaja et al., 2020; Vogrincic-Haselbacher et al., 2021), until the mental costs of processing the larger selection outweigh the benefits of each additional alternative (Oppewal & Koelemeijer, 2005; Roberts & Lattin, 1991), resulting in the curvilinear relationship (Aljukhadar et al., 2012; Jacoby, Speller, & Berning, 1974; Reutkaja et al., 2021) portrayed in **Figure 6**.

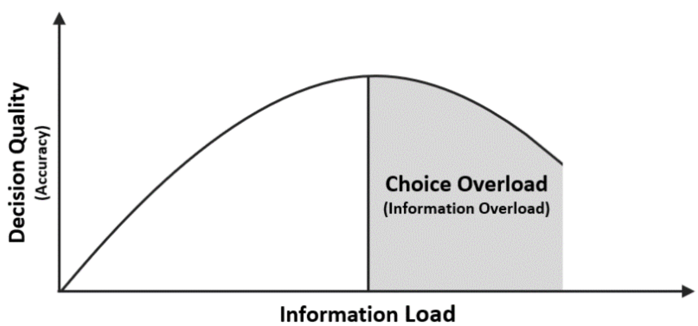


Figure 6. Relationship between choice overload and decision quality, adapted from Eppler and Mengis (2004)

In the context of e-commerce, research suggests that the phenomenon of choice overload not only degrades purchase decision quality (Arora & Narula, 2018; Broniarczyk & Griffin, 2014; Calvo et al., 2022; Deck & Jahedi, 2015; Vogrincic-Haselbacher et al., 2021), but also adversely impacts customer experience as a whole (Calvo et al., 2022; Lee & Lee, 2004). When confronted with choice overload, consumers are more likely to experience frustration (Deng & Poole, 2010; Haynes, 2009; Lee & Lee, 2004) and other negative emotions (Appiah Kusi et al., 2022; Wheeler & Arunachalam, 2009). Subsequently, they become prone to feeling less satisfied with their shopping experience (Diehl & Poynor, 2010; Huber et al., 2012; Lee & Lee, 2004) and are more troubled by regret (Gourville & Soman, 2005; Hassan et al., 2019) and a lack confidence regarding their purchase decision (Calvo et al., 2022; Lee & Lee, 2004; Zhang et al., 2018). Moreover, choice overload may hinder decision-making to a point where consumers are so overwhelmed that they ultimately withdraw from making a decision or taking action, an outcome coined as "analysis paralysis" (Koenig, 1995; Kurien et al., 2014). According to Andersone (2022), such decision paralysis occurs when the opportunity cost, i.e., the thought and analysis involved in a decision, exceeds the benefits the consumer may gain from making a selection. This is a particularly unfavourable outcome for online retailers, as it translates into consumers delaying (Kurien et al., 2014) or not completing their purchase at all (Deng & Poole, 2010; Iyengar & Lepper, 2000; Kuksov & Villas-Boas, 2010; Manolică et al., 2021; Özkan & Tolon, 2015). These negative impacts of choice overload on both online shoppers and retailers raise the necessity for a viable solution.

3.2.2 Recommendations to Counter Choice Overload

3.2.2.1 E-Commerce Strategies to Cope with Choice Overload

E-commerce strategies that facilitate decision-making for users that are faced with choice overload are manifold. Some online retailers manipulate visual stimuli (Deng & Poole, 2010; Kahn, 2017), either through adding multimedia elements, such as icons and videos, aimed to alternatively present product information (Wheeler & Arunachalam, 2009), through visual contrasts and boundaries between pieces of information (Donkers et al., 2020; Wen & Lurie, 2019), or through purging interfaces of superfluous hyperlinks (Chen, 2018). Others resort to product filtering features (Calvo et al., 2022; Chen et al., 2009), subgrouping products to enable multiple smaller choices, rather than a single large one (Besedeš et al., 2015), pre-selecting default options (Brown & Krishna, 2004; Madrian & Shea, 2001), or aiming to decrease the perceived risk of a poor decision through guaranteed money-back policies (Schulz et al., 2019).

Whilst tactics vary among businesses, one of the most prominent and promising is providing customers with product recommendations (Nunes & Jannach, 2017; Shen, 2014). Already in 2013, such recommendations generated 35% of Amazon's revenue (Linden et al., 2003; MacKenzie et al., 2013). More recently, a 2019 Forrester report approximated that 67% of large-scale online retailers employed recommendation systems to aid users in their decision-making (Kodali, 2019). Given their customizable (Chen et al., 2016; Sarwar et al., 2000) and trustworthy (Wang & Benbasat, 2007) character, and their ability to positively influence decision quality (Aljukhadar et al., 2012; Dellaert & Häubl, 2012), recommendations have some of the highest potential to effectively offset the phenomenon of choice overload (Aksoy et al., 2011; Bollen et al., 2010; Lee & Benbasat, 2011; Malone & Lusk, 2019).

3.2.2.2 Strategies to Optimize Recommendations

With the exception of retailers that recommend products based on their self-serving interests (Hunold et al, 2020), most strategies encompassing recommendations explore how to improve their quality and acceptance, in order to reduce choice overload and facilitate decision-making for consumers (Blut et al., 2023; Huseynov et al., 2014; Jiang et al., 2010; Pereira, 2001). The tactics span three main classifications: the mode of presenting the recommendations (Blut et al., 2023; Tsekouras et al., 2022), the algorithm that determines which products to recommend, and the source of data used for this algorithm, and the mode of presenting the recommendations. Presentation methods vary, with some recommendations appearing only if manually requested by users (Marchand & Marx, 2020; Tsekouras et al., 2022) and others providing unsolicited suggestions, either by being embedded within a retailer's website (Nilashi et al., 2016; Whang & Im, 2021)or by showcasing separate comprehensive lists of recommended products (Tsekouras et al., 2022; Xiao & Benbasat, 2007). Commonly used algorithms involve content-based and collaborative filtering, which respectively focus on recommendations based on products that were previously liked or visited by e-shoppers, or on preferences of consumers with similar user profiles (Huang et al., 2007; Lops et al., 2011; Ricci et al., 2022; Sarwar et al., 2000; Sharma et al., 2021). The sources of information most commonly used for these techniques include a user's geographic location (Divyaa & Nargis, 2019; Zhu et al., 2014), personal or historical purchase information (Jiang & Benbasat, 2005; Köcher et al., 2019), or social media filtering. The latter either focuses on social tags predictions from blogs and online communities (Yuan et al., 2015), or suggestions from friends and other peers (Adabi & de Alfaro, 2012; Garcia Esparza et al., 2012).

While these sophisticated computational techniques prove effective in industry applications, they are less practical in a research context, due to limited access to the large amount of consumer data required to fuel these algorithms (Baier & Stüber, 2010; Mild & Reutterer, 2003), and the privacy concerns that arise, as these algorithms necessitate the usage of sensitive user information (Zhu et al., 2014). In academic contexts, an acknowledged recommendations algorithm is the Multi-Attribute Decision Making method (MADM), specifically the Simple Additive Weighting (SAW) formula. Stemming from the effort-accuracy framework of Payne et al. (1993) and Johnson and Payne (1985), the MADM-SAW method uses direct user input to consider the subjective importance of each product criterion for each individual, while simultaneously assessing the product performance relative to other products (Adriyendi, 2015; Sun et al., 2019). While this information may be difficult to obtain in practice, the approach has been widely used in research to optimize recommendations in the contexts of education (Aminudin et al., 2018; Pratiwi et al., 2014; Santoso et al., 2018), media (Hdioud et al., 2013), and e-commerce (Engel et al., 2017). For a more comprehensive overview of these algorithms and their sources, please refer to the meta-analysis by Blut et al. (2023).

Although presentation modes receive much less attention than research involving recommendations algorithms, scholars and online retailers alike agree on the importance of personalizing recommendations, in order to optimize their effectiveness against choice overload and its unfavourable effects (Liang et al., 2006; Xiao & Benbasat, 2018). Yet, a sparse number of studies have explored alternative personalization methods, beyond those highlighted in the meta-analysis of Blut et al. (2023).

3.2.3 The Drawbacks of Current Recommendations Systems

3.2.3.1 Inconsistent Results Fueling an Ongoing Debate

In light of this lack of additional personalization strategies, a few limitations emerge from existing recommendations systems. Many findings have come to contrary conclusions regarding the assistive role of recommendations in decision-making and their regulating effect against choice overload (Bollen et al., 2010; Willemsen et al., 2011). For example, Willemsen et al. (2016) found that recommendations, on the opposite, tend to increase a consumer’s perception of choice overload and decrease their choice satisfaction. Häubl et al. (2010) and Lajos et al. (2009) arrived to similar conclusions, with the latter also underscoring the resulting deterred attitude and purchase intention. Some researchers have argued that these detriments arise from insufficiently personalized recommendations strategies (Liang et al., 2006; Shen, 2014) and that when presented beyond their need, recommendations may induce a lack of desired control (André et al., 2018; Konstan & Riedl, 2012; Wertenbroch et al., 2020). Moreover, some scholars have found that recommendations lead to a decline in decision quality (Aksoy et al., 2006), as users were more likely to “blindly” trust recommendations, without noticing they were suboptimal (Banker & Khetani, 2019; Xiao & Benbasat, 2018) or remain within a “cocoon” of options that are not necessarily optimal (Chen et al., 2022; Dellaert et al., 2017). The authors also posit that the inconsistencies in results feeding these opposing positions in regard to recommendations also arise from users’ individual differences.

3.2.3.2 Limitations in Strategies and Evaluation Methods

Although many scholars endeavored to establish a universal information limit that triggers choice overload (Appiah Kusi et al., 2022; Ho et al., 2021; Lurie, 2004), it is recognized that the quantity of information required for a user to experience choice overload is different for every individual. Albeit the presence of some common patterns, the specific threshold for choice overload largely depends on an individual’s cognitive workload capacity and individual differences, such as product expertise for example (Chen et al., 2009; Deck & Jahedi, 2015; Lee & Lee, 2004; Lurie, 2004). Yet, current e-commerce retailers do not account for these variances and showcase recommendations systematically, without accounting for a user’s cognitive state, as an indication of choice overload. As a result, the uncertainty from not knowing precisely when a user is experiencing choice overload and, therefore, when decision-making might benefit from or be hindered by recommendations, is likely a significant factor contributing to the inconsistent results observed in the literature (Gevins & Smith, 2000; Jin et al., 2017).

Another limitation commonly discussed by research groups is the need for novel methods and measurement tools (Chen et al., 2009; Konstan & Riedl, 2012). As pointed out by Häubl and Trifts (2000) and Yan et al. (2016), recommendations may be most optimal when consumers have gone beyond the initial screening of alternatives stage of decision-making and reached the stage of in-depth product comparisons. Though these researchers aimed to predict the latter, cognitively strenuous decisional stage, through the user's location on the site, they bring forward the limitation of this method in terms of potential prediction inaccuracy. Other approaches were only capable of determining the occurrence of choice overload after the user's interaction with the system was completed, either through retrospective, self-reported measures (Aljukhadar et al., 2012; Appiah Kusi et al., 2022; Liang et al., 2006; Rose et al., 2004; Wang & Benbasat, 2007; Zhang et al., 2018) or neurophysiological tools, such as electroencephalography (EEG) (Antonenko et al., 2010; Gevins & Smith, 2003; Peng et al., 2021; Zhou et al., 2022), functional magnetic resonance imaging (fMRI) (Miri Ashtiani & Daliri, 2023; Reutkaja et al., 2021; Whelan, 2007) or pupillometry (Fehrenbacher & Djamasbi, 2017; Sirois & Brisson, 2014; Weber et al., 2021). Some researchers noted the need for reliable measures to assess choice overload, to regulate the amount of information displayed to online consumers, in order to avoid choice overload (Appiah Kusi et al., 2022). These limitations in current methods could benefit from a reliable tool to identify choice overload in real-time and provide users with recommendations accordingly.

3.2.4 Brain-Computer Interfaces

3.2.4.1 Measuring Choice Overload Through Cognitive Load

A few recent studies have solidified the connection between choice overload and its neurophysiological manifestation in form of heightened cognitive workload (Ariga, 2018; Bawden & Robinson, 2020; Chen et al., 2020; Fehrenbacher & Djamasbi, 2017; Peng et al., 2021; Reutskaja et al., 2020). Cognitive workload (or cognitive load) refers to the amount of mental effort that is necessary to complete a learning, problem-solving, or decisional task, which is subject to an individual's working memory capacity (Malhotra, 1982; Sweller, 1988, 2011). As highlighted by Reutskaja et al. (2020), while some increase in cognitive load is necessary to adequately complete a task, excessive cognitive load hinders information processing, leading to inaccurate and low-quality decisions, and negative impacts on decision-makers' emotional states. This conclusion is congruent with research on choice overload impeding decision-making, and studies that revealed akin detrimental effects of excessive cognitive load on a decision-making process (Allen et al., 2014; Bigras et al., 2019; Collins & Collins, 2021; Deck & Jahedi, 2015).

Electroencephalography (EEG) is a well-established modality to measure cognitive workload through a user's electrical brain activity (Al-Samarraie et al., 2019; Antonenko et al., 2010; Fernandez Rojas et al., 2020; Gredin et al., 2020; Guan et al., 2022). Moreover, due to its high temporal fidelity, portability, and customizability, it has contributed to recent developments in data processing technology, which allowed for the possibility of assessing neurophysiological EEG signal in real-time and give rise to neuro-adaptive systems (Aricò et al., 2018; Fernandez Rojas et al., 2020; Guan et al., 2022; Spuler, 2017).

3.2.4.2 Leveraging Neuro-Adaptive Systems

A neuro-adaptive system, also termed a Brain-Computer Interface (BCI), is a system that continuously monitors a user's neurophysiological activity, in order to identify a change in their cognitive or affective states. When such a change is detected, the system responsively adapts in real-time, often through an adjustment of on-screen visual stimuli (Andreessen et al., 2021; Krol & Zander, 2017; Tadson et al., 2023; Wolpaw et al., 2020). Though the technology originated in the field of biomedical engineering, neuro-adaptive systems have now extended their application to diverse fields. For example, BCIs have been used to aid users in controlling or communicating with a device remotely, without the need for touch or manual manipulation (Ron-Angevin et al., 2019; Velasco-Álvarez et al., 2021; Yangyang Miao et al., 2020). Other applications have been created for educational purposes to facilitate learning (Eldenfria & Al-Samarraie, 2019) and reading (Andreessen et al., 2021), or to assist in air traffic control (Di Flumeri et al., 2019). The flexibility of these systems allows to target both cognitive indices of attention and engagement (Chen et al., 2020; Perry et al., 2012), and also cognitive load (Andreessen et al., 2021; Eldenfria & Al-Samarraie, 2019).

Recognizing an opportunity to leverage such neuro-adaptive technology, we aimed to explore a novel dimension of personalization in presenting e-commerce recommendations using the system built by Tadson et al. (2023). Such a system could continuously capture a user's cognitive load during their interaction with an e-commerce website and, upon detecting an excessive cognitive workload, indicative of choice overload, the system could display product recommendations. This approach could both (a) accommodate users that require recommendations to alleviate choice overload, thereby facilitating their decision-making, and (b) avoid impeding the decision-making process by indistinctively providing recommendations even when they are beyond need to users not experiencing choice overload. This strategy addresses the conflicting findings resulting from generic recommendations and the limitations in current measurement tools, both discussed in the previous subsection.

3.3 Conceptual Framework and Hypotheses

We began to explore the connection between recommendations and decision-making outcomes through the lens of the behavioural decision theory first proposed by Simon (1959). This theory offers a foundational structure for understanding the mechanisms and patterns of human behaviour that comprise a decision-making process. We adopted two established models of this theory to guide our own research: the effort-accuracy framework (Johnson & Payne, 1985; Payne et al., 1993) and the metacognitive model of the decision-making process under information overload (Takemura, 1985, 2014). The former considers that at the core of decision-making lies the trade-off between the cognitive effort, i.e., "cost" required for a decision, and the "benefit" of making an accurate selection. In other words, in given circumstances, some decision-makers prioritize decision quality (accuracy), even if it requires substantial mental effort, while others opt for ease of decision, compromising on decision accuracy. The second model, the metacognitive model of the decision-making process under information overload (Takemura, 1985, 2014), complements the first one by positing that decision-making relies not only on the interplay of task complexity, but also on individual factors (such as level of expertise, involvement, and other aspects) and a metacognitive mechanism. This mechanism refers to how difficult an individual perceives a task to be, enabling them to allocate appropriate cognitive resources to complete the decision.

In the context of our research, we therefore isolated the display of recommendations as the sole manipulated variable to investigate its effects on two key dimensions: first, we looked at subjective and objective decisional outcomes of recommendations proposed by Xiao and Benbasat (2007). Secondly, we considered the context of choice overload and individual characteristics that could influence decision-making, as per the model by Takemura (2014) and the discourse brought forth by numerous studies to explore the influence of individual differences on the effects of recommendations (Aljukhadar et al., 2017; Appelt et al., 2011; Johnson et al., 2012; Xiao & Benbasat, 2014).

Our theorizing and hypotheses are summarized in a proposed conceptual framework (**Figure 7**) and in the subsections below. **Table 4**, at the end of this section, provides an overview of these hypotheses.

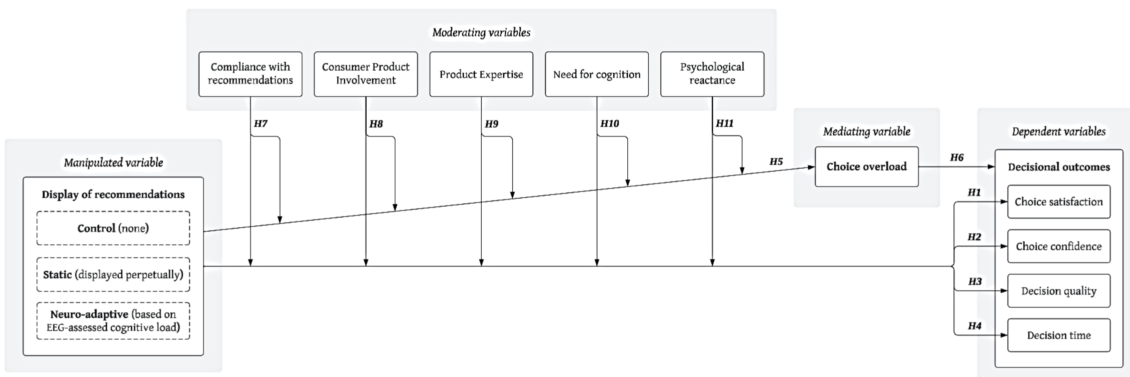


Figure 7. Proposed Conceptual Framework

3.3.1 The Direct Effects of Recommendations on Decision-Making Outcomes in a Context of Choice Overload

3.3.1.1 Choice Satisfaction

Choice satisfaction has been regarded an important construct commonly addressed in consumer and marketing research involving decision-making, primarily because it has been conceptualized to precede the act of purchase (Yi, 1990; Yoon et al., 2013) and indirectly link to more frequent consumption through increasing customer loyalty (Arora & Narula, 2018; Leninkumar, 2017). It has also served as a close indicator of overall perceived service quality (Zeithaml et al., 2006), a feature online retailers strive towards. In the context of larger assortment sizes, despite consumers enjoying the variety of choice

(Iyengar & Lepper, 2000; Yan et al., 2016), research suggests they are prone to experiencing less choice satisfaction, even if they would select the same product as in a smaller assortment of goods (Diehl & Poynor, 2010).

Though with exceptions, current literature thus largely supports industry practices in showcasing product recommendations to increase choice satisfaction (Addepalli et al., 2016; Angela Chang & Kukar-Kinney, 2011; Bettman et al., 2008; Dabholkar & Sheng, 2012; Heitmann et al., 2007; Jiang et al., 2010). We therefore aligned our hypotheses with these findings, which suggest that consumers receiving recommendations experience greater choice satisfaction than those that are not exposed to recommendations, particularly in a context where there are copious quantities of product alternatives and attributes to evaluate (Blut et al., 2023; Bollen et al., 2010).

H1a: *In a context of choice overload, perceived choice satisfaction will be higher when recommendations are presented statically than when recommendations are not presented.*

H1b: *In a context of choice overload, perceived choice satisfaction will be higher when recommendations are presented neuro-adaptively than when recommendations are not presented.*

However, given the absence of prior research employing a neuro-adaptive system, we framed our next assumption based on a salient consideration highlighted by studies that emphasized the importance of personalizing recommendations and the overall online shopping experience to ensure the former indeed play a positive role in increasing choice satisfaction (Knijnenburg et al., 2010; Liang et al., 2006; Shen, 2014). We thus posited that the neuro-adaptive condition's ability to tailor the display of recommendations based on individual workload capacity would contribute to perceiving the experience as more personalized, resulting in participants attributing, in that instance, a higher level of satisfaction to their choice of product.

H1c: *In a context of choice overload, perceived choice satisfaction will be higher when recommendations are presented neuro-adaptively than when recommendations are presented statically.*

3.3.1.2 Choice Confidence

Choice confidence is another salient component of decision-making commonly studied hand-in-hand with choice satisfaction (Aljukhadar et al., 2010; Harris & Gupta, 2008; Zhu et al., 2018), as it provides insight into how online shoppers think and behave (Andrews, 2016; Heitmann et al., 2007). Some research groups go as far as operationalizing the concept as perceived decision quality (Pereira, 2001; Xiao & Benbasat, 2018), the extent to which consumers believe their decision is correct (Petrocelli et al., 2007) and justifiable (Heitmann et al., 2007), and how much they consider themselves in control of a choice situation (Nataraajan & Angur, 1998). In practical terms, higher choice confidence translates to a higher willingness-to-pay (Thomas & Menon, 2007), increased purchase intention (Laroche et al., 1996), and stronger choice commitment (Clarkson et al., 2008).

According to Heitmann et al. (2007), choice confidence is an inherent goal of decision-making, but becomes increasingly harder to achieve as choice sets grow in number and complexity, hence the widely adopted usage of recommendations. Based on this assumption and prior research by Harris and Gupta (2008) and Reed et al. (2012), we proposed a positive impact of recommendations on choice confidence.

> ***H2a:*** *In a context of choice overload, perceived choice confidence will be higher when recommendations are presented statically than when recommendations are not presented.*

> ***H2b:*** *In a context of choice overload, perceived choice confidence will be higher when recommendations are presented neuro-adaptively than when recommendations are not presented.*

Additionally, as the current state of the art often implies a correlation between choice satisfaction and choice confidence (Heitmann et al., 2007; Xiao & Benbasat, 2018; Zhu et al., 2018), we followed the logic of choice satisfaction to introduce an akin hypothesis in favour for the more personalized, neuro-adaptive recommendations condition.

> ***H2c:*** *In a context of choice overload, perceived choice confidence will be higher when recommendations are presented neuro-adaptively than when recommendations are presented statically.*

3.3.1.3 Decision Quality

At the core of facilitating consumers' decision-making through recommendations lies the objective of improving the behavioural outcomes of their decision, concentrating on decision quality. Specifically, in addressing objective decision quality, we aimed to complement subjective decision quality, which has been explored as a proxy of choice confidence, based on the work of Xiao and Benbasat (2018) and Pereira (2001). Despite the ongoing debate that questions the positive outcomes of recommendations, we referred to the compelling results of the larger body of research as a basis for our hypotheses. The latter suggest that recommendations help consumers in selecting more optimal products, thereby improving decision quality (Blut et al., 2023; Häubl & Trifts, 2000; Swaminathan, 2003; Todd & Benbasat, 1994). Other findings extend this idea, advancing that when presented with decisional aids in form of recommendations, some consumers will mostly rely on this assistance to select a product (Xiao & Benbasat, 2007, 2014). As such, as long as recommended products comprise optimal choices for given consumers, decision quality should improve. Building on these assumptions, we hypothesized that the presence of recommendations will effectively aid users in improving the quality of their decision.

> ***H3a:*** *In a context of choice overload, objective decision quality will be higher when recommendations are presented statically than when recommendations are not presented.*

> ***H3b:*** *In a context of choice overload, objective decision quality will be higher when recommendations are presented neuro-adaptively than when recommendations are not presented.*

As no previous study has specifically examined the effects of neuro-adaptive recommendations, we drew our subsequent hypothesis based on the scant research that suggests a greater acceptance of product recommendations, resulting in improved decision quality, when a temporal component guides their presentation: recommendations would either be presented on a separate webpage, assuming that was an indicator of users having reached the in-depth comparison of alternatives decision stage (Häubl & Trifts, 2000; Yan et al., 2016), or recommendations would be presented during a different browsing session altogether, sometimes several days apart (Campos et al., 2010; Gantner et al., 2010; Köhler et al., 2011; Li et al., 2017). Moreover, other studies have found that consumers are prone to follow recommendations when they are unexpected, regardless of their subjective perception about the quality of the suggestion (Robinette et al., 2016; Salem et al., 2015). With this premise, we hypothesized that participants' behaviour in the neuro-adaptive condition would mirror this pattern, thus enhancing decision quality.

> ***H3c:*** *In a context of choice overload, objective decision quality will be higher when recommendations are presented neuro-adaptively than when recommendations are presented statically.*

3.3.1.4 Decision Time

While contradicting findings fuel the debate between different researchers on whether higher decision times are a favourably or unfavourably decisional outcome, a common ground prevails in attributing higher decision times for larger quantities of information, product choices, and more complex product attributes (Chernev et al., 2015; Eppler & Mengis, 2004; Häubl & Trifts, 2000; Iyengar & Lepper, 2000; Scheibehenne et al., 2010). Based on these conclusions, we believed that showcasing recommendations would result in individuals focusing not on the total array of products, but only on the product options that are recommended instead, hence having less choice items to evaluate, which could reduce decision times (Bollen et al., 2010; Crocoll & Coury, 1990). As a result, with lower quantities of products and information to evaluate, we assumed that recommendations will lead to, in general, lower decision times, compared to conditions without such assistance.

> ***H4a:*** *In a context of choice overload, decision time will be lower when recommendations are presented statically than when recommendations are not presented.*

> ***H4b:*** *In a context of choice overload, decision time will be lower when recommendations are presented neuro-adaptively than when recommendations are not presented.*

On the other hand, given the dearth of investigations of neuro-adaptive recommendations, we formulated our following hypothesis based on a rare study by Tokushige et al. (2017) involving recommendations showcased unexpectedly. Participants in this study were unaware of when or if these recommendations would appear, which aligns with our neuro-adaptive approach. Tokushige et al. (2017) found that unexpected recommendations lengthened decision time only if they were inaccurate. As our system was designed to provide accurate recommendations and at a moment deemed optimal, we assumed decision time in the neuro-adaptive condition would be the shortest.

> ***H4c:*** *In a context of choice overload, decision time will be lower when recommendations are presented neuro-adaptively than when recommendations are presented statically.*

3.3.2 The Mediating Role of Choice Overload between Recommendations and Decision-Making Outcomes

3.3.2.1 The Impact of Recommendations on Perceptions of Choice Overload

Despite many findings supporting the regulating effect of recommendations against choice overload (Chen et al., 2016; Mishra & Kumar, 2023; Rose et al., 2004; Wang & Benbasat, 2007), some have yielded inconsistent results (Chen et al., 2022; Dellaert et al., 2017; Liang et al., 2006; Zhang et al., 2018). As it is unclear when precisely a given user might be overloaded and thus need recommendations, the latter studies argue that unnecessary recommendations comprise information that is potentially of no use to consumers, which may in fact lead to more information overload (Edmunds & Morris, 2000; Eppler & Mengis, 2004). Considering this debate, we positioned our hypotheses in alignment with the larger body of knowledge, which attributes a generally positive role to recommendations in managing choice overload.

> ***H5a:*** *In a context of choice overload, perceived choice overload will be lower when recommendations are presented statically than when recommendations are not presented.*

> ***H5b:*** *In a context of choice overload, perceived choice overload will be lower when recommendations are presented neuro-adaptively than when recommendations are not presented.*

However, we introduce a granularity to support the potential limitation raised by the smaller group of researchers regarding the conflicting effect of recommendations in the absence of choice overload (Edmunds & Morris, 2000; Eppler & Mengis, 2004). To investigate this limitation, we employed the neuro-adaptive condition, which displayed recommendations only when they are necessary (i.e., when users were experiencing excessive cognitive workload). Hence, we formulated the following hypothesis.

> ***H5c:*** *In a context of choice overload, perceived choice overload will be lower when recommendations are presented neuro-adaptively than when recommendations are presented statically.*

3.3.2.2 The Impact of Recommendations on Decisional Outcomes Mediated Through Choice Overload

Though some studies examine the direct impact of recommendations on decisional outcomes, many point to the phenomenon of choice overload to explain the effects of this e-commerce strategy. Notable studies and meta-analyses (Chernev et al., 2015; Liu et al., 2023; Scheibehenne et al., 2010) have examined a wide spectrum of studies to come to the common conclusion that choice overload negatively impacts a range of decisional factors including our aforementioned constructs of interest, i.e., choice satisfaction (Hu & Krishen, 2019) and confidence (Haynes, 2009), as well as decision quality (Lee & Lee, 2004) and time (Fasolo et al., 2007; Haynes, 2009).

We therefore deemed necessary to incorporate in our conceptual framework the mediator of choice overload between our recommendations display conditions and the decisional outcomes measured. As the role of choice overload is holistically hindering to decision-making (Fasolo et al., 2007; Haynes, 2009; Hu & Krishen, 2019; Lee & Lee, 2004), we formulated our hypotheses accordingly.

> ***H6a****:* *In a context of choice overload, the relationship between the type of recommendations and perceived choice satisfaction will be mediated by perceived choice overload, where higher perceived choice overload will contribute to lower perceived choice satisfaction.*

> ***H6b:*** *In a context of choice overload, the relationship between the type of recommendations and perceived choice confidence will be mediated by perceived choice overload, where higher perceived choice overload will contribute to lower perceived choice confidence.*

> ***H6c:*** *In a context of choice overload, the relationship between the type of recommendations and objective decision quality will be mediated by*

perceived choice overload, where higher perceived choice overload will contribute to lower objective decision quality.

H6d: *In a context of choice overload, the relationship between the type of recommendations and decision time will be mediated by perceived choice overload, where higher perceived choice overload will contribute to higher decision time.*

3.3.3 Moderators Affecting Choice Overload and Decision-Making Outcomes

3.3.3.1 Compliance with Recommendations

An important consideration is that any observed effect of recommendations may be moderated by whether individuals acknowledge and accept the system's recommendation or not – a concept we labeled as compliance with recommendations. While factors impacting the intent of accepting recommendations are commonly explored in research (Baier & Stüber, 2010; Gershoff et al., 2003; Köhler et al., 2011; Sheng et al., 2014), this avenue fell outside of the scope of our study. Instead, we focused on compliance in terms of behaviour observed among participants (Baier & Stüber, 2010; Bigras et al., 2019; Melovic et al., 2020; Xu et al., 2020). Though we considered that the mere presence of recommendations may affect the decision-making process and thus outcomes, we posited that the effect may be amplified if participants follow one of the recommendations. Building on our hypotheses related to decisional outcomes, we predicted that participants that follow recommendations would have a smaller range of products to focus on and would thus experience less choice overload (Iyengar & Lepper, 2000), higher levels of choice satisfaction and confidence (Aljukhadar et al., 2010; Xiao & Benbasat, 2018), which would also lead to optimized decision quality and time (Blut et al., 2023; Eppler & Mengis, 2004). Conversely, users that would not select the recommendations, would have the full range of products to consider, thus resulting in a reduced positive impact of recommendations.

H7a: *In a context of choice overload, compliance with recommendations will moderate the relationship between the type of recommendations and perceived choice overload, where greater compliance with recommendations will contribute to decreasing perceived choice overload.*

H7b: *In a context of choice overload, compliance with recommendations will moderate the relationship between the type of recommendations and perceived choice satisfaction, where greater compliance with recommendations will contribute to increasing perceived choice satisfaction.*

H7c: *In a context of choice overload, compliance with recommendations will moderate the relationship between the type of recommendations and perceived choice confidence, where greater compliance with recommendations will contribute to increasing perceived choice confidence.*

H7d: *In a context of choice overload, compliance with recommendations will moderate the relationship between the type of recommendations and objective decision quality, where greater compliance with recommendations will contribute to increasing objective decision quality.*

H7e: *In a context of choice overload, compliance with recommendations will moderate the relationship between the type of recommendations and decision time, where greater compliance with recommendations will contribute to decreasing decision time.*

3.3.3.2 Consumer Product Involvement

Consumer product involvement is a measure that helps predict the subjective value an individual attributes to a specific product category (Mcquarrie & Munson, 1992). As per Takemura's (1985, 2014) metacognitive mechanism model, one of the guiding frameworks of our research described earlier, the level of involvement, specifically product involvement – as opposed to situational involvement, which is context-dependent according to Slama and Tashchian (1985) – is among the psychological states of the decision-maker which help the latter allocate appropriate cognitive resources to formulate a decision. It was thus included in our study, as it has been demonstrated to also have potential implications in decision-making related to purchase (Verhagen & Bloemers, 2018) and online shopping behaviour (Kean Yew & Kamarulzaman, 2020). This guided the elaboration of our hypotheses regarding product involvement.

Specifically, a high degree of involvement is prone to stimulate cognitive elaboration, leading to increased mental resources allocated to the decision-making process

(Takemura, 2014). We posited that this inclination for individuals to engage additional processing resources may result in an increase in their perception of choice overload. Additionally, consistent with the well documented discussion about higher involvement motivating individuals to spend more time searching for products (Brucks, 1985; Hoch & Deighton, 1989), we hypothesized that this deeper processing of product information could occasion greater decision times. In turn, because choice confidence and choice satisfaction are recognized to follow the pattern of expended effort (Liberman & Tversky, 1993; Maheswarappa et al., 2017), we suggested that higher levels of involvement would bring increased choice satisfaction and confidence. On the other hand, lower levels of involvement may occasion consumers to resort to heuristics and easily understood but potentially misleading cues, which may give rise to decisional errors (Chen & Chaiken, 1999). As such, we speculated that the tendency of highly involved consumers to further scrutinize product information (Petty & Cacioppo, 2012) could lead to more optimal decision-making. Below is a detailed breakdown of the aforementioned hypotheses.

H8a: *In a context of choice overload, consumer product involvement will moderate the relationship between the type of recommendations and perceived choice overload, where higher consumer product involvement will contribute to increasing perceived choice overload.*

H8b: *In a context of choice overload, consumer product involvement will moderate the relationship between the type of recommendations and perceived choice satisfaction, where higher consumer product involvement will contribute to increasing perceived choice satisfaction.*

H8c: *In a context of choice overload, consumer product involvement will moderate the relationship between the type of recommendations and perceived choice confidence, where higher consumer product involvement will contribute to increasing perceived choice confidence.*

H8d: *In a context of choice overload, consumer product involvement will moderate the relationship between the type of recommendations and objective decision quality, where higher consumer product involvement will contribute to increasing decision quality.*

H8e: *In a context of choice overload, consumer product involvement will moderate the relationship between the type of recommendations and* *decision time, where higher consumer product involvement will contribute to increasing decision time.*

3.3.3.3 Product Expertise

Another influential factor that plays a role in consumer decision-making and choice overload is the level of perceived product expertise. Referring to the subjective degree of knowledge individuals believe they possess about a specific product category (Brucks, 1985), product expertise has been widely recognized as an intrinsic factor affecting decision-making (Broniarczyk & Griffin, 2014; Hadar et al., 2013; Senecal & Nantel, 2004). It is also theorized that the level of product expertise is an indicator of "the degree to which individuals have articulated preferences with respect to the decision at hand" (Chernev et al., 2015, p. 336). It thus serves an important dimension in assessments of purchase decision-making in consumer research (Heitmann et al., 2007; Yoon et al., 2013), which led us to include it in our study to assess its moderating role.

Concretely, studies have demonstrated that a high level of expertise in a certain product category leads to consumers exerting less cognitive effort during a product selection process (Xiao & Benbasat, 2007). This can be attributed to both their higher ability to efficiently encode novel information about product choices (Chinchanachokchai et al., 2021; Hutchinson & Herrmann, 2008), and their capacity to concentrate solely on the information that is relevant to the task at hand (Eppler & Mengis, 2004; Petty & Cacioppo, 2012; Shanteau, 1992). As a result, researchers have shown that higher levels of product expertise play a moderating role in alleviating perceptions choice overload (Chernev et al., 2015; Hadar & Sood, 2014; Hu & Krishen, 2019; Mogilner et al., 2008), which served as a foundation of our first hypothesis. Choice satisfaction, on the other hand, has been shown to be positively moderated by product expertise (Richins & Bloch, 1991; Soliha et al., 2019), which led us to speculate that the moderation effect in our research framework would follow the same pattern. Moreover, as suggested by Chernev et al. (2015), the more articulated preferences of expert individuals tend to bring higher levels of confidence to decision-makers. Regarding behavioural outcomes, those with lower levels of product expertise have shown to be more prone to biases and focus on easy to understand, but irrelevant product attributes, leading to lower decision quality (Maheswarappa et al., 2017; Punj, 2012; Swaminathan, 2003). In the same vein, some research groups suggest that product expertise fosters more selectivity and efficiency in acquiring and processing product information (Bei & Widdows, 1999; Yoon et al., 2013), which guided our assumption that this construct may moderate decision times by reducing them.

H9a: *In a context of choice overload, product expertise will moderate the relationship between the type of recommendations and perceived choice overload, where higher product expertise will contribute to reducing perceived choice overload.*

H9b: *In a context of choice overload, product expertise will moderate the relationship between the type of recommendations and perceived choice satisfaction, where higher product expertise will contribute to increasing perceived choice satisfaction.*

H9c: *In a context of choice overload, product expertise will moderate the relationship between the type of recommendations and perceived choice confidence, where higher product expertise will contribute to increasing perceived choice confidence.*

H9d: *In a context of choice overload, product expertise will moderate the relationship between the type of recommendations and objective decision quality, where higher product expertise will contribute to increasing decision quality.*

H9e: *In a context of choice overload, product expertise will moderate the relationship between the type of recommendations and decision time, where higher product expertise will contribute to reducing decision time.*

3.3.3.4 Psychological Reactance

An additional individual trait (Fitzsimons & Lehmann, 2004) that has shown to moderate decisional outcomes is psychological reactance. It describes an individual’s perceived threat of freedom which results in unpleasant arousal (Steindl et al., 2015), i.e., the sense of discomfort stemming from a feeling of being limited in one’s freedom of choice or response (Brehm, 1966; Brehm & Brehm, 1981). Some research findings have noted that the presence of unsolicited product recommendations, despite being well intended, may evoke a lack of desired control (Konstan & Riedl, 2012; Wertenbroch et al., 2020) and a feeling of reduced freedom, particularly among individuals with a high degree of psychological reactance (Kwon & Chung, 2010; Lee & Lee, 2009; Yanping & Yan, 2012). Occasionally, this perceived loss of autonomy has resulted in resistance to recommendations and a behavioural tendency to oppose them (Fitzsimons & Lehmann, 2004; Steindl et al., 2015). Given these conclusions, we deemed relevant to include the construct in our research framework.

As such, we posited that the favourable effects of product recommendations on decisional outcomes would be less pronounced for individuals with a high psychological reactance. Though no direct interplay between psychological reactance and choice overload has, to our knowledge, been studied, research has shown that when a state of reactance is experienced, individuals exert behavioural and cognitive efforts to restore their threat of freedom (Kim et al., 2013; Nesterkin, 2013; Rains, 2013; L. Shen & J. Dillard, 2005; Steindl et al., 2015). Moreover, high reactance individuals may perceive recommendations as a form of persuasion technique, which may manifest itself in the form of negative cognition, such as anger and disagreement (Lee et al., 2010; Rosenberg & Siegel, 2018; Steindl et al., 2015). In turn, this may impede the allocation of cognitive resources to efficiently process information and concentrate on the decision or task at hand (Allen et al., 2014; Kalanthroff et al., 2013; Padmala et al., 2011; Shields et al., 2016). Therefore, we suggested that an individual's perceptions of choice overload and, incidentally, decision time may be increased due to these impaired executive functions. Moreover, we devised our choice satisfaction and confidence hypotheses based on findings by Kwon and Chung (2010), which showed that high-reactance consumers experienced lower levels of satisfaction and confidence regarding their choice, when exposed to traditional product recommendations. These results are congruent with those of research groups that accentuate the negative affect that could be experienced by individuals with high reactance scores, when they perceive their freedom as threatened (Rosenberg & Siegel, 2018; Steindl et al., 2015). Finally, as demonstrated by many studies on recommendations (Fitzsimons & Lehmann, 2004; Lee et al., 2010; Steindl et al., 2015), the predisposition of high reactance individuals to defy this decisional aids, may reduce their likelihood of selecting a product that is recommended, which may result in reducing the objective optimality of their choice, i.e., their decision quality.

H10a: *In a context of choice overload, psychological reactance will moderate the relationship between the type of recommendations and perceived choice overload, where higher psychological reactance will contribute to increasing perceived choice overload.*

H10b: *In a context of choice overload, psychological reactance will moderate the relationship between the type of recommendations and perceived choice satisfaction, where higher psychological reactance will contribute to decreasing perceived choice satisfaction.*

H10c: *In a context of choice overload, psychological reactance will moderate the relationship between the type of recommendations and perceived choice confidence, where higher psychological reactance will contribute to decreasing perceived choice confidence.*

H10d: *In a context of choice overload, psychological reactance will moderate the relationship between the type of recommendations and objective decision quality, where higher psychological reactance will contribute to decreasing objective decision quality.*

H10e: *In a context of choice overload, psychological reactance will moderate the relationship between the type of recommendations and decision time, where higher psychological reactance will contribute to increasing decision time.*

3.3.3.5 Need for Cognition

Another individual difference that, though less frequently addressed, has been demonstrated to influence information processing and decision making, is need for cognition (Curşeu, 2006; Kuvaas & Kaufmann, 2004; Smith & Levin, 1996). A concept initially proposed by Cacioppo and Petty (1982), it refers to the tendency of individuals to vary in their intrinsic motivation to engage in and enjoy cognitively effortful activities. In other words, individuals that score high on need for cognition are inclined to actively seek and find satisfaction in deliberate thinking and problem-solving. In contrast, those with low scores do not engage in such cognitive processes, unless compelled by necessity or provided incentives (Leary & Hoyle, 2009). This construct was deemed particularly relevant to include in our hypotheses, given the metacognitive dimension in Takemura's (1998, 2014) framework described earlier; individuals high in need for cognition have also been shown to engage in more metacognition through pondering about the thoughts they generate (Petty et al., 2007) and self-assessing their validity (Petty et al., 2002). We therefore posited that need for cognition will serve as a moderator in the context of our framework.

On a finer-grained level, we hypothesized that the tendency of individuals with a high need for cognition to involve themselves in more effortful analysis (Liu et al., 2015; Petty et al., 2009; Verplanken, 1993) could engender a perception of higher choice overload. However, as those with higher need for cognition scores also enjoy such more thorough cognitive activities (Cacioppo et al., 1996; Curşeu, 2006; Petty et al., 2009), and prefer making decisions when more thinking rather than intuition is involved (Petty et al., 2009; Petty et al., 2007; Wegener & Petty, 2001), we assumed that levels of satisfaction will be positively moderated by higher scores of need for cognition. As advanced by Cacioppo et al. (1996), individuals with a high need for cognition tend to engage in such thought-seeking behaviour as a means of reducing choice uncertainty. This aligns with Curşeu's (2006) findings, whose results showed a significant negative relationship between higher levels of need for cognition and choice uncertainty (indecisiveness). Translating these results into our framework, we proposed that a higher need for cognition would tend to increase choice confidence. Furthermore, not only do high need for cognition decision-makers seek out deeper thinking, and therefore engage with information at "greater depth and breadth" (Levin et al., 2000, p. 174), they also tend to reflect more thoroughly on pertinent, task-related information, as observed by Curşeu (2006). This inclination toward deeper cognitive reasoning has shown to make them less susceptible to external cues, decision-making biases and heuristics (Cacioppo et al., 1996). Consequently, in line with the findings by Levin et al. (2000), we expected that these individuals would demonstrate higher levels of decision quality. Lastly, as more time is required for the in-depth and comprehensive processing of information that individuals with high need for cognition scores engage in, we believe such behaviour would underlie longer decision times.

> ***H11a:*** *In a context of choice overload, need for cognition will moderate the relationship between the type of recommendations and perceived choice overload, where higher need for cognition will contribute to increasing perceived choice overload.*

H11b: *In a context of choice overload, need for cognition will moderate the relationship between the type of recommendations and perceived choice satisfaction, where higher need for cognition will contribute to increasing perceived choice satisfaction.*

H11c: *In a context of choice overload, need for cognition will moderate the relationship between the type of recommendations and perceived choice confidence, where higher need for cognition will contribute to increasing perceived choice confidence.*

H11d: *In a context of choice overload, need for cognition will moderate the relationship between the type of recommendations and objective decision quality, where higher need for cognition will contribute to increasing objective decision quality.*

H11e: *In a context of choice overload, need for cognition will moderate the relationship between the type of recommendations and decision time, where higher need for cognition will contribute to increasing decision time.*

Table 4. Summary of all hypotheses

H		Hypothesis[4]
Direct Effects of Recommendations on Decision-Making Outcomes in a Context of Choice Overload		
H1	***H1a***	Choice satisfaction is higher in static vs control condition
	H1b	Choice satisfaction is higher in neuro-adaptive vs control condition
	H1c	Choice satisfaction is higher in neuro-adaptive vs static condition
H2	***H2a***	Choice confidence is higher in static vs control condition
	H2b	Choice confidence is higher in neuro-adaptive vs control condition
	H2c	Choice confidence is higher in neuro-adaptive vs static condition
H3	***H3a***	Decision quality is higher in static vs control condition
	H3b	Decision quality is higher in neuro-adaptive vs control condition

[4] All our hypotheses are built on the assumption of association between the variables. The formulation "increase/decrease" is used for sake of simplicity, and not to allude to a causal relationship.

	H3c	Decision quality is higher in neuro-adaptive vs static condition
H4	***H4a***	Decision time is lower in static vs control condition
	H4b	Decision time is lower in neuro-adaptive vs control condition
	H4c	Decision time is lower in neuro-adaptive vs static condition
The Mediating Role of Choice Overload between Recommendations and Decision-Making Outcomes		
H5	***H5a***	Choice overload is lower in static vs control condition
	H5b	Choice overload is lower in neuro-adaptive vs control condition
	H5c	Choice overload is lower in neuro-adaptive vs static condition
H6	***H6a***	Choice overload decreases choice satisfaction.
	H6b	Choice overload decreases choice confidence.
	H6c	Choice overload decreases decision quality.
	H6d	Choice overload increases decision time.
Moderators Affecting Choice Overload and Decision-Making Outcomes		
H7	***H7a***	Compliance with recommendations decreases choice overload.
	H7b	Compliance with recommendations increases choice satisfaction.
	H7c	Compliance with recommendations increases choice confidence.
	H7d	Compliance with recommendations increases decision quality.
	H7e	Compliance with recommendations decreases decision time.
H8	***H8a***	Consumer product involvement increases choice overload.
	H8b	Consumer product involvement increases choice satisfaction.
	H8c	Consumer product involvement increases choice confidence.
	H8d	Consumer product involvement increases decision quality.
	H8e	Consumer product involvement increases decision time.
H9	***H9a***	Product expertise decreases choice overload.
	H9b	Product expertise increases choice satisfaction.
	H9c	Product expertise increases choice confidence.
	H9d	Product expertise increases decision quality.
	H9e	Product expertise decreases decision time.
H10	***H10a***	Psychological reactance increases choice overload.

	H10b	Psychological reactance decreases choice satisfaction.
	H10c	Psychological reactance decreases choice confidence.
	H10d	Psychological reactance decreases decision quality.
	H10e	Psychological reactance increases decision time.
H11	***H11a***	Need for cognition increases choice overload.
	H11b	Need for cognition increases choice satisfaction.
	H11c	Need for cognition increases choice confidence.
	H11d	Need for cognition increases decision quality.
	H11e	Need for cognition increases decision time.

3.4 Methodology

3.4.1 Experimental Design

The experiment used a within-subjects study design, and consisted of three experimental conditions: control, static, and neuro-adaptive (see below). The experimental task was designed to replicate the essence of an online shopping experience, where participants would need to select one laptop within a provided assortment. A total of three trials was presented in each condition, for a total of nine trials per participant. The order of assigned conditions was randomized for each individual to avoid selection bias, but trials within each condition followed the same order to preserve consistency in stimulus presentation within conditions (Ersner-Hershfield et al., 2009; Tian et al., 2022).

The control and static conditions were congruent with currently employed all-or-nothing methods of assessing the effects of product recommendations and choice overload (Diehl, 2005; Maheswarappa et al., 2017; Wu et al., 2011). In the control condition, no recommendations were displayed, and in the static condition, recommendations were displayed to users continuously, from the start until the end of the trial. These two conditions were included to effectively benchmark our newly proposed, neuro-adaptive method aimed to evaluate the effects of recommendations more optimally in a context of choice overload. This neuro-adaptive method comprised a condition that began without any recommendations but automatically triggered their display if the system would receive a real-time neurophysiological signal that the participant was experiencing excessive cognitive load, a recognized indicator choice overload (Ariga, 2018; Bawden & Robinson, 2020; Chen et al., 2020; Fehrenbacher & Djamasbi, 2017; Peng et al., 2021; Reutskaja et al., 2020). The signal was based on electroencephalographic (EEG) data that was recorded throughout the experiment. To capture the purest and highest signal quality, the experiment was conducted in a laboratory setting and participants were placed in a Faraday cage, which purged all electrical signals from the surrounding environment.

3.4.2 Participants

The study was conducted on a sample number of 55 participants, aged 19 to 50 years (28 female; *M*: 27.4; *SD*: 7.9). Most participants were recruited through the university's research panel, and a few through word-of-mouth. All were required to sign a consent form, in line with our institution's ethics review board, which also approved the study under certificate ID 2023-5071. Participants received a compensatory amount of $50 for their participation. Recruited individuals were screened for right-handedness, having normal or corrected vision, not having undergone laser eye surgery, not possessing any skin allergies, not being diagnosed with any psychophysiological disorder (neurodiversity) and having low to average hair density.

3.4.3 Stimuli

3.4.3.1 Design for Potential Choice Overload

As we wanted to evaluate recommendations in the context of choice overload, we designed the user interface with an interest of complexifying the decision-making associated with the task and potentially inducing choice overload. To achieve this, we presented an array of 24 products per trial, a quantity considered a high assortment size (Greifeneder et al., 2009; Iyengar & Lepper, 2000). However, as Chernev et al. (2010) and Scheibehenne et al. (2010) suggested, merely increasing the number of available options might not be sufficient to evoke choice overload. We therefore selected a product category that could accommodate at least 8 attributes per product, as proposed by Greifeneder et al. (2009). Laptops were thus our product category of choice due to their prior use in consumer decision-making research (Dhar, 1996; Jiang et al., 2010; Sela & Berger, 2012), and because they enabled us to incorporate multiple product attributes. To define our attributes, we adapted those from a similar study on smartphone product selection, conducted by Okfalisa et al. (2020), resulting in: screen size (inches), RAM (GB), price (CAD $), SSD memory (GB), battery life (hours), screen resolution (px), processor speed (GHz), and weight (kg).

To remain consistent with the literature, the product selection interface for each trial took form of a table, akin to notable decision-making studies (Bączkiewicz, 2021; Dhar, 1996; Häubl & Trifts, 2000). Rows represented the different products and columns showcased their different attributes. This matrix format was also selected in an aim to eliminate the possible impact of other on-screen elements on choice overload (Emami & Chau, 2020; Townsend & Kahn, 2014), other than the products and their attributes. Additionally, to avoid biasing participants in their decision-making, we purged the interface of all product images (Petty et al., 2009) and brand names (Misuraca et al., 2019; Rahinel et al., 2021). The product display table was also designed to include an extra column entitled "Recommendations", which served to identify products that were recommended by the system (see Manipulation of Recommendations section). Though the control condition presented no recommendations, an empty "Recommendations" column was still present in the product matrix to keep the visual stimuli as consistent as possible across the experimental conditions.

3.4.3.2 Manipulation of Recommendations

Since the display of recommendations aimed to potentially reduce choice overload, only three products were recommended per trial, congruent prior research (Chernev et al., 2015; Iyengar & Lepper, 2000), which identified three products as a small enough assortment size to generally be considered cognitively manageable by consumers. When recommendations would be displayed, the row of the recommended product would be highlighted in pastel green and the "Recommendations" column would display the text "Based on your personal preferences, this is one of the best products for you." vis-à-vis the product that was recommended. Such verbal language was chosen, based on previous work by Senecal and Nantel (2004) that posited that optimal formulation of recommendations consists of identifying the source of aid to be non-personal (i.e., from the system, not an expert or peer), but the proposed recommendation to be clearly portrayed as personalized.

The on-screen adaptation in form of recommendations, however, would not appear during the first and last 12 seconds of every trial (that is, the first two and last two cognitive load classifications received by the system). This buffer was introduced in the beginning of the trial to allow participants to get a first initial perception of the products before showcasing recommendations (Fitzsimons & Lehmann, 2004; Goodman et al., 2013). Likewise, the recommendations would be withheld during the last 12 seconds of every trial, no matter the participant's cognitive load, in order to avoid exposing participants to new information (in form of recommendations) during their decision finalization stage (Häubl & Trifts, 2000; Shang et al., 2023).

3.4.3.3 Personalization of Recommendations

Recommendations displayed to participants were personalized using the Simple Weighted Averages calculation of the Multi-Attribute Decision-Making method (Adriyendi, 2015; Johnson & Payne, 1985; Payne et al., 1993; Sun et al., 2019). Simple in implementation, this method was successfully utilized to personalize recommendations in other studies (Aminudin et al., 2018; Engel et al., 2017; Hdioud et al., 2013; Pratiwi et al., 2014; Santoso et al., 2018) and notably in the aforementioned smartphone selection study (Okfalisa et al., 2020). In line with the MADM-SAW approach, before beginning the experiment, participants were asked to rate different laptop criteria (attributes), using a 5-point Likert scale, based on a subjective level of importance they attribute to each characteristic (with 1 being "Not important at all" and 5 being "Very important"). Participants were also instructed of the directionality of each criterion: the price and weight characteristics were considered more optimal if they had lower values (e.g. a price of $900 is generally preferred to a price of $1200), whereas screen size, RAM size, SSD memory, battery life, screen resolution, processor speed were considered best if their value was higher (e.g. a RAM size of 64 GB was more optimal than a size of 16 GB).

The importance rating given to each characteristic was then stored in an Excel spreadsheet, which computed the MADM-SAW calculation and determined the three personalized products to recommend for each trial of the static and neuro-adaptive conditions. The calculation thus considered the subjective importance attributed by participants to each product attribute, and the objective comparative performance of products in those highly ranked attributes. The product ID's of the three products to recommend in each trial were then input into a web application that ran the participant's interface (Tadson et al., 2023). This step was done before the beginning of the experimental trials, to ensure the recommendations, when displayed, were personalized based on each participant's individual preferences.

3.4.3.4 Cognitive Load Calibration

Consistent with currently employed methods of calibration of the EEG equipment, two measures were employed: a baseline task (Fishel et al., 2007; Karran et al., 2022), which consisted of participants staring at a small black square on a blank grey background for a duration of 90 seconds, and an N-Back task[5]. The latter is an acknowledged neuroscientific test, designed to make participants engage their working memory, which in turn raises their cognitive workload (Karran et al., 2019; Kirchner, 1958; Wang et al., 2016). First, the 0-Back and then a 2-Back task were recorded, as they are deemed by the neuroscientific community to be appropriate indicators of low and high cognitive load (Biondi et al., 2020; Fridman et al., 2018). The recording was uploaded into a Simulink model that ran the EEG apparatus to allow for a personalization of individual cognitive load thresholds for each participant (Tadson et al., 2023).

3.4.4 Procedure[6]

After greeting the participant, ensuring they fulfill the inclusion criteria, and receiving their signed consent to pursue the experiment, they were asked to complete a pre-experiment questionnaire. It collected basic demographic data (age and gender) and

[5] Please see Appendix A for a demonstration of the N-Back task and the cognitive load threshold classification index.
[6] A holistic view of this experimental procedure is presented in Appendix C.

measures of product expertise, product involvement, and product attributes preferences for the MADM-SAW calculation (Adriyendi, 2015; Payne, 1976). As qualified and trained research assistants then proceeded to install the EEG headset, participants' product attribute preferences were entered in the Excel spreadsheet to obtain the ID's of products to recommend in each of the static and neuro-adaptive trials. These product ID's were then input in the web application than ran the experimentation, which then generated a unique web link with the task interface for the participant, in which all recommendations would be personalized for each individual. For details, please refer to Tadson et al. (2023).

The next step involved the calibration of the EEG headset for each participant's individual cognitive workload thresholds, which was followed by the experiment itself. Participants were informed about the goal of the tasks and were shown a demonstration of how to pick a product on the interface: they needed to select the product by clicking on it and confirm their selection by clicking a "Submit" button at the bottom of the screen (Tadson et al., 2023). After the demonstration, participants were given the appropriate task instructions.

For the control condition, where no recommendations were displayed, participants were simply instructed to select a product that, according to them, best matched their personal preferences. Prior to the static condition, where recommendations were displayed perpetually, from the beginning until the end of each trial, they were given the same instructions, but were also informed that the selection of products would also include some recommendations. To mitigate the effects of potential reactance, we avoided the usage of "should", "ought", "must", and "need" in our instructions, and informed participants that they were fully free to decide whether to follow the recommendations or not (Rosenberg & Siegel, 2018; Steindl et al., 2015). Before the neuro-adaptive condition, participants were told that the task would begin with only the assortment of products, but if the system would determine that they required assistance, recommendations would be showcased. It was specified that their display was not guaranteed, as they would only appear if the system deemed it necessary. Such generic formulation was used based on the findings that acknowledged the benefit of providing users with a rationale behind recommendations (Tintarev & Masthoff, 2012; Wang & Benbasat, 2007), while avoiding too complex explanations that could informationally overwhelm the participants (Naiseh et al., 2020). As a last point, just as for the static condition, instructions of the neuro-adaptive conditions reminded participants that they possessed full freedom of either going along with the recommendations or to ignoring them.

After receiving appropriate instructions, participants were asked to proceed with the first trial. Upon completing it, they were invited to fill out a post-trial questionnaire, which assessed their levels of choice overload, choice satisfaction, and choice confidence. The rest of the trials continued with the same procedure, until all 9 trials (3 trials per each of the 3 conditions) and all 9 post-trial questionnaires were completed.

Upon finalizing the tasks, participants were required to complete a post-experiment questionnaire, which assessed their need for cognition and psychological reactance. To conclude the experiment, they were wholeheartedly thanked for their time and participation, and were brought to complete the compensation form.

3.4.5 Measures

After every trial, participants were asked to report on their perceived level of choice overload, choice satisfaction and choice confidence regarding the product selection task they had just undertaken. We measured this trial-based perceptual quantitative data using a 7-point Likert scale (1 = "strongly disagree", and 7 = "strongly agree"), using items from established and previously validated scales. Being measured 9 times in total (once after every trial), devised scales attempted to strike a balance between comprehensive measures of constructs, while avoiding exhaustive questionnaires to evade respondent fatigue. All scale items were randomized within each measure to prevent rating biases.

Regarding the per-participant measures, as suggested by Maheswarappa et al. (2017), the mere exposure to a certain product category in a decision-making context could influence the individual's measures of product involvement and expertise. In line with the guidance of these authors, we administered these two assessments at the beginning of the experiment. The other constructs were not found to be influenced by such exposure and therefore adhered to canon research practice by being assessed at the end of the study. For a recapitulative list of constructs and measures, please see **Table 5**[7].

3.4.5.1 Perceived Choice Satisfaction

Perceived choice satisfaction aimed to assess how content participants were with the product they selected, rather than their overall satisfaction with the e-shopping experience. The scale thus comprised three items adapted from Aksoy et al. (2006, 2011) and Jacoby et al. (1974), granularly observed as choice satisfaction, fit with preferences, and choice liking. The items have been correlated for internal validity using Cronbach's alpha analysis with a reliable result of $\alpha = 0.8904$.

3.4.5.2 Perceived Choice Confidence

The extent to which participants were confident about their choice of product was measured with a scale of perceived choice confidence. The items for this scale were selected and adapted from previously acknowledged measures of this construct (Aksoy et al., 2006; Aksoy et al., 2011; Jacoby, Speller, & Berning, 1974). When tested for validity, all three items reported a Cronbach's alpha of $\alpha = 0.7143$[8].

3.4.5.3 Decision Quality - Selected Product Rank

The rank of products selected by participants served as a means to operationalize decision quality. For every trial, the ID of the chosen product was recorded automatically by the system, as participants completed their product selection on the interface. Upon extraction of the data, a ranking process was applied to each product selected by every participant. As each trial presented 24 products, the selected product was ranked from 1 to 24 (with 1 being most and 24 being least optimal), based on the same Simple Weighted Averages formula of the Multi-Attribute Decision Making method (Adriyendi, 2015; Payne, 1976) that served to provide users with personalized product recommendations. The method thus

[7] For an overview of scale items, please consult Appendix E.

[8] While considered acceptable, but not ideal, we further refined the scale by eliminating one of the items, resulting in an increased reliability with a more optimal $\alpha = 0.9031$. Notably, although enhancing reliability, this adjustment yielded no impact on the final results and inferential statistical analyses. The decision was therefore made to retain the originally designed questionnaire, ensuring consistency with the research's initial framework.

considered the objective performance of products based on criteria that each individual subjectively identified as most important to them. To the 5 instances (out of 495 observations), where participants did not have enough time to select a product within the allocated time of 2 minutes, we attributed the lowest possible product rank of 24.

3.4.5.4 Decision Time - Response Time per Trial

To capture the time participants took to complete their product selection decision, the system was conceived to record a start and end timestamp (in milliseconds) for every trial. We used the difference between the two timestamps to determine the response time per trial (also measured in milliseconds), which served as the operationalization of the decision time construct.

3.4.5.5 Perceived Choice Overload

To assess perceived choice overload, we employed a thoughtfully amalgamated scale comprising four items, constructed from previously validated and reliable scales. Two of these items were adapted from the overload scale used by Diehl and Poynor (2010), which span affective (Iyengar & Lepper, 2000) and cognitive overload (Huffman & Kahn, 1998; Jacoby, Speller, & Kohn, 1974). To further enrich this scale, we incorporated two additional items adapted from the assessment of perceived choice difficulty introduced by Iyengar & Lepper (2000). Perceived choice difficulty has been widely acknowledged as an effective proxy to evaluate choice overload (Nagar & Gandotra, 2016; Stanton & Cook, 2019). All items were rated on a 7-point Likert scale, ranging from 1 (“strongly disagree”) to 7 (“strongly agree”) and demonstrated a high level of reliability ($\alpha = 0.8942$).

3.4.5.6 Compliance with Recommendations

In an aim to concentrate on the behavioural, rather than intentional dimension of compliance with recommendations, this variable evaluated whether the product selected by the participant in each trial matched one of the three products recommended by the system. Following a similar approach used by Senecal and Nantel (2004), it was measured during the post-hoc analysis, where each participant’s trial of the static and neuro-adaptive condition (the two conditions that included recommendations) was attributed a Boolean indicator of 1 (participant complied with recommendations) or 0 (participant did not comply with recommendations).

3.4.5.7 Consumer Product Involvement

Consumer product involvement is a measure that helps predict the subjective value an individual attributes to a specific product category (Mcquarrie & Munson, 1992). we assessed the cognitive dimensions of importance, relevance and essentialness (Zaichkowsky, 2012), traditionally used since Mcquarrie and Munson (1992), through a 5-point Likert-like scale. Based on the work of these authors and Richins 1991, the scale was aggregated using a median-split, categorizing participants into low and high involvement groups (Bei & Widdows, 1999; Hu & Krishen, 2019; Kwon & Chung, 2010; Richins & Bloch, 1991). The reliability assessment of the scale's items resulted in an acceptable $\alpha = 0.7492$.

3.4.5.8 Product Expertise

To gauge the level of product expertise among our participants, we employed the eponymous 4-item scale adapted from the work of Goodman et al. (2013) and Mitchell and Dacin (1996), bringing it to 7-point Likert scale and adjusting the product to specifically assess participants' knowledge of laptops. The assessment considers self-assessed, rather than actual product knowledge, as prior research has shown that this subjective knowledge poses a greater impact on the decision-making process, compared to objective knowledge (Alba & Hutchinson, 2000; Moorman et al., 2004; Park & Lessig, 1981). Following the aggregation approach used by Aertsens et al. (2011) and de Bont and Schoormans (1995), the scale's collected values were added for each participant to create a continuous product expertise score. The Cronbach's alpha for this scale yielded $\alpha = 0.8689$, suggesting a strong internal reliability of scale items.

3.4.5.9 Psychological Reactance

Psychological reactance, or the inclination of certain individuals to experience a perceived threat of freedom, was measured through the Hong Psychological Reactance Scale – HPRS (Hong & Page, 1989). Conversely to its qualitatively assessed precursors which raise reliability concerns (Kim et al., 2020), the 14-item HPRS comprises a 4-factor structure, labeled as Freedom of Choice, Conformity Reactance, Behavioural Freedom, and Reactance to Advice and Recommendations (Hong & Page, 1989). Despite the latter factor seeming most relevant to our research framework, we nonetheless opted for the comprehensive 14-item scale, as recent research has proposed treating the HPRS as a unidimensional scale (L. Shen & J. Dillard, 2005). These authors have also concluded that the scale possesses both face and content validity, which could explain its preferred usage when measuring psychological reactance scores. The score was aggregated by summing the values obtained in each scale item (Buboltz Jr et al., 2003; Woller et al., 2007).

Similar to the need for cognition, the scale's higher number of items prompted us to conduct a more comprehensive assessment of its internal reliability. As such, the calculation of Cronbach's alpha has yielded a $\alpha = 0.839$ and the Spearman-Brown coefficient revealed a value of 0.747. Both coefficients collectively support the reliability of the scale's consistency. Additionally, we validated the scale through a factor analysis, based on a principal component analysis. The results yielded strong factor loadings, thereby supporting the construct validity of the measure.

3.4.5.10 Need for Cognition

Participants' need for cognition, i.e., their tendency to seek out and find enjoyment in cognitively effortful tasks, was assessed through the 18-item need for cognition scale proposed by the original authors of the construct (Cacioppo et al., 1984). This version was optimized for ease of administration, reduced respondent fatigue and enhanced internal validity compared to their initially proposed 34-item scale (Cacioppo & Petty, 1982). On the other hand, given its greater construct coverage and more extensive validation evidence (Cacioppo et al., 1984), the comprehensive 18-item scale was used, instead of the abbreviated 6-item versions proposed by Manfredo and Bright (1991) and Lins de Holanda Coelho et al. (2020). For increased scale sensitivity, as well as consistency across other scales administered during the post-trial and post-experiment questionnaires, the measure was expanded from its original 5-point Likert format to a 7-point scale (1 = "extremely uncharacteristic of me", and 7 = "extremely characteristic of me"). To aggregate the measure for analysis, we applied a median-split to classify participants as low and high need for cognition to enable our analyses (Kim & Kramer, 2006; Kuvaas & Kaufmann, 2004).

Considering the scale's larger item count, we supplemented our Cronbach's alpha computation of $\alpha = 0.856$ with the Spearman-Brown coefficient, which was determined to be 0.781, signifying a sufficiently strong level of internal reliability of the scale. We also examined the latent structure of the variable through a factor analysis, focusing on principal component analysis. The extracted factors revealed strong loadings, providing additional support for the reliability of the scale.

Table 5. Summary of assessed constructs and corresponding measures

Construct	Measure	Description	Sources
Dependent Variables (Decisional Outcomes)			
Choice Satisfaction	7-point Likert scale	Composite choice satisfaction scale based on 3 items: choice satisfaction, fit with preferences, choice liking.	Aksoy et al. (2006, 2011); Jacoby et al. (1974)
Choice Confidence	7-point Likert scale	Choice confidence scale.	Aksoy et al. (2006, 2011); Jacoby, Speller, & Berning (1974)
Decision Quality	MADM-SAW	Extent to which a decision is objectively optimal.	(Xiao & Benbasat, 2007)Adriyendi, (2015); Payne (1976) Recorded by the system automatically.
Decision Time	Difference between trial end and start timestamps	Response time per trial (in milliseconds).	Recorded by the system automatically.
Mediating Variable			
Choice Overload	7-point Likert scale	Composite choice overload scale based on 4 items: affective informational overload, cognitive informational overload, and two items of perceived choice difficulty.	Diehl and Poynor (2010); Iyengar & Lepper (2000); Huffman & Kahn (1998); Jacoby, Speller, & Kohn (1974)
Moderating Variables			
Compliance with Recommendations	Boolean indicator: 0 = no compliance 1 = compliance	Whether the product selected by participants was among the three recommended by the system.	Recorded by the system automatically.

Consumer Product Involvement	5-point Likert-like scale	• Value attributed by the participant to the laptop product category. • Cognitive dimensions of consumer product involvement scale: relevance, importance, and essentialness.	Zaichkowsky (2012); Mcquarrie & Munson (1992)
Product Expertise	7-point Likert scale	• Level of subjective knowledge about the laptop product category. • Product expertise scale.	Goodman et al. (2013); Mitchell & Dacin (1996)
Psychological Reactance	7-point Likert scale	• Participant's tendency towards experiencing a perceived threat of freedom. • 14-item Hong Psychological Reactance Scale (HPRS).	Hong & Page (1989)
Need for Cognition	7-point Likert scale	• Participant's tendency to seek out and enjoy cognitively demanding tasks. • 18-item need for cognition scale.	Cacioppo et al. (1984)

3.4.6 Apparatus

The interfaces of the system ran on a Google Chrome web browser and received real-time cognitive load classification once every 6 seconds through a WebSocket client. The latter received the real-time cognitive load classification from a Python-based Lab Streaming Layer (LSL), which was the output of a Simulink model designed in MATLAB (version R2021b, IBM) (Tadson et al., 2023). Neurophysiological activity that fueled this cognitive load classification index was sampled at a rate of 250 Hz and underwent standard Butterworth low-pass, high-pass, and notch filtering. The data was recorded using a 32-channel wireless electroencephalographic hardware (EEG) with gel-based active electrodes, installed according to the standard montage by g.tec Research[9]. The MADM-SAW calculations for each participant were done through Microsoft Excel (64-bit, 2022 software version). All questionnaires were administered through Qualtrics. For a detailed explanation of how the artifact functions, please refer to Tadson et al. (2023).

[9] For an illustration of the montage, please refer to Appendix C.

3.4.7 Analysis

We initiated our analysis with IBM SPSS Statistics software, Version 27, in which we prepared the data, focusing on assessing the reliability of the dependent, mediating, and moderating variables[10]. In addition, we examined underlying assumptions of normality, homoscedasticity, and equality of means.

Following visual inspection, a skewness and a kurtosis analysis, only the construct of decision quality (operationalized as the rank of the selected product) indicated a violation of the normality of distribution assumption. Given the Pearson's skewness coefficient indicating substantial positive skewness and a kurtosis analysis exposing a Leptokurtic distribution (with a prominent peak and "fat" tails), the distribution was normalized using a logarithmic transformation: Ln ($\chi + 1$). This transformed variable was used in all our analyses and data visualizations.

Subsequent analyses, namely multifactor ANOVAs for non-independent observations (**H1-H4** and **H7-H11**) were conducted with SAS software, Version 9.4, given its advanced analytical techniques suitable for the multilevel relationships and within-subject repeated measures present within our data set. A mixed effect model was used for the ANOVAs to account for random individual differences among participants, as well a fixed effect of trial order that was observed ($p < 0.0001$ to $p = 0.0441$) and included as a covariate in our analyses. All presented results already account for these covariates. Moreover, a compound symmetry model was used, based on the lower AIC (Akaike Information Criteria) values it resulted in, thus indicating a better fit for our analysis. When applicable, all reported results were adjusted using the Šídák method to account for multiple comparisons and to reduce the likelihood of Type I errors.

Lastly, a linear regression with random intercept was used for the mediation analysis (**H5** and **H6**) and was conducted in R programming (Version 4.3.2), using the "mediation" package (Imai et al., 2010). This package allowed for a mixed-effects mediation model, suitable for our repeated measures design. The estimation of confidence intervals was based on the recommended 5,000 simulations to ensure robustness. It was carried out

[10] For additional information regarding the reliability analysis, please consult Appendix D.

using the Quasi-Bayesian estimation available within the package, grounded in the assumption of normality in our data distribution, supported by our appropriately large sample size (n = 55, which resulted in 495 observations) and the normal (or normalized) distribution exhibited by both the mediator and dependent variables, as mentioned above.

In an aim to balance accuracy and simplicity of our models, we refrained from including gender and age variables in our analyses. The aforementioned multi-factor ANOVAs demonstrated that these covariates had no significant influence on decisional outcomes, nor on the mediating variable of choice overload. The decision to exclude the variables also aligns with the parsimony principle, encouraging the use of simpler models.

3.5 Results

3.5.1 Assessing the Direct Effects of Recommendations Display Conditions on Decisional Outcomes (H1-H4)

The findings regarding the direct effects of recommendations on decisional outcomes are based on multifactor ANOVAs for non-independent observations and use one-tailed tests with a significance level of 0.05. When pertinent, the results have been supplemented by figures. The conclusions regarding each hypothesis are summarized towards the end of this subsection, in **Table 6**.

3.5.1.1 Choice Satisfaction Partially Impacted by Recommendations Display Conditions (H1)

In ***H1a*** and ***H1b***, we hypothesized that both forms of recommendations would increase choice satisfaction. Specifically, ***H1a***, which foresaw higher satisfaction in the static than in the control condition, is confirmed (t = -2.05, p = 0.0205). ***H1b***, which predicted higher satisfaction scores in the neuro-adaptive compared to the control condition, was significant only at the less conservative significance level of 0.10 (t = -1.41, p = 0.0801). The assumption ***H1c***, suggesting greater satisfaction in the neuro-adaptive than in the static condition, was insignificant (t = 0.64, p = 0.2607) and hence not supported.

3.5.1.2 *Choice Confidence Improves with Recommendations, Occasionally More So when They Are Neuro-Adaptive (H2)*

As expected in ***H2a*** and ***H2b***, where we posited that choice confidence would increase in the presence of recommendations, both forms of this decisional aid outperformed the control condition (static: $t = -3.22$, $p = 0.0007$; neuro-adaptive: $t = -4.57$, $p < 0.0001$). For ***H2c***, we anticipated higher choice confidence levels for the neuro-adaptive than static recommendations. Though no general significant difference was observed between the two conditions ($t = -1.34$, $p = 0.0898$), unless employing a more marginal significance level of 0.10, the directionality of means followed our predictions. Moreover, when comparing Trial 2 in each of the two conditions, participants rated their choice confidence levels as higher in the neuro-adaptive condition than in the static condition ($t = -2.29$, $p = 0.0113$), as portrayed in **Figure 8**. We therefore consider ***H2c*** to be partially supported.

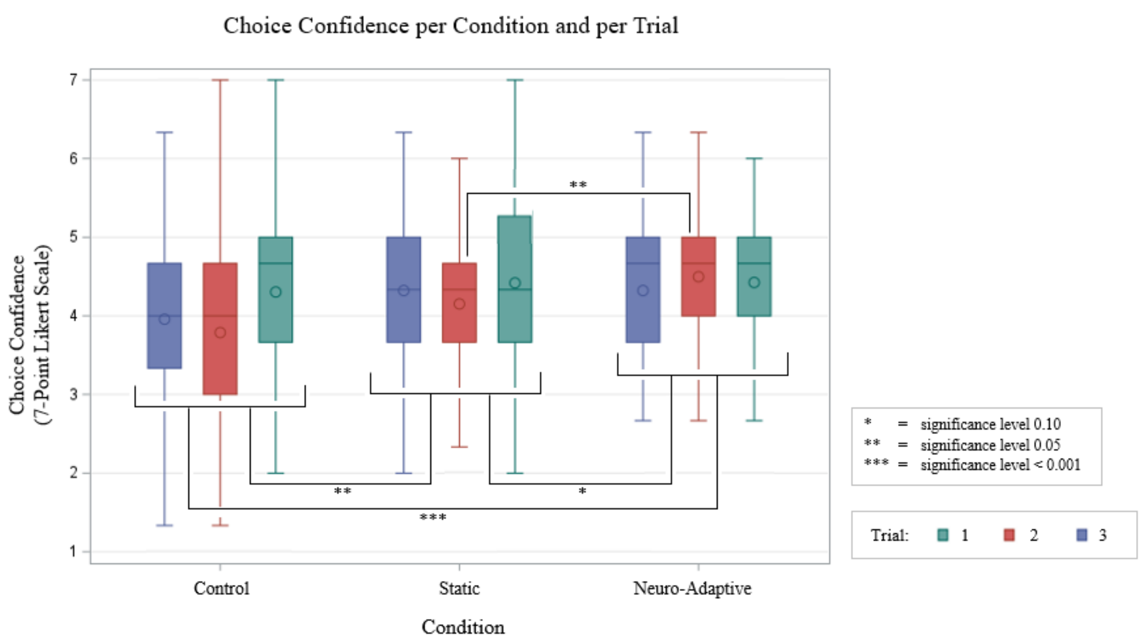


Figure 8. Choice Confidence per Condition and per Trial

3.5.1.3 *Recommendations Optimize Decision Quality, Occasionally More So when They Are Neuro-Adaptive (H3)*

Our ***H3a*** and ***H3b*** stipulated that decision quality would be optimized in conditions with static and neuro-adaptive recommendations respectively. In line with these predictions, participants selected significantly more optimal products when recommendations were displayed statically (t = 5.66, p < 0.0001) or neuro-adaptively (t = 6.29, p < 0.0001), compared to when recommendations were not presented, thereby supporting both ***H3a*** and ***H3b***. Yet, our ***H4c***, predicting better decision quality with neuro-adaptive compared to static recommendations, is not confirmed by the data (t = 0.64, p = 0.2622). Interestingly though, this conclusion entails some nuance: on a more granular level, a statistically significant difference was noted between Trial 1 of the static versus Trial 1 of the neuro-adaptive condition (t = 1.94, p = 0.0268), with an improved decision quality in the latter, as illustrated in **Figure 9**.

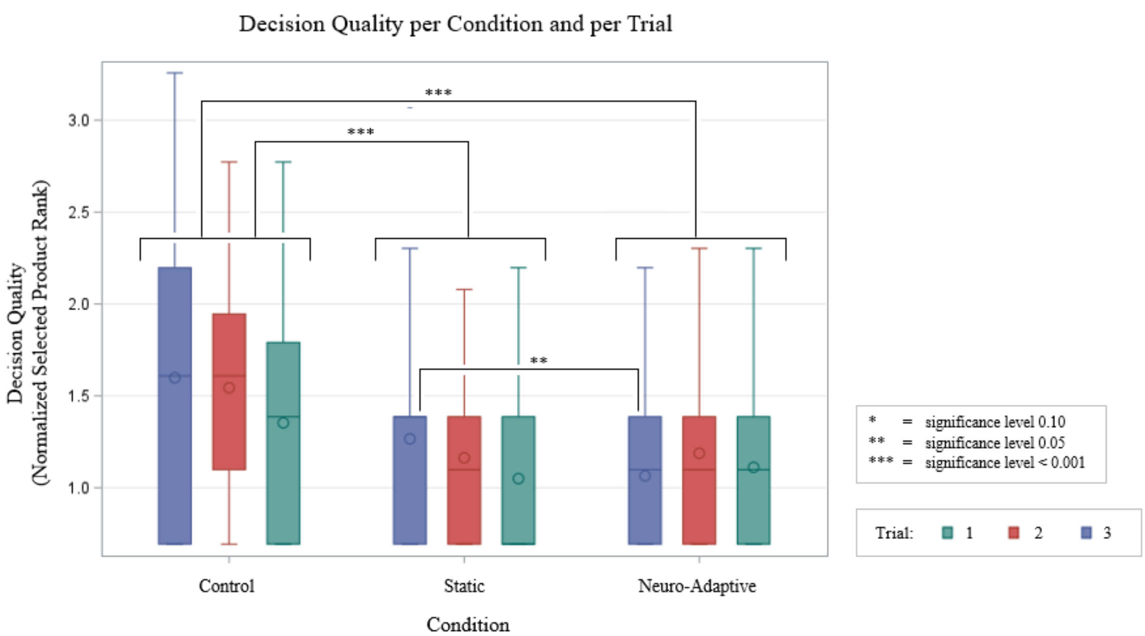


Figure 9. Decision Quality per Condition and per Trial

3.5.1.4 Decision Time Is Not Impacted by Recommendations Display Conditions (H4)

In ***H4a***, we suggested that decision time would be lower in the static compared to the control condition. Results, however, did not show statistically significant differences in decision times (t = 0.22, p = 0.4249), thus failing to support the hypothesis. Akin conclusions are formed for ***H4b***, where neuro-adaptive recommendations did not reduce decision times in relation to the control condition (t = -0.45, p = 0.3256), and for ***H4c***, where decision times were not inferior in the neuro-adaptive condition, compared to the static condition (t = -0.24, p = 0.4063).

Table 6. Summary and results of hypotheses **H1-H4**

H		Hypothesis[11]	Result	Note
Direct Effects of Recommendations Display Conditions on Decision-Making Outcomes in a Context of Choice Overload				
Choice Satisfaction				
H1	***H1a***	Choice satisfaction is higher in static vs control condition	Supported	
	H1b	Choice satisfaction is higher in neuro-adaptive vs control condition	Marginally supported	
	H1c	Choice satisfaction is higher in neuro-adaptive vs static condition	Not supported	
Choice Confidence				
H2	***H2a***	Choice confidence is higher in static vs control condition	Supported	
	H2b	Choice confidence is higher in neuro-adaptive vs control condition	Supported	
	H2c	Choice confidence is higher in neuro-adaptive vs static condition	Marginally supported	Also, fully supported for one of the three trials (Trial 2).
Decision Quality				
H3	***H3a***	Decision quality is higher in static vs control condition	Supported	
	H3b	Decision quality is higher in neuro-adaptive vs control condition	Supported	
	H3c	Decision quality is higher in neuro-adaptive vs static condition	Not supported	Also, fully supported for one of the three trials (Trial 1).
Decision Time				
H4	***H4a***	Decision time is lower in static vs control condition	Not supported	
	H4b	Decision time is lower in neuro-adaptive vs control condition	Not supported	
	H4c	Decision time is lower in neuro-adaptive vs static condition	Not supported	

[11] All our hypotheses are built on the assumption of association between the variables. The formulation "increase/decrease" is used for sake of simplicity, and not to allude to a causal relationship.

3.5.2 Evaluating the Mediating Role of Choice Overload on Decision-Making Outcomes (H5-H6)

The following results pertain to the mediating role of choice overload in the relationship between recommendations display conditions and decisional outcomes, and therefore employ a linear regression model with a random intercept in the assessments. All conclusions use a 0.05 significance level and are built on one-tailed tests.

3.5.2.1 Recommendations Increase Choice Overload (H5)

In ***H5a*** and ***H5b***, we anticipated that choice overload would be alleviated with static and neuro-adaptive recommendations respectively, compared to the control condition. Yet, our results suggest that participants reported feeling more choice overload in both cases with recommendations (static: $t = -4.29$, $p < 0.0001$; neuro-adaptive: $t = -3.84$, $p < 0.0001$), thereby not supporting ***H5a*** and ***H5b*** respectively. Likewise, ***H5c***, which assumed lower choice overload in the neuro-adaptive recommendations versus the static ones, is not validated either, as no statistical difference was observed between the two conditions ($t = 0.45$, $p = 0.3272$).

3.5.2.2 Experiencing Higher Choice Overload Increases Choice Satisfaction (H6a)

Through ***H6a***, we assumed a mediating role of choice overload between recommendations display conditions and choice satisfaction, where higher levels of choice overload would reduce choice satisfaction. The results confirmed a significant indirect effect when comparing the control and static ($b = 0.2101$, $t = -4.143$) and control and neuro-adaptive ($b = 0.1873$, $t = -3.746$), but not the static and neuro-adaptive conditions ($b = -0.0218$, $t = -0.429$). As no significant direct effect was observed between any combination of conditions on choice satisfaction when accounting for the presence of the mediator (control vs static: $b = -0.0410$, $t = -0.635$; control vs neuro-adaptive: $b = -0.0717$, $t = -1.115$; static vs neuro-adaptive: $b = -0.0308$, $t = -0.482$), we may conclude that when mediation occurs, it is full. Interestingly though, the results oppose our prediction, revealing that higher choice overload, on the opposite, increases choice satisfaction, thereby not supporting ***H6a***. The mediation analysis is summarized in **Table 7**.

Table 7. Summary of Mediation Analysis:
Recommendations Display Conditions → Choice Overload → Choice Satisfaction

Relationship	Total Effect	Direct Effect	Indirect Effect	Confidence Intervals		*t*-statistics	Conclusion
				Lower Bound	Upper Bound		
Control vs Static	0.1689 (p = 0.034)	-0.0410 (p = 0.526)	0.2101	0.111	0.312	-4.1428	Complete mediation, ***H6a*** unsupported
Control vs Neuro-adaptive	0.1151 (p = 0.150)	-0.0717 (p = 0.265)	0.1873	-0.286	-0.090	-3.7460	Complete mediation, ***H6a*** unsupported
Static vs Neuro-adaptive	-0.0531 (p = 0.500)	-0.0308 (p = 0.628)	-0.0218	-0.119	0.082	0.4290	No mediation, ***H6a*** unsupported

3.5.2.3 Choice Overload Boosts Choice Confidence and Highlights the Advantage of Neuro-Adaptive Recommendations (H6b)

Based on ***H6b***, we suggested that the impact of recommendations display conditions on choice confidence would be mediated by choice overload, where elevated levels of the latter would diminish perceptions of choice confidence. The data unveils that this indirect effect is significant when comparing the control with both the static (b = 0.2296, t = -4.155) and neuro-adaptive (b = 0.2070, t = -3.774) conditions, but not between the static and neuro-adaptive conditions (b = -0.0246, t = 0.462). Remarkably though, in the presence of choice overload, the direct comparison of the control and neuro-adaptive (b = 0.1915, t = 2.783, p = 0.006) and the static and neuro-adaptive (b = 0.1412, t = 2.081, p = 0.038) conditions was revealed to be significant, where neuro-adaptive recommendations resulted in higher scores of choice confidence. These results indicate that the mediation is full between the control and static conditions, but is only partial between the control and neuro-adaptive conditions. On the other hand, akin to choice satisfaction, despite these mediating relationships being significant, higher perceptions of choice overload contributed to increasing choice confidence, rather than impeding it, which contradicted our assumption, resulting an unsupported ***H6b***. **Table 8** provides an overview of the mediation analysis.

Table 8. Summary of Mediation Analysis:
Recommendations Display Conditions → Choice Overload → Choice Confidence

Relationship	Total Effect	Direct Effect	Indirect Effect	Confidence Intervals		t-statistics	Conclusion
				Lower Bound	Upper Bound		
Control vs Static	0.2798 ($p = 0.001$)	0.0503 ($p = 0.467$)	0.2296	0.123	0.344	-4.1553	Complete mediation, ***H6b*** unsupported
Control vs Neuro-adaptive	0.3985 ($p < 0.0001$)	0.1915 ($p = 0.006$)	0.2070	-0.315	-0.100	-3.7741	Complementary partial mediation, ***H6b*** unsupported
Static vs Neuro-adaptive	0.1172 ($p = 0.173$)	0.1412 ($p = 0.038$)	-0.0246	-0.129	0.081	0.4616	No mediation, but significant direct effect, ***H6b*** unsupported

3.5.2.4 Choice Overload Perceptions Have no Effect on Decision Quality (H6c)

In our ***H6c***, we expected decision quality to be impacted by recommendations display conditions through the choice overload mediator, where higher levels of this construct would impede on the objective quality of users' decisions. The findings oppose these expectations, as no indirect effect was present between the control and static ($b = -0.0125$, $t = 1.164$), control and neuro-adaptive ($b = -0.0111$, $t = 1.271$), and static and neuro-adaptive ($b = 0.0013$, $t = -0.319$) conditions. Results do point to a direct effect, when accounting for the presence of choice overload, where static ($b = -0.3267$, $t = -5.407$, $p < 0.0001$) and neuro-adaptive ($b = -0.3661$, $t = -6.039$, $p < 0.0001$) recommendations resulted in optimized decision quality, when compared with the control condition. The mediation hypothesis (***H6c***), though, is therefore not supported, as demonstrated in the summary **Table 9** below.

Table 9. Summary of Mediation Analysis:
Recommendations Display Conditions → Choice Overload → Decision Quality

Relationship	Total Effect	Direct Effect	Indirect Effect	Confidence Intervals		t-statistics	Conclusion
				Lower Bound	Upper Bound		
Control vs Static	-0.3420 ($p < 0.0001$)	-0.3267 ($p < 0.0001$)	-0.0125	-0.032	0.011	1.1639	No mediation, but significant direct effect, ***H6c*** unsupported
Control vs Neuro-adaptive	-0.3773 ($p < 0.0001$)	-0.3661 ($p < 0.0001$)	-0.0111	-0.004	0.031	1.2710	No mediation, but significant direct effect, ***H6c*** unsupported
Static vs Neuro-adaptive	-0.0344 ($p = 0.519$)	-0.0395 ($p = 0.510$)	0.0013	-0.006	0.014	-0.3188	No mediation, ***H6c*** unsupported

3.5.2.5 Experiencing Higher Choice Overload Increases Decision-Making Times (H6d)

According to ***H6d***, we supposed that choice overload would mediate the relationship between recommendations display conditions and decision time by increasing them when perceptions of choice overload would be higher. The results indeed uncover a significant indirect effect between decision time and the control versus both the static (b = -4566.78, t = 1.900) and the neuro-adaptive (b = -4009.03, t = 3.446) conditions. The indirect effect was, however, insignificant between the static and neuro-adaptive recommendations (b = 481.84, t = -1.002). Given the absence of a direct effect between any comparison of conditions, we may conclude that the observed mediations are complete. Moreover, the directionality of results follows our prediction, where higher choice overload resulted in higher decision time. As such, the findings validate our ***H6d*** for comparisons of control and static, and control and neuro-adaptive conditions. An overview of the mediation analysis is presented in **Table 10**.

Table 10. Summary of Mediation Analysis:
Recommendations Display Conditions → Choice Overload → Decision Time

Relationship	Total Effect	Direct Effect	Indirect Effect	Confidence Intervals		*t*-statistics	Conclusion
				Lower Bound	Upper Bound		
Control vs Static	-625.62 (p = 0.865)	3735.29 (p = 0.266)	-4566.78	-7093.92	2326.03	1.9004	Complete mediation, ***H6d*** supported
Control vs Neuro-adaptive	817.02 (p = 0.824)	4857.79 (p = 0.1520)	-4009.03	-6510.80	-1950.03	3.4458	Complete mediation, ***H6d*** supported
Static vs Neuro-adaptive	1572.89 (p = 0.659)	1087.10 (p = 0.749)	481.84	-1606.58	278.74	-1.0019	No mediation, ***H6d*** unsupported

Table 11. Summary and results of hypotheses **H5-H6**

H		Hypothesis[12]	Result	Note
The Mediating Role of Choice Overload between Recommendations and Decision-Making Outcomes				
Recommendations Display Conditions → Choice Overload (CO)				
H5	***H5a***	Choice overload is lower in static vs control condition	Not supported	CO increases with static recommendations.
	H5b	Choice overload is lower in neuro-adaptive vs control condition	Not supported	CO increases with neuro-adaptive recommendations.
	H5c	Choice overload is lower in neuro-adaptive vs static condition	Not supported	
Choice Overload (CO) → Decisional Outcomes				
H6	***H6a***	Choice overload mediates choice satisfaction by decreasing it.	Not supported	• Complete mediation for static vs control condition. • Complete mediation for neuro-adaptive vs control condition. • But CO increases choice satisfaction.
	H6b	Choice overload mediates choice confidence by decreasing it.	Not supported	• Complete mediation for static vs control condition. • Partial, complementary mediation for neuro-adaptive vs control condition. • But CO increases choice confidence.
	H6c	Choice overload mediates decision quality by decreasing it.	Not supported	• No mediation, only direct effects.
	H6d	Choice overload mediates decision time by increasing it.	Supported	• Complete mediation for static vs control condition. • Complete mediation for neuro-adaptive vs control condition. • Not supported for static vs neuro-adaptive condition.

[12] All our hypotheses are built on the assumption of association between the variables. The formulation "increase/decrease" is used for sake of simplicity, and not to allude to a causal relationship.

3.5.3 Exploring the Effect of Moderators on Choice Overload and Decisional Outcomes (H7-H11)

In our assessment of the impact moderating variables on choice overload and decisional outcomes, we employed once more the multifactor ANOVAs for non-independent observations. Unless specified otherwise, we also maintained one-tailed tests and a significance level of 0.05. We concluded this subsection with a recapitulative **Table 12**, summarizing all evaluated hypotheses, as well as graphical representations of obtained results, when relevant, for easier visualization.

3.5.3.1 Moderation of Compliance with Recommendations (H7)

Increasing Choice Overload (H7a)

Through ***H7a***, we predicted that participants that comply with recommendations would qualify their choice overload as lower. While significant, our findings do not support this assumption, as they reveal that when participants complied with recommendations, they rated their choice overload as significantly higher, compared to when they did not adhere to recommendations (F (270) = 8.39, p = 0.0021), as represented in **Figure 10**.

Increasing Choice Satisfaction (H7b)

Within ***H7b***, we anticipated that compliance with recommendations would favour participants' ratings of choice satisfaction compared to when they would select products that are not recommended. The results thus validate this hypothesis (F (272) = 3.91, p = 0.0245), as illustrated in **Figure 10**.

Increasing Choice Confidence (H7c)

In line with our assumption from ***H7c***, participants that complied with recommendations attributed higher choice confidence to their selected product, compared to when they did not follow the recommendations (F (270) = 4.22, p = 0.0205), as depicted in **Figure 10**. The data hence provides evidence in support of ***H7c***.

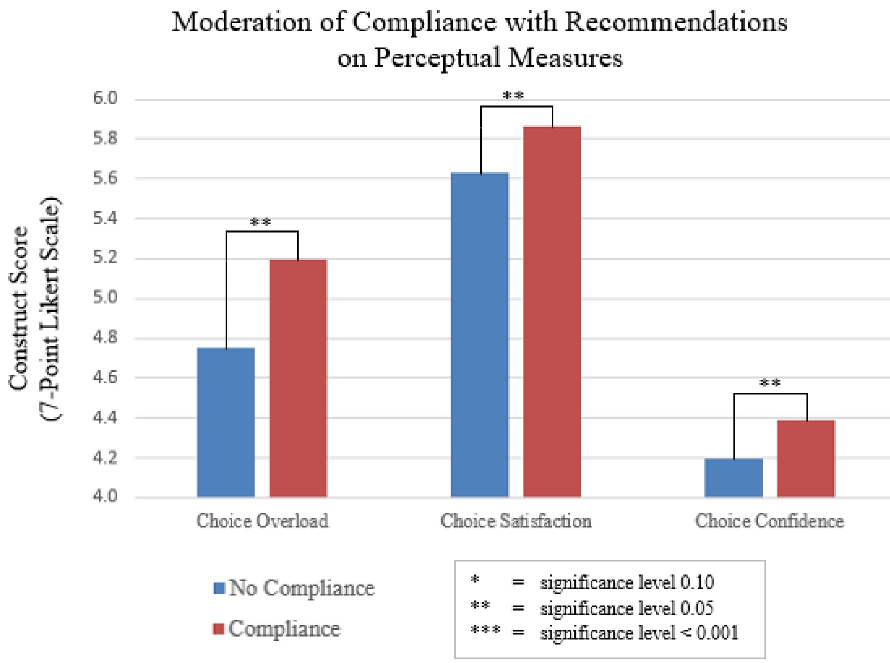


Figure 10. Moderation of Compliance with Recommendations on Perceptions of Choice Overload, Choice Satisfaction, and Choice Confidence

Increasing Decision Quality (H7d)

In ***H7d***, we proposed that compliance with recommendations would be linked to higher decision quality. Indeed, in instances where participants complied with recommendations, their decision quality was also significantly optimal, compared to occurrences when they did not abide by the recommendations (F (270) = 555.31, $p < 0.0001$), as such validating the hypothesis.

Reducing Decision Time (H7e)

Our ***H7e*** projected that when complying with recommendations, participants would reduce their decision time. This hypothesis is supported by our results, which confirm the moderating effect of compliance with recommendations on reducing decision times (F (270) = 0.57, $p = 0.0484$).

3.5.3.2 Moderation of Consumer Product Involvement (H8)

Recommendations Increase Choice Overload Only When Product Involvement is Low; Slight Advantage of Neuro-Adaptivity for High Involvement (H8a)

We predicted in ***H8a*** that high consumer product involvement would contribute to increasing choice overload perceptions. The results reveal no significant differences between low and high involvement participants in their response to reported choice overload (F (487) = 0.00, p = 0.4737), thereby not supporting our hypothesis ***H8a***. However, a strong interaction effect was revealed (F (487) = 8.87, $p < 0.0001$): while low involvement participants reported significantly lower levels of choice overload in the control condition, compared to the static condition (t = -5.07, $p < 0.0001$) and the neuro-adaptive condition (t = -5.67, $p < 0.0001$), participants with high involvement demonstrated no such variances (see **Figure 11**). A noteworthy difference, albeit at a marginal significance level of 0.10, was present among high involvement participants, who reported experiencing lower choice overload in the neuro-adaptive condition than in the static condition (t = 1.41, p = 0.0796).

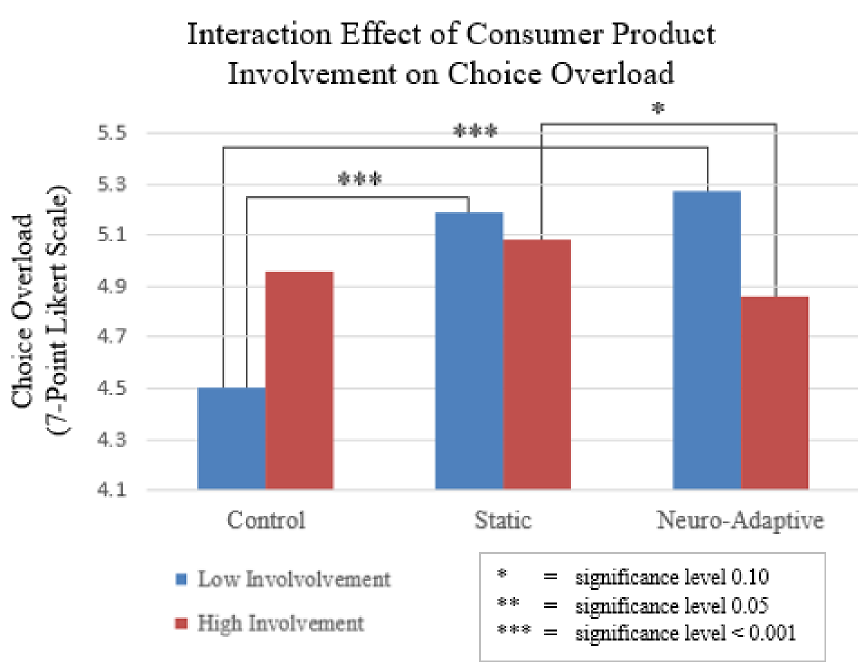


Figure 11. Interaction Effect of Consumer Product Involvement on Choice Overload

Consistent Choice Satisfaction with Recommendations Across High and Low Involvement Levels (H8b)

Our prediction ***H8b*** anticipated that high involvement would foster higher choice satisfaction. The observed results, however, do not substantiate this hypothesis, as there is no overall impact of high involvement in increasing choice satisfaction (F (436) = 0.21, p = 0.3236). There is nonetheless a noteworthy interaction effect (F (436) = 3.56, p = 0.0146), depicted in **Figure 12**. It revealed that while participants with high product involvement scores experienced no significant differences in satisfaction scores across experimental conditions, participants with low involvement experienced significantly lower choice satisfaction in the control condition, when contrasted with the static condition (t = -2.31, p = 0.0107) or the neuro-adaptive condition (t = -2.80, p = 0.0027).

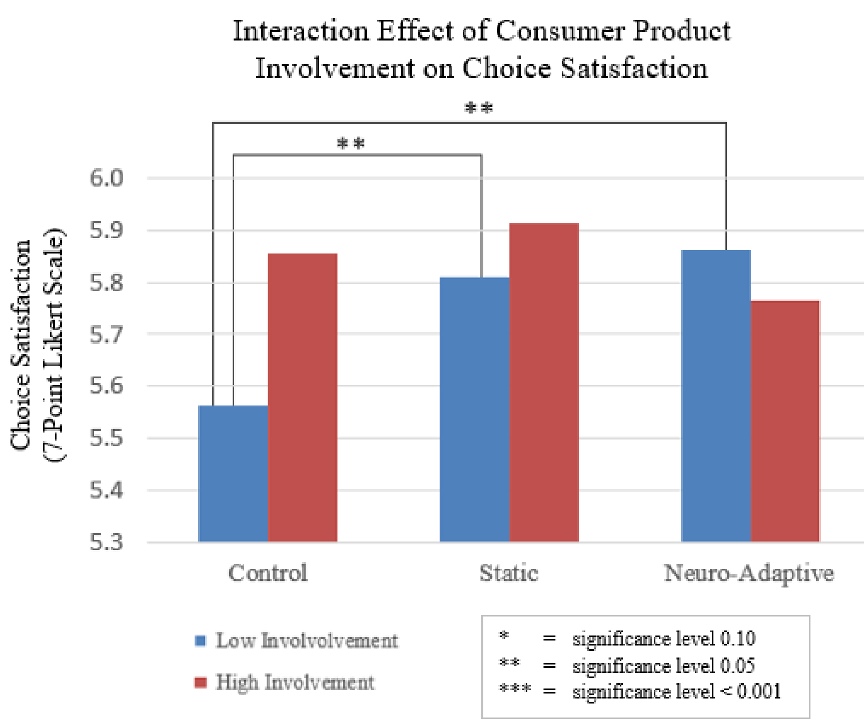


Figure 12. Interaction Effect of Consumer Product Involvement on Choice Satisfaction

Choice Confidence Fluctuates Only When Product Involvement Is Low, Being at Its Best with Neuro-Adaptive Recommendations (H8c)

Our ***H8c***, positing an overall increase in choice confidence among participants with high product involvement, is unsupported by our data (F (434) = 1.06, p = 0.1514). However, is a degree of nuance is brought to this conclusion by the exception in the control condition, where high involvement consumers indeed reported higher choice confidence than those with low involvement (t = -2.46, p = 0.0072). Through this particularity, the data uncovered a strong interaction effect (F (434) = 8.47, p < 0.0001), as illustrated by **Figure 13**. Similar to choice satisfaction, no significant differences were observed when pairing different conditions among participants with high product involvement levels. In contrast, participants with low involvement rated their confidence as significantly higher in the static (t = -3.97, p < 0.0001) and neuro-adaptive (t = -6.18, p < 0.0001), compared to the control condition. Moreover, they reported even higher scores in the neuro-adaptive condition, compared to the static condition (t = -2.21, p = 0.0137).

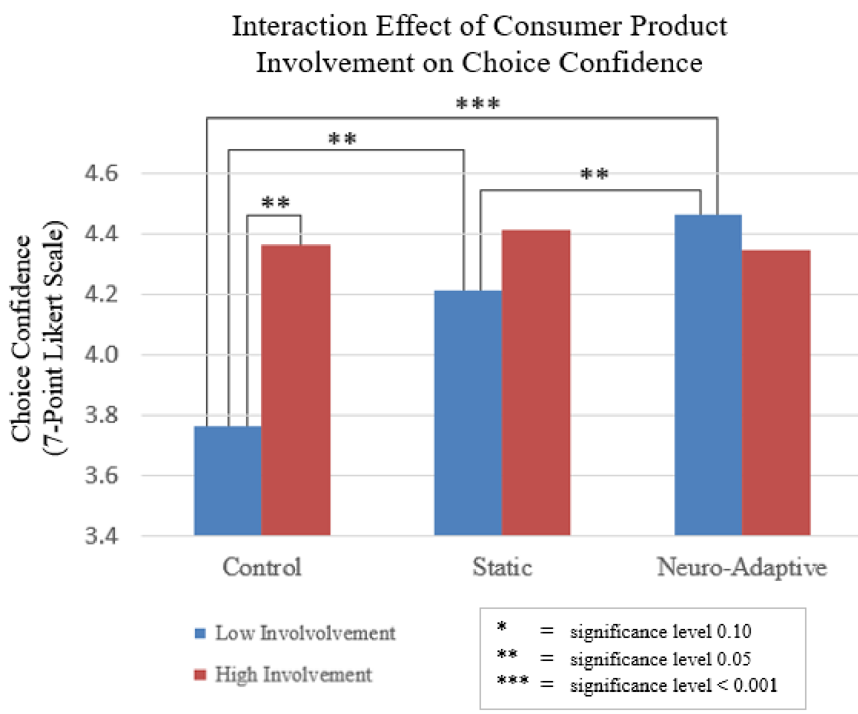


Figure 13. Interaction Effect of Consumer Product Involvement on Choice Confidence

Decision Quality Consistently Optimized by the Presence of Recommendations (H8d)

Our ***H8d*** proposed a higher decision quality to be found among high product involvement individuals. The results show no overall increase in decision quality among participants with high product involvement scores (F (434) = 0.03, p = 0.4306), thereby not validating our ***H8d***. Yet, our results reveal a significant interaction effect (F (434) = 2.42, p = 0.0452). The data suggests that this stems from high-involvement participants selecting objectively somewhat more optimal products than their low involvement counterparts within the control condition (significant at the less conservative alpha of 0.10: t = 1.57, p = 0.05825), but with no such trend observed within the static (t = -0.85, p = 0.1971), nor the neuro-adaptive conditions (t = -1.06, p = 0.1457), as portrayed in **Figure 14**.

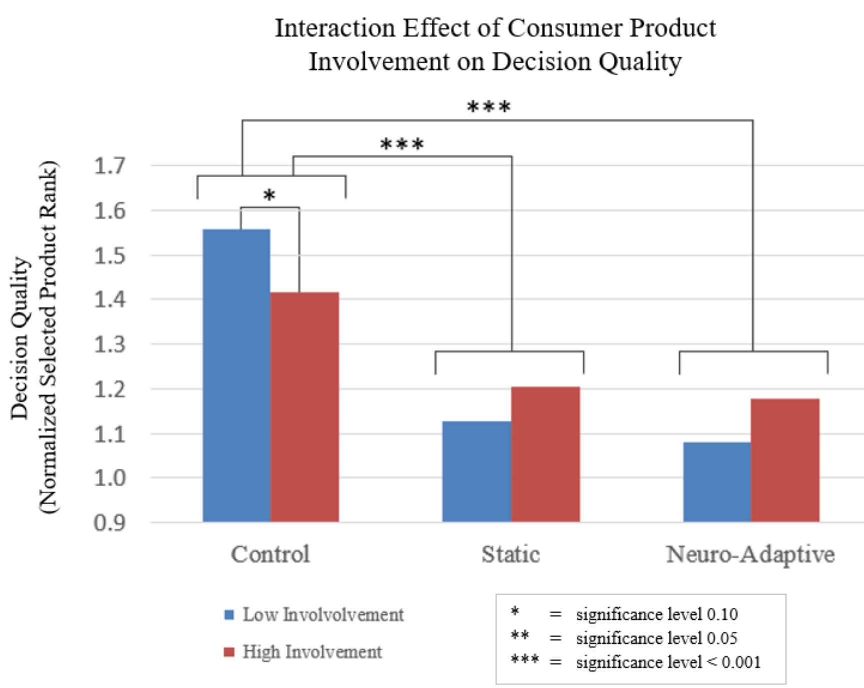


Figure 14. Interaction Effect of Consumer Product Involvement on Decision Quality

No Significant Moderation on Decision Time (H8e)

We envisioned in ***H8e*** that decision times would increase among participants with high product involvement. Though, the data suggests that decision times did not fluctuate with higher involvement scores, no matter the condition (F (434) = 0.15, p = 0.3538), hence providing no support for ***H8e***, nor was there any interaction effect observed (F (434) = 0.17, p = 0.4224).

3.5.3.3 Moderation of Product Expertise (H9)

Lower Expertise Increases Perceived Choice Overload Only with Static Recommendations (H9a)

Our ***H9a*** predicted that higher expertise would contribute to reduced perceptions of choice overload. Yet, no significant difference was observed in reducing perceived choice overload among participants with higher product expertise scores (F (434) = 0.01, p = 0.4561), thus not supporting ***H9a***. On the other hand, despite no general interaction effect (F (434) = 1.84, p = 0.0802), an interaction was noted on a finer level between the control and the static condition (t = 1.80, p = 0.0365), as portrayed in **Figure 15**; participants with lower product expertise scores reported significantly higher choice overload in the static condition, compared to the control one, whereas no such tendency was observed among consumers with higher expertise scores. No significant differences were observed within any other combination of conditions.

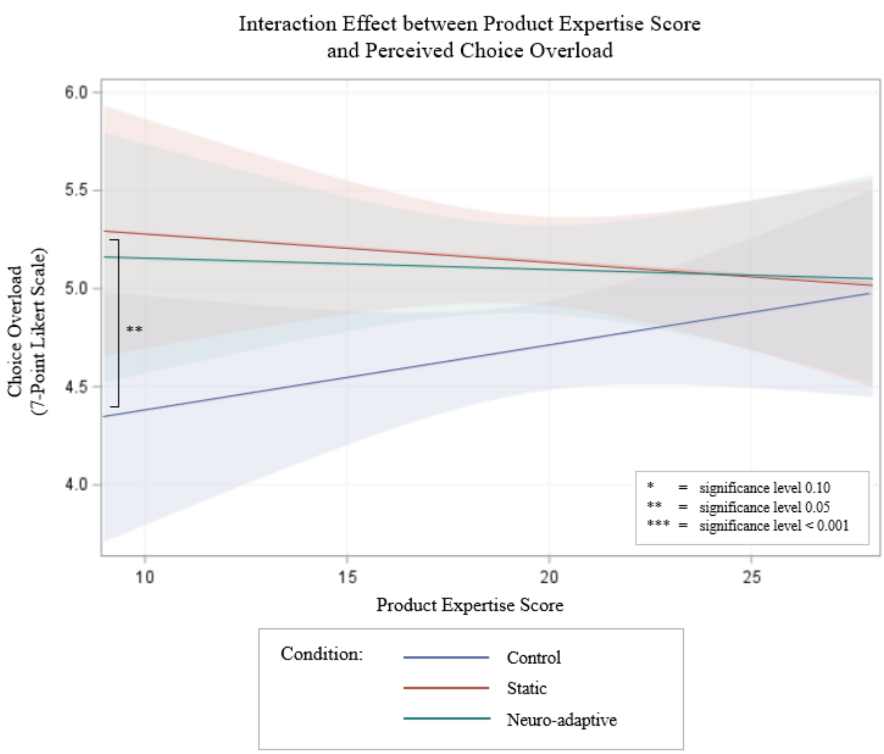


Figure 15. Interaction Effect of Product Expertise on Choice Overload

Lower Expertise Enhances Choice Satisfaction Only with Neuro-Adaptive Recommendations (H9b)

We speculated in ***H9b*** that higher expertise users would perceive higher degrees of choice satisfaction, but the data provides no support for this assumption. Despite no general effect of higher product expertise promoting an increase in choice satisfaction (F (436) = 2.20, p = 0.0696) – and, incidentally, the directionality of results opposes what we proposed ***H9b*** – the data nonetheless unpacks a significant interaction effect (F (436) = 2.57, p = 0.0387). Upon closer examination, this effect showcases significantly higher levels of choice satisfaction in the neuro-adaptive, compared to the control condition, among users that rated their product expertise as low (t = 2.26, p = 0.0123). Yet, as illustrated in **Figure 16**, higher expertise participants did not demonstrate such differences. Moreover, no other combination of conditions revealed any significant difference among participants with high versus low levels of product expertise (control vs static: t = 0.93, p = 0.1772; static vs neuro-adaptive: t = 1.33, p = 0.0928).

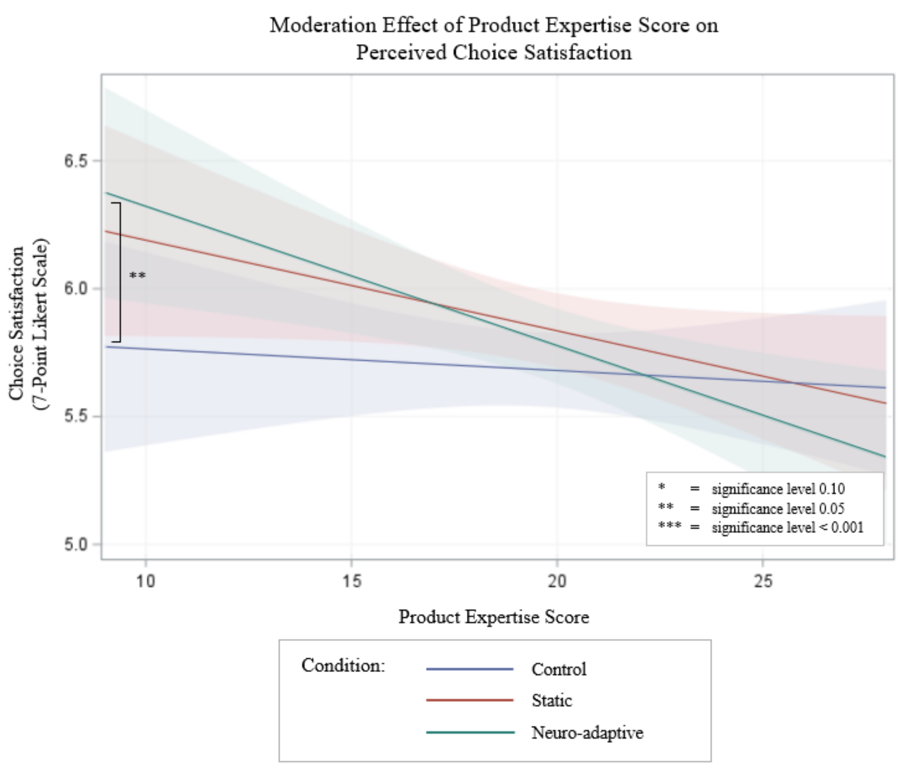


Figure 16. Interaction Effect of Product Expertise on Choice Satisfaction

Neuro-Adaptive Recommendations Stabilize Choice Confidence Across Different Levels of Product Expertise (H9c)

We suggested in ***H9c*** that choice confidence would increase with higher levels of product expertise. The results behave in alignment with our expectations, increasing unidirectionally as product expertise increased, allowing us to validate our ***H9c*** (F (434) = 2.99, p = 0.0424). Upon closer examination though, as it can be seen in **Figure 17**, this moderation is mostly present within the control condition (F (108) = 1.78, p = 0.0386). In the static condition, it could be interpreted as significant only at a less conservative significance level of 0.10 (F (108) = 2.30, p = 0.0661), and it is not present at all in the neuro-adaptive condition (F (108) = 1.32, p = 0.1268). Despite these differences, no interaction effect was observed within the data (F (434) = 0.65, p = 0.2608).

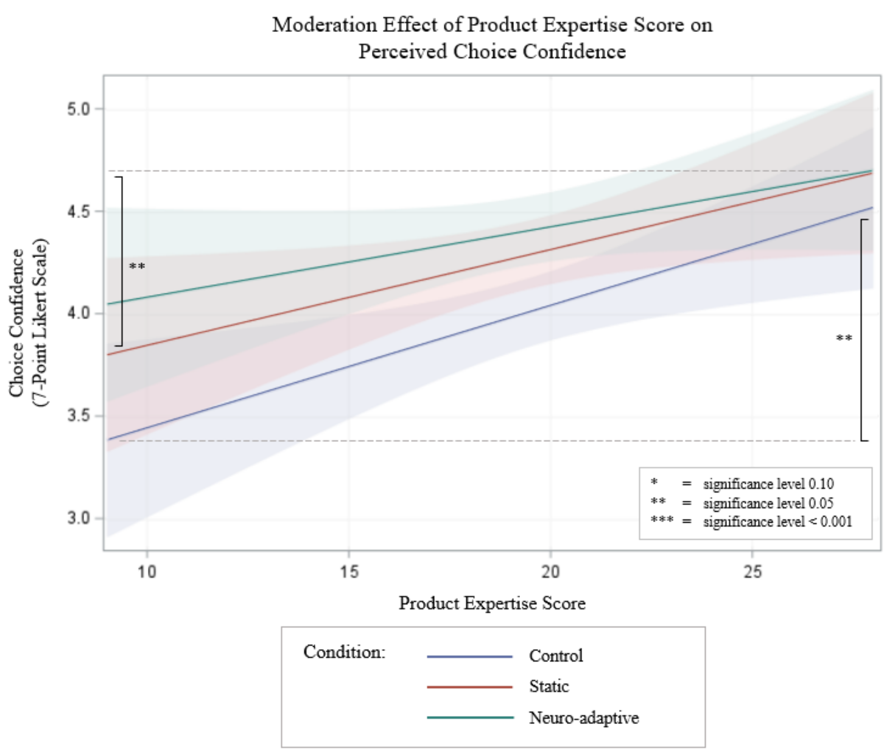


Figure 17. Moderation Effect of Product Expertise on Choice Confidence

No Significant Moderation on Decision Quality (H9d)

In ***H9d***, we posited that higher product expertise would improve decision quality. The data does not provide enough evidence to support this, as levels of product expertise appear to have no significant moderating effect on decision quality (F (434) = 0.89, p = 0.1734) in general, nor in any specific condition. No interaction effect is observed either (F (434) = 0.63, p = 0.2674).

No Significant Moderation on Decision Time (H9e)

Through ***H9e***, we esteemed that expert participants would exhibit reduced decision times. Yet, our findings show that product expertise levels did not exert a significant moderating influence on decision time, failing to support ***H9e*** (F (434) = 0.02, p = 0.4376). These findings are consistent across all conditions, and with no observed interaction effect either (F (434) = 0.10, p = 0.4546).

3.5.3.4 Moderation of Psychological Reactance (H10)

Choice Overload Is Highest with Static Recommendations Among Low Reactance Participants (H10a)

In ***H10a***, we hypothesized that higher psychological reactance would provide for heightened choice overload perceptions. The lack of a general increase of choice overload from higher psychological reactance scores (F (434) = 0.09, p = 0.3846) fail to validate our prediction. By contrast, an interaction effect was indeed present (F (434) = 2.39, p = 0.0463), as illustrated in **Figure 18**. Specifically, participants scoring low on psychological reactance reported higher choice overload in the static condition, in comparison with the control condition (t = 2.12, p = 0.0173), though no such distinction existed among high reactance participants. The effect was not observed for high reactance participants.

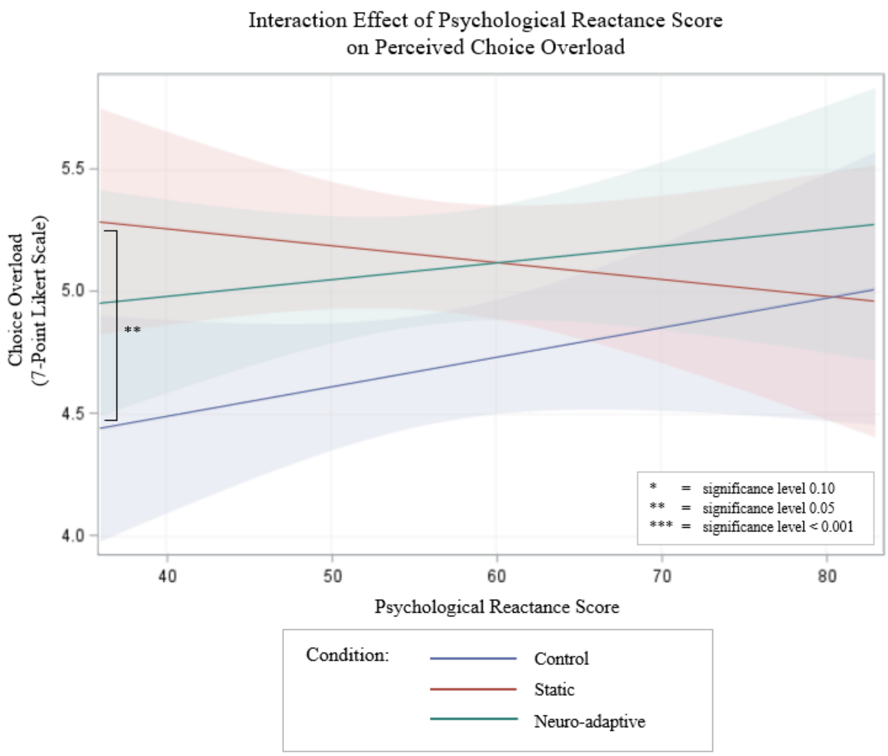


Figure 18. Interaction Effect of Psychological Reactance on Choice Overload

No Significant Moderation on Choice Satisfaction (H10b)

Our assumption ***H10b*** envisioned a decrease in choice satisfaction among higher reactance scores. The data fails to demonstrate any moderating effect of high psychological reactance scores in decreasing perceived choice satisfaction (F (53) = 1.95, p = 0.0845), so we are unable to confirm our ***H10b***. Likewise, the dataset unveils no interaction effect between psychological reactance and the experimental conditions (F (436) = 0.53, p = 0.2939).

Higher Reactance Scores Marginally Associated with Higher Choice Confidence (H10c)

Based on ***H10c***, we assumed that higher psychological reactance scores would entail reduced choice confidence. The results uncover that such an effect is marginally significant (F (434) = 2.67, p = 0.0516). However, even with a higher level of significance, our ***H10c*** could not be supported, as the directionality of the results opposes our predictions: higher reactance scores tend to increase perceptions of choice confidence.

Upon closer examination, this effect, however, is only present within the control condition (t = 3.84, p = 0.0264), but not within the static (t = 0.89, p = 0.1734), nor the neuro-adaptive (t = 1.69, p = 0.0983). Moreover, no general interaction effect is present within the data (F (434) = 1.42, p = 0.1220), as portrayed in **Figure 19**.

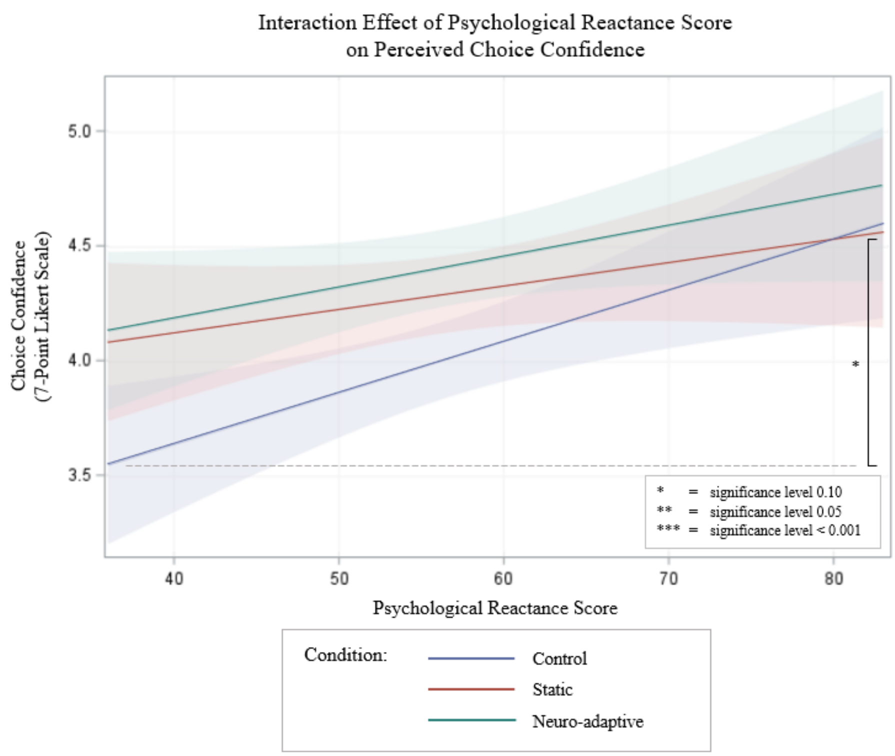


Figure 19. Interaction Effect of Psychological Reactance on Choice Confidence

No Significant Moderation on Decision Quality (H10d)

We predicted in ***H10d*** that higher reactance levels would contribute to reducing decision quality. Our results yield no significant moderating effect of higher psychological reactance scores on decreasing decision quality (F (434) = 0.01, p = 0.4590), nor any significant interaction effect (F (434) = 0.02, p = 0.4917), no matter the condition. Our ***H10d*** is thus not supported.

Decision Times Increase with Higher Reactance Scores When Recommendations Are Static (H10e)

The hypothesis ***H10e*** assumed that high reactance would result in a rise of decision time. The findings do not provide enough empirical evidence to validate ***H10e***, based on the absence of any general effect of the reactance scores (F (434) = 0.89, p = 0.1725) in increasing decision times. However, the results obtained within the control condition in isolation suggest that participants with higher reactance scores took significantly less time to decide on a product (t = 3.50, p = 0.0321), which runs counter to our predictions. This effect was not present within the static (t = 0.65, p = 0.2118), nor the neuro-adaptive (t = 1.76, p = 0.0940) conditions. Stemming from these variations, the data also demonstrates a significant interaction effect (F (434) = 5.10, p = 0.0033), as shown in **Figure 20**. Specifically, participants with high reactance scores took more time to make a decision during the static condition, compared to the control (t = -2.92, p = 0.0019) and the neuro-adaptive conditions (t = -2.58, p = 0.0051). The differences in decision time were not as pronounced among low reactance participants.

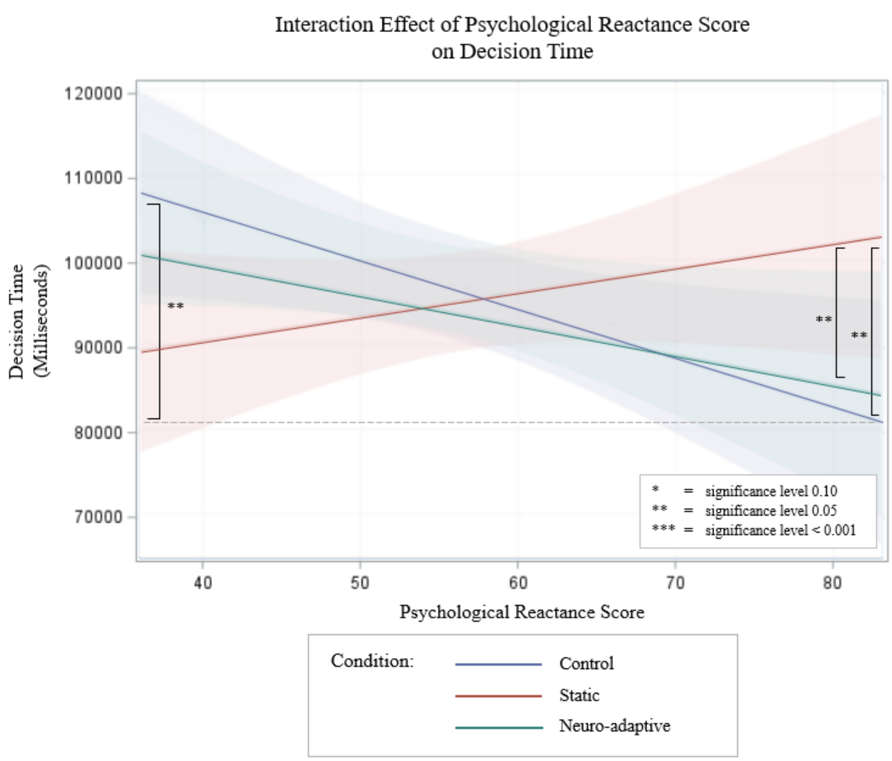


Figure 20. Interaction Effect of Psychological Reactance on Decision Time

3.5.3.5 Moderation of Need for Cognition (H11)

Choice Overload Increases with Recommendations Only When Need for Cognition Is Low (H11a)

Through ***H11a***, we stipulated that a high need for cognition would result in increased perceptions of choice overload. Although the data does not offer full support for ***H11a*** (F (487) = 3.54, p = 0.1886), the effect was in fact observed within the control condition (see **Figure 21**). Specifically, in the control condition, participants with high need for cognition judged their choice overload as significantly higher than those with low need for cognition (t = -1.76, p = 0.0394), as such partially validating ***H11a***. Moreover, a notable interaction effect (F (487) = 3.54, p = 0.0149) derived from this stark contrast, where low need for cognition participants rated their choice overload as significantly higher in the static condition (t = -4.79, p < 0.0001) and the neuro-adaptive one (t = -4.19, p < 0.0001), in comparison with the control condition.

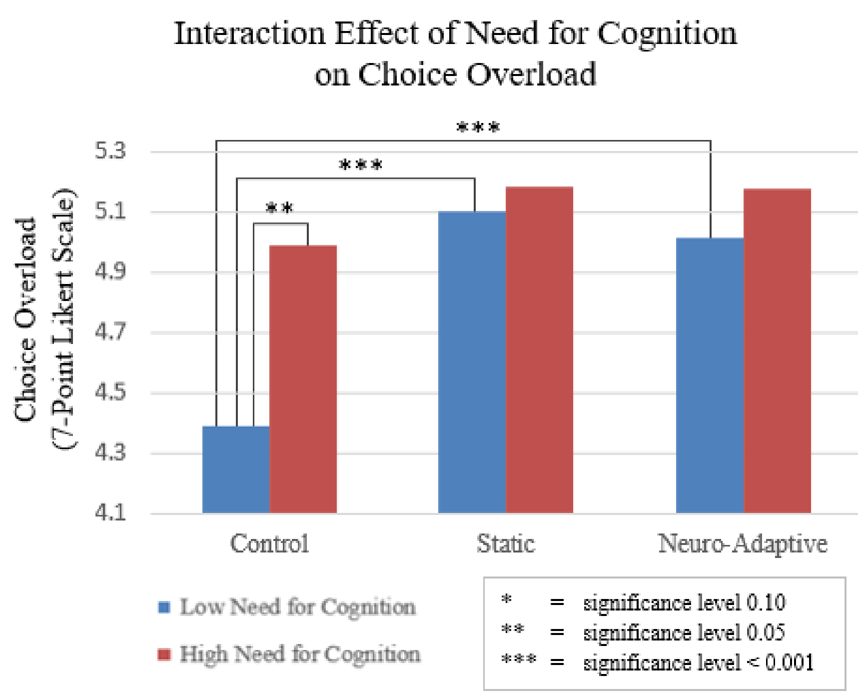


Figure 21. Interaction Effect of Need for Cognition on Choice Overload

Recommendations Enhance Choice Satisfaction Only When Need for Cognition Is Low (H11b)

In ***H11b***, we implied an overarching increase in choice satisfaction among individuals with high need for cognition. The data does not reveal such a tendency in general (F (436) = 1.51, p = 0.1100), but does support the assumption in the control condition (t = -2.51, p = 0.0062), providing slight support for ***H11b***. However, the data demonstrates an interaction effect (F (436) = 4.67, p = 0.0050), where low need for cognition participants reported being more satisfied with their product choice in the static condition (t = -3.34, p = 0.0005) and the neuro-adaptive condition (t = -2.29, p = 0.0021), when each was compared to the control condition. No differences in satisfaction scores across conditions were observed among high need for cognition participants, as represented in **Figure 22**.

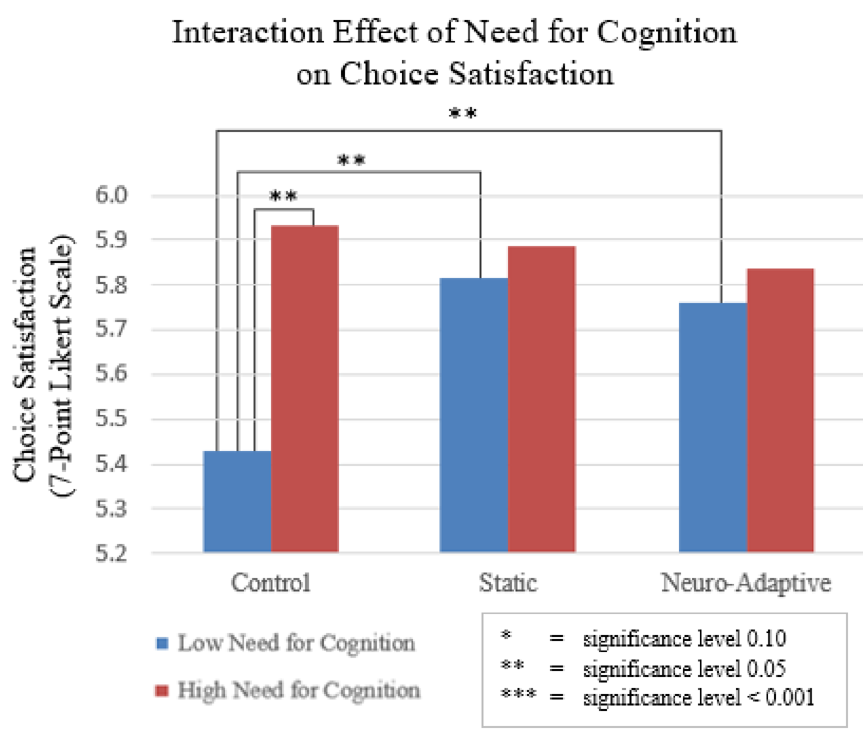


Figure 22. Interaction Effect of Need for Cognition on Choice Satisfaction

Neuro-Adaptive Recommendations Are Most Beneficial for Choice Confidence Among High Need for Cognition Participants (H11c)

Our ***H11c*** implied that individuals high in need for cognition would display higher choice confidence. The data does not result in a general heightening effect of need for cognition on choice confidence (F (434) = 0.36, p = 0.2735), which prevents us from validating ***H11c***. Notably though, if allowing for a less conservative significance level of 0.10, the estimated effect is indeed present in the control condition (t = -2.16, p = 0.0725), which contributes to uncovering a significant interaction effect (F (434) = 3.67, p = 0.0141). Participants with low need for cognition rated their choice confidence as significantly lower in the control condition than in conditions that showcased recommendations (static: t = -4.14, p < 0.0001; neuro-adaptive: t = -4.54, p < 0.0001), which can be viewed in **Figure 23**. Interestingly, high need for cognition participants also attributed significantly higher choice confidence to their selected products in the neuro-adaptive condition, compared to the control one (t = -1.95, p = 0.0209). This effect was not present when comparing the static and the control (t = -0.46, p = 0.4246).

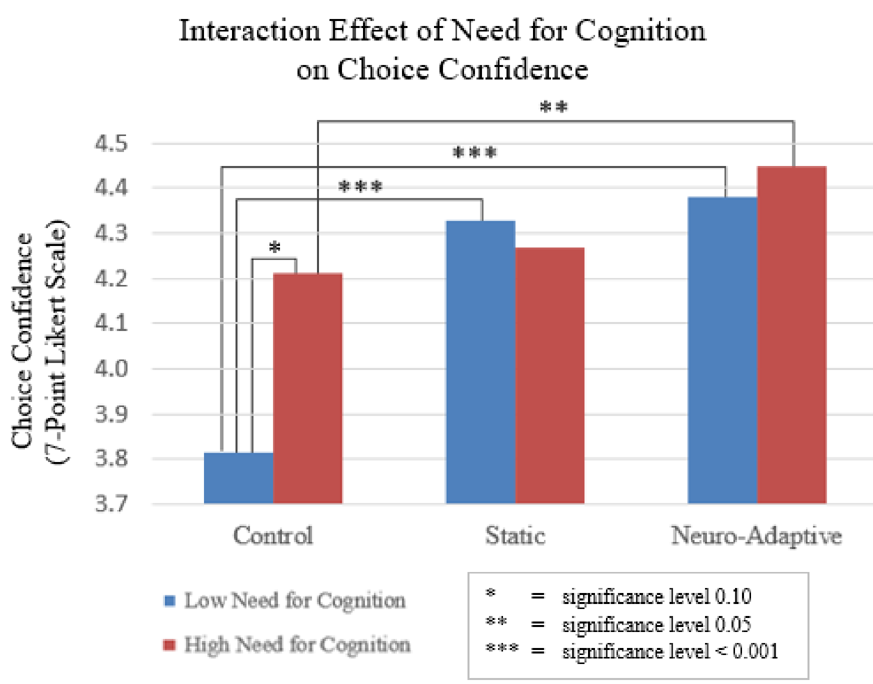


Figure 23. Interaction Effect of Need for Cognition on Choice Confidence

No Significant Moderation of Decision Quality (H11d)

We postulated in ***H11d*** that high need for cognition would promote greater decision quality. Yet, our observations do not support this hypothesis, as high need for cognition did not play any general role in optimizing participants' decision quality (F (434) = 0.01, p = 0.4626) and no interaction effect was present in the data (F (434) = 0.21, p = 0.4055).

Decision Times Increase with Lower Need for Cognition Only When Recommendations Are Absent (H11e)

With ***H11e***, we speculated that high need for cognition individuals would exhibit higher decision times. The results reflect that participants' decision times did not follow the anticipated tendency (F (434) = 0.71, p = 0.2000), leaving our ***H11e*** unsupported. If employing a more lenient significance level of 0.10, a noteworthy increase in decision times is observed in the control condition among participants with low need for cognition (t = 1.62, p = 0.0529). This fueled a significant interaction effect (F (434) = 2.53, p = 0.0404), demonstrated in **Figure 24**. This substantial increase in decision times in the control condition, among participants with low need for cognition, was not observed in neither the static condition (t = -0.43, p = 0.3342), nor the neuro-adaptive contrasts with their significantly higher decision times of the static condition (t = 0.94, p = 0.1735).

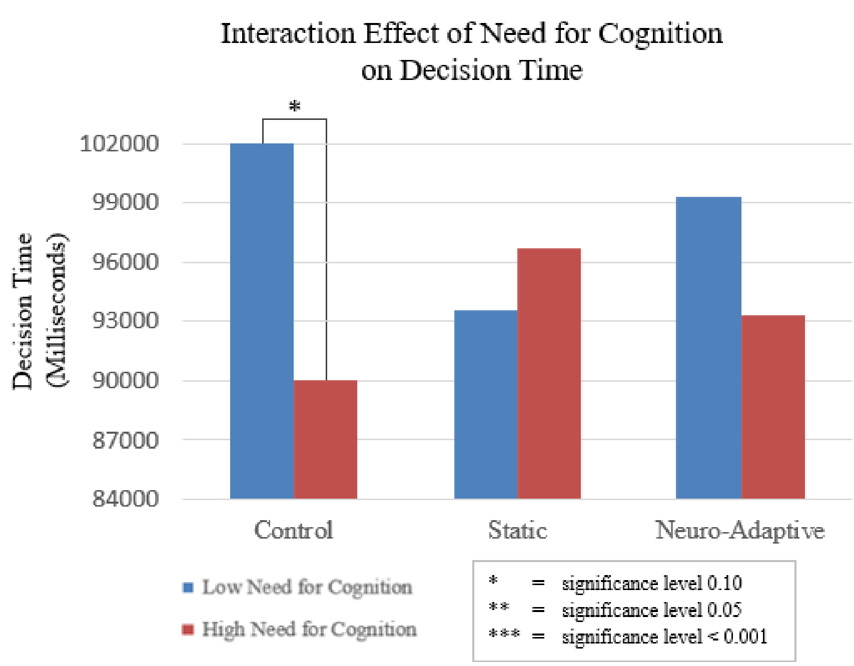


Figure 24. Interaction Effect of Need for Cognition on Decision Time

Table 12. Summary and results of hypotheses **H7-H11**

H		Hypothesis[13]	Result	Note
Moderators Affecting Choice Overload (CO) and Decision-Making Outcomes				
Compliance with Recommendations (CWR)				
H7	***H7a***	CWR decreases choice overload.	Not supported	CWR increases CO ($p = 0.0021$).
	H7b	CWR increases choice satisfaction.	Supported	
	H7c	CWR increases choice confidence.	Supported	
	H7d	CWR increases decision quality.	Supported	
	H7e	CWR decreases decision time.	Supported	
Consumer Product Involvement (CPI)				
H8	***H8a***	CPI increases choice overload.	Not supported	Interaction effect ($p < 0.0001$).
	H8b	CPI increases choice satisfaction.	Not supported	Interaction effect ($p = 0.0146$).
	H8c	CPI increases choice confidence.	Not supported	Interaction effect ($p < 0.0001$).
	H8d	CPI increases decision quality.	Not supported	Interaction effect ($p = 0.0452$).
	H8e	CPI increases decision time.	Not supported	
Product Expertise (PE)				
H9	***H9a***	PE decreases choice overload.	Not supported	Interaction effect between the static and control conditions ($p = 0.0365$).
	H9b	PE increases choice satisfaction.	Not supported	Interaction effect ($p = 0.0387$).
	H9c	PE increases choice confidence.	Supported	Mostly within the control ($p = 0.0387$) and static ($p = 0.0661$) conditions.
	H9d	PE increases decision quality.	Not supported	
	H9e	PE decreases decision time.	Not supported	

[13] All our hypotheses are built on the assumption of association between the variables. The formulation "increase/decrease" is used for sake of simplicity, and not to allude to a causal relationship.

Psychological Reactance (PR)				
H10	***H10a***	PR increases choice overload.	Not supported	Interaction effect ($p = 0.0463$).
	H10b	PR decreases choice satisfaction.	Not supported	
	H10c	PR decreases choice confidence.	Marginally supported	Mostly within the control condition ($p = 0.0264$).
	H10d	PR decreases decision quality.	Not supported	
	H10e	PR increases decision time.	Not supported	Interaction effect ($p = 0.0033$).
Need for Cognition (NFC)				
H11	***H11a***	NFC increases choice overload.	Not supported	Interaction effect ($p = 0.0149$).
	H11b	NFC increases choice satisfaction.	Not supported	Interaction effect ($p = 0.0050$).
	H11c	NFC increases choice confidence.	Not supported	• Marginally supported only within the control condition ($p = 0.0725$). • Also presence of interaction effect ($p = 0.0141$).
	H11d	NFC increases decision quality.	Not supported	
	H11e	NFC increases decision time.	Not supported	Interaction effect ($p = 0.0404$).

3.6 Discussion

Our results indicated that choice satisfaction, choice confidence and decision quality benefit from the display of both forms of recommendations, occasionally demonstrating superior outcomes for the two latter constructs when the decisional aid is neuro-adaptive. Contrary to our expectations though, recommendations increased the mediator of perceived choice overload, but this mediation resulted in mostly positive outcomes: enhanced choice satisfaction and choice confidence, but increased decision time. Moreover, the direct effect on choice confidence in the presence of the mediator, accentuated the benefit of neuro-adaptive recommendations even compared to static ones.

The findings also provided evidence in support of the moderating effect of all five moderators. First, compliance with recommendations was related to significantly increased perceptions of perceived choice overload, but was associated with optimized decisional outcomes. Second, consumer product involvement moderated most decisional outcomes, except for decision quality, through interaction. Highly involved participants demonstrated no differences, while low involvement individuals perceived higher choice overload, but their decisional outcomes benefited from recommendations, especially when they were neuro-adaptive. Third, product expertise revealed a predominantly interactive effect on perceptual outcomes, and no impact on performance measures: expert participants demonstrated no differences across conditions, but lower knowledge was associated with higher choice overload, but increased choice satisfaction and confidence in the presence of neuro-adaptive recommendations. Fourth, the role of psychological reactance was also interactive and revealed rather undesirable effects in relation to the static form of recommendations: low reactance individuals reported heightened choice overload within this condition, whereas high reactance participants took significantly longer to select a product. Fifth, need for cognition moderated both choice overload and most decisional outcomes, apart from decision quality, through interaction as well. Both forms of recommendations increased choice overload and decision times, but also enhanced choice satisfaction only when need for cognition was low. High need for cognition participants, though, benefited from increased choice confidence when exposed to neuro-adaptive recommendations.

3.6.1 Theoretical Contributions

3.6.1.1 Promising Advantages of Neuro-Adaptive Recommendations

A key contribution of our research lay in responding to a call from researchers for more personalized and interactive e-commerce recommendations, in an aim to provide a more nuanced solution against choice overload. Through neuro-adaptive technology, we assessed a novel approach to personalize the display of recommendations based on a real-time predictor of choice overload, and benchmarked our method to standard, perpetually showcased recommendations and the absence thereof.

The outcome of this assessment contributes to the body of knowledge by providing empirical evidence in support of our proposed neuro-adaptive approach. While many of our initial hypotheses have not been validated by our data, the outcome of our assessment nonetheless allowed us to tap into a more nuanced understanding of users' responses to different types of recommendations. Specifically, not only did neuro-adaptive decisional aid yield results that were similar to currently employed recommendations, it occasionally outperformed them, particularly when taking into account individual user characteristics.

Improving Decisional Outcomes, at Times Surpassing Conventional Recommendations

Firstly, in one of the three experimental trials, neuro-adaptive recommendations demonstrated the highest levels of choice confidence and decision quality. In the remaining two trials, these constructs produced comparably optimal outcomes to those achieved through currently employed, conventional recommendations.

Likewise, through the mediation of perceived choice overload, neuro-adaptive recommendations enhanced choice satisfaction to the same extent as static ones. Although, just like the latter, neuro-adaptive recommendations increased decision time, some researchers such as Tokushige et al. (2017) posit that longer decision times occur when recommendations are perceived as trustworthy by users. Hence, the authors advocate that higher decision times should not be systematically considered a drawback, as it simply implies that participants take more time to evaluate the rationale behind the recommendations and decide whether to accept it or not.

Mitigating the Some Drawbacks of Traditional Recommendations

Additional promising advantages to neuro-adaptive recommendations were unveiled through the interaction effects of the moderators. For one, users with low product expertise and psychological reactance scores did not experience higher choice overload perceptions with neuro-adaptive recommendations, unlike they did in the case of static recommendations. This phenomenon could be attributed to neuro-adaptivity inadvertently adhering to the user experience principle of progressive disclosure (Ding et al., 2020), characterized by the acknowledged practice of gradually revealing more information to users, as they progress through a task or interface. It could thus be concluded that, specifically for these individuals, neuro-adaptive recommendations improved decisional outcomes, while mitigating the downside of generic recommendations that increased perceptions of choice overload.

Moreover, neuro-adaptive recommendations did not significantly increase decision time among participants with high psychological reactance scores, unlike recommendations that were displayed statically. A possible reason could be that standard recommendations trigger a sense of threat of personal freedom of choice among high reactance individuals (Brehm & Brehm, 1981; Fitzsimons & Lehmann, 2004), which, in turn, may require longer times from them to re-establish their sense of freedom (L. Shen & J. P. Dillard, 2005), before they can proceed to decision-making. Neuro-adaptive recommendations, in contrast, might not cause this sense of threat because they appear only when the system deems necessary. As a result, high reactance participants may perceive their appearance as more justified, and not imposed upon them systematically.

Providing a Nuanced Solution, Tailored to Individual Differences

Only the neuro-adaptive form of recommendations allowed participants with low product expertise to experience higher choice confidence and satisfaction, when compared to the absence of recommendations. These positive differences could stem from the additional dimension of personalization inherent to neuro-adaptivity. With low expertise come lower levels of certainty about a decision (Kamal & Burkell, 2011; Urbany et al., 1989). Therefore, providing recommendations at the optimal moment, rather than constantly, promotes a feeling of being attentively heard in one’s decisional struggles and receiving assistance accordingly, leading to elevated choice satisfaction and confidence.

Furthermore, for consumers that possess low product involvement, choice confidence scores were also most optimal in the case of neuro-adaptive recommendations. This could be explained by low product involvement among consumers translating into more carelessness, detachment, and a lack of relatedness to a product category (Slama & Tashchian, 1985). Therefore, by allowing participants to first build a rapport with the products without any recommendations – as being exposed to a certain category of goods may increase product involvement (Maheswarappa et al., 2017; Petty & Cacioppo, 2012), – they became more involved and thereby confident about their decision.

Lastly, high need for cognition individuals reported higher degrees of choice satisfaction with neuro-adaptive assistance. A potential explanation could be that providing these participants with the chance to autonomously select a product first offers them the pleasure they experience from cognitively engaging tasks (Cacioppo & Petty, 1982), an experience they are deprived of when recommendations appear from the beginning. Moreover, the behaviour of the latter condition assumes that these individuals require assistance, which may (a) not be the case, and (b) lead them to interpret the task as targeted at people "who don't like to think" (Wheeler et al., 2005), which, consequently, tends to make them feel less compelled to diligently complete the task and reduces their engagement with it (Petty et al., 2007; Wheeler et al., 2005). Whereas in the neuro-adaptive condition, if recommendations do appear, it is due to participants, in fact, experiencing choice overload, recognizing this decisional aid as more justified.

3.6.1.2 Understanding Contradictory Findings in Existing Literature

Our second main contribution provides insightful considerations into the theoretical discrepancies surrounding the debate on the benefits of recommendations. Specifically, our results challenge the conventional dichotomic perspective by acknowledging a more nuanced synthesis of the effects of recommendations, partially supporting both positions.

More precisely, we uncover that conversely to our expectations, recommendations increase users' perception of choice overload, instead of alleviating it. However, recommendations also led to beneficial decisional outcomes in form of improved decision quality (affected directly), enhanced choice satisfaction (mediated by choice overload), and improved choice confidence (impacted both directly and through the mediation). Only decision times resulted in a less advantageous outcome (also mediated by perceived choice overload), though, as outlined above based on Tokushige et al. (2017), the optimal directionality of this construct could be debatable.

Being aligned with both sides of the ongoing debate, our findings offer theoretical insights into explaining the contradictory findings pertaining to recommendations, advocating for a non-binary view of the merits of this decisional aid.

3.6.1.3 A Holistic Integration of Multiple Moderators

An additional noteworthy contribution arises from our conceptual framework, which integrated elements from various theoretical perspectives. Although most of our assessed moderators have been studied individually in the context of choice overload (with the exception of psychological reactance which, based on our review of the literature, has only been evaluated in respect to recommendations), our study provides an improved understanding of these individual factors through a holistic review of the effects of recommendations on decision-making in the context of choice overload.

Considering the prevailing significance of all five of our assessed moderators on decisional outcomes – manifesting as a general moderating effect for compliance with recommendations and as interaction effects for consumer product involvement, product expertise, psychological reactance and need for cognition, – our results enrich the theoretical understanding of these mechanisms under our cohesive framework. We posit that this could prompt a re-evaluation of current assessment models that may have overlooked the collective significance these influential factors.

3.6.2 Methodological Contributions

To our knowledge, this research also marks the first instantiation of a neuro-adaptive system within the realm of e-commerce. While conventional methodologies relied on self-reported measures of identifying choice overload, captured after the user's interaction with the system, we leveraged neuro-adaptive technology to predict a neuro-physiological response to choice overload, and enable a system adaptation accordingly, while the user's interaction with it was still ongoing. By pushing the boundaries of this technology into the e-commerce landscape, our results underscore the potential and relevance of integrating neuro-adaptivity to enhance the field's current testing methods and lay a foundation for neuro-adaptive applications in future explorations pertaining to consumer behaviour and decision-making research. Moreover, this investigation may entice the scientific community to diversify the implementation of neuro-adaptive technology in other domains and, as such, enable the progress and refinement of methodological approaches in other fields even beyond those concerned by this study.

3.6.3 Practical Implications

The predominant implication of our findings allows to affirm the viability and justify the worthiness for online retailers to tailor the display of recommendations based on users' experience of choice overload. The promising benefits uncovered through this new dimension of personalization suggest that such a solution could help them enhance decisional outcomes for their customers beyond what they could currently achieve with traditional recommendations. A collective effort between practitioners and researchers may now investigate how to implement this improved personalization without resorting to neuro-adaptive technology, as we propose in the future work subsection below.

In the meantime, a practical insight derived from our study suggests that e-merchants may continue employing personalized recommendations to enhance the overall decision-making experience for their users. Despite increasing perceptions of choice overload and certain drawbacks among specific types of users, this form of decisional aid, in general, tends to improve outcomes of choice satisfaction, choice confidence and decision quality.

However, an interesting consideration is derived from the observed moderation of compliance with recommendations: adhering to suggested products significantly amplified the aforementioned benefits, as well as diminished decision time. Online retailers may therefore leverage this insight to further facilitate decision-making for their customers by exploring e-commerce strategies that encourage the adoption of recommendations. This also underscores the relevance for marketing and consumer behaviour researchers to complement this endeavour by delving deeper into tactics through which practitioners may improve the acceptance of recommendations, as it is currently done by Köhler et al. (2011), Lee and Benbasat (2011), and Shang et al. (2023).

Additionally, the knowledge gained from our research through moderation analyses could help marketing and user experience practitioners in guiding their design decisions when dealing with specific customer niches or types of products. Namely, upon conducting research on the individual characteristics of their target customers, they could predict their perceptions and behaviours in response to recommendations or an absence thereof. For instance, antique furniture, special interest and hobby products, as well as video game consumers are known to be highly involved (Bloch, 1986; Bloch, 1984; Taylor-West et al., 2008), so because their experience may not significantly differ depending on whether the online merchants provide recommendations or not, there may not be any need to invest time and monetary resources in developing complex recommendations systems. Conversely, designing any form of recommendations may be beneficial for products on which consumers typically possess low expertise levels. A few examples are food items with different "organic" certifications (Stanton & Cook, 2019), initiation or entry-level technology like 3D printers (Conner et al., 2015), green products sold by non-specialized, wholesale retailers (Stanton & Cook, 2019), first-time purchasers of homecare items, such as household cleaners and laundry detergents (Blackwell et al., 2001), and feminine care products (Fagerstrøm & Ghinea, 2010).

3.6.4 Limitations and Future Work

3.6.4.1 Future Iterations of the Artifact and Stimuli Design

Despite having undergone multiple rounds of formative testing and fine-tuning (Tadson et al., 2023), the EEG-based real-time cognitive load classification index we used to identify the occurrence of choice overload has its limitations. The algorithm and the calibration method to determine individual cognitive load thresholds could benefit from further investigation to assess their efficacy in providing dependable estimates of real-time cognitive workload. While not applicable to our tasks as they were relatively short in duration, the performance of the classification over time has not been assessed for factors like signal drift and user adaptation. Moreover, the complexity of the research protocol and meticulousness required for equipment installation imply many moving parts, which could have resulted in inadvertent procedural and human oversights.

Furthermore, the design of our interface intentionally stripped our product matrices of any superfluous or bias-encouraging items, such as images, brand names, and usability elements. This, however, does not necessarily replicate a real-world user interface of a typical e-commerce website. Although, this limitation could be addressed in future research that could aim to replicate the obtained results on a website that is more congruent with current industry design practices.

3.6.4.2 Exploring Alternative Predictors of Choice Overload

As most neuro-adaptive interfaces, we acknowledge that while being innovative, the real-world usability of this technology outside of the controlled laboratory environment is difficult. As such, the goal of our research was first and foremost exploratory, as we aimed to determine whether timing the display of recommendations to when users are experiencing choice overload is a research avenue worth considering. We therefore did not yet require a mainstream, widely applicable solution at this stage. However, having obtained promising results that demonstrated that recommendations that are optimally timed to measures of choice overload perform just as well and, in certain instances and categories of users, even better than traditional recommendations, we believe new research gaps could be filled by exploring less invasive methods of obtaining objective and reliable cognitive load measures, i.e., indicators of choice overload.

For example, this could be achieved by first combining modalities, such as EEG signals with other physiological measures, like oculometry, to find parallels in signals to devise a less-invasive method of identifying cognitive load through pupil dilation (Fehrenbacher & Djamasbi, 2017; Sirois & Brisson, 2014; Weber et al., 2021). Eventually, the EEG could be removed, and, in the long run, the cognitive load assessment could be done through a standard web camera, a device accessible to most users. We believe this approach could bridge the gap between the promising results obtained through this research and the practical usability of our proposed method of personalizing the display of recommendations.

Another potential future research avenue could be to explore proxy techniques of determining real-time cognitive workload. For instance, some preliminary findings by Beierle et al. (2020) have investigated indicators of increased cognitive load through users' clicking behaviour. Others have identified specific mouse movement patterns and trajectories (Grimes & Valacich, 2015; Thorpe et al., 2022). The two proposed explorations are also not mutually exclusive, as pupillometry could be used in combination with behavioural data, such as mouse movements or clicking, to enhance the reliability of these methods in assessing choice overload in real-time.

3.6.4.3 The Relevance of Cultural and Sociodemographic Differences

Finally, research has shown that the effects of choice overload may not be universal across cultures and age groups. As such, consumers of individualistic cultures, such as those from our North American sample group, differ from those of collectivistic cultures, as they engage higher cognitive and emotional costs when choosing products, given the premium they place on personal freedom of choice (Herrmann et al., 2007). Moreover, the experience might also be dissimilar in countries that are more likely to regularly experience choice deprivation, rather than overload, such as Brazil, Russia, China, Japan, and India (Reutskaja et al., 2021). Lastly, some authors also posit that the effects of choice overload largely manifest themselves only among teenagers and adults, while not so much among children and seniors (Misuraca et al., 2016), who incidentally were not represented within our sample aged 19 to 50.

3.7 Conclusion

Our research contributes to the state of the art by investigating a novel dimension of personalizing decisional aids to assist users during an online product selection: we assessed the effects of presenting product recommendations precisely at the moment when individuals experience choice overload, which we identified in real-time through an EEG-based neuro-adaptive system. We contrasted this approach to the two current methods of evaluating the effects of product recommendations: no recommendations (control) and recommendations displayed perpetually throughout the decision-making process.

The findings of our investigation reveal that both static and neuro-adaptive recommendations, rather than alleviating, increase perceptions of choice overload, which in turn, increases decision times. However, their impact on decisional outcomes has revealed to be rather beneficial, which may serve to relieve ongoing concerns about the potential detrimental effects of current recommendations systems. Interestingly though, while both forms of recommendations enhance choice satisfaction, confidence, and decision quality, neuro-adaptive recommendations exhibited occasional superiority in some trials, leading to higher choice confidence and decision quality. Moreover, they show an advantage in enhancing choice satisfaction and confidence among users with low product expertise and involvement. Additionally, they also benefit individuals with high need for cognition, improving their choice satisfaction, and reduce decision times among users with high psychological reactance scores. These findings shed light on the potential of improving decision-making in an online shopping experience by customizing the display of product recommendations according to individuals' experience of choice overload. The study now paves the way to further research that could explore alternative approaches to identify real-time occurrences of choice overload, beyond the less accessible and intrusive EEG-based neuro-adaptive system utilized in our study.

References

Adabi, A., & de Alfaro, L. (2012, 2012//). Toward a Social Graph Recommendation Algorithm: Do We Trust Our Friends in Movie Recommendations? On the Move to Meaningful Internet Systems: OTM 2012 Workshops, Berlin, Heidelberg.

Addepalli, S. L., Addepalli, S. G., Kherajani, M., Jeshnani, H., & Khedkar, S. (2016). A proposed framework for measuring customer satisfaction and product recommendation for ecommerce. *International Journal of Computer Applications*, *138*(3), 30-35.

Adriyendi, M. (2015). Multi-Attribute Decision Making Using Simple Additive Weighting and Weighted Product in Food Choice. *International Journal of Information Engineering and Electronic Business*, *7*(6), 8-14. https://doi.org/10.5815/ijieeb.2015.06.02

Aertsens, J., Mondelaers, K., Verbeke, W., Buysse, J., & Van Huylenbroeck, G. (2011). The influence of subjective and objective knowledge on attitude, motivations and consumption of organic food. *British Food Journal*, *113*(11), 1353-1378. https://doi.org/10.1108/00070701111179988

Aksoy, L., Bloom, P. N., Lurie, N. H., & Cooil, B. (2006). Should Recommendation Agents Think Like People? *Journal of Service Research*, *8*(4), 297-315. https://doi.org/10.1177/1094670506286326

Aksoy, L., Cooil, B., & Lurie, N. H. (2011). Decision Quality Measures in Recommendation Agents Research. *Journal of Interactive Marketing*, *25*(2), 110-122. https://doi.org/https://doi.org/10.1016/j.intmar.2011.01.001

Al-Samarraie, H., Eldenfria, A., Zaqout, F., & Price, M. L. (2019). How reading in single- and multiple-column types influence our cognitive load: an EEG study. *The Electronic Library*, *37*(4), 593-606. https://doi.org/10.1108/EL-01-2019-0006

Alba, J. W., & Hutchinson, J. W. (2000). Knowledge calibration: What consumers know and what they think they know. *Journal of Consumer Research*, *27*(2), 123-156. https://doi.org/10.1086/314317

Aljanabi, A. R. A., & Al-Hadban, W. K. H. M. (2023). The impact of information factors on green consumer behaviour: The moderating role of information overload. *Information Development*, 02666669231207590. https://doi.org/10.1177/02666669231207590

Aljukhadar, M., Senecal, S., & Daoust, C.-E. (2010). Information Overload and Usage of Recommendations.

Aljukhadar, M., Senecal, S., & Daoust, C.-E. (2012). Using Recommendation Agents to Cope with Information Overload. *International Journal of Electronic Commerce*, *17*(2), 41-70. http://www.jstor.org/stable/41739511

Aljukhadar, M., Trifts, V., & Senecal, S. (2017). Consumer self-construal and trust as determinants of the reactance to a recommender advice. *Psychology and Marketing*, *34*, 708-719. https://doi.org/10.1002/mar.21017

Allen, P. M., Edwards, J. A., Snyder, F. J., Makinson, K. A., & Hamby, D. M. (2014). The Effect of Cognitive Load on Decision Making with Graphically Displayed Uncertainty Information [Article]. *Risk Analysis: An International Journal*, *34*(8), 1495-1505. https://doi.org/https://doi.org/10.1111/risa.12161

Aminudin, N., Huda, M., Kilani, A., Embong, W. H. W., Mohamed, A. M., Basiron, B., Ihwani, S. S., Noor, S. S. M., Jasmi, K. A., & Safar, J. (2018). Higher education selection using simple additive weighting. *International Journal of Engineering and Technology (UAE)*, *7*(2.27), 211-217.

Andersone, I. (2022). Marketing Decision Making by Generations: Problems and Solutions. *Regional Formation and Development Studies*, *11*(3), 18-23. https://doi.org/10.15181/rfds.v11i3.606

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., & Yang, H. (2018). Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. *Customer Needs and Solutions*, *5*(1), 28-37. https://doi.org/10.1007/s40547-017-0085-8

Andreessen, L. M., Gerjets, P., Meurers, D., & Zander, T. O. (2021). Toward neuroadaptive support technologies for improving digital reading: a passive BCI-based assessment of mental workload imposed by text difficulty and presentation speed during reading [Article]. *User Modeling & User-Adapted Interaction*, *31*(1), 75-104. https://doi.org/10.1007/s11257-020-09273-5

Andrews, D. (2016). Product information and consumer choice confidence in multi-item sales promotions. *Journal of Retailing and Consumer Services*, *28*, 45-53. https://doi.org/https://doi.org/10.1016/j.jretconser.2015.07.011

Angela Chang, C. c., & Kukar-Kinney, M. (2011). The effects of shopping aid usage on consumer purchase decision and decision satisfaction. *Asia Pacific Journal of Marketing and Logistics*, *23*(5), 745-754. https://doi.org/10.1108/13555851111183110

Antonenko, P. P., Paas, F., Grabner, R., & Gog, T. (2010). Using Electroencephalography to Measure Cognitive Load. *Educational Psychology Review*, *22*, 425-438. https://doi.org/https://doi.org/10.1007/s10648-010-9130-y

Appelt, K. C., Milch, K. F., Handgraaf, M. J. J., & Weber, E. U. (2011). The Decision Making Individual Differences Inventory and guidelines for the study of individual differences in judgment and decision-making research. *Judgment and Decision Making*, *6*(3), 252-262. https://doi.org/10.1017/S1930297500001455

Appiah Kusi, G., Azmira Rumki, Z., Hammond Quarcoo, F., Otchere, E., & Fu, G. (2022). The Role of Information Overload on Consumers' Online Shopping Behavior. *Journal of Business and Management Studies*, *4*(4), 162-178. https://doi.org/10.32996/jbms

Aricò, P., Borghini, G., Di Flumeri, G., Sciaraffa, N., & Babiloni, F. (2018). Passive BCI beyond the lab: current trends and future directions. *Physiol Meas*, *39*(8), 08tr02. https://doi.org/10.1088/1361-6579/aad57e

Ariga, A. (2018, 31 Jan.-3 Feb. 2018). Is Choice Overload Replicable? 2018 10th International Conference on Knowledge and Smart Technology (KST),

Arora, P., & Narula, S. (2018). Linkages Between Service Quality, Customer Satisfaction and Customer Loyalty: A Literature Review. *IUP Journal of Marketing Management*, *17*(4), 30.

Bączkiewicz, A. (2021). MCDM based e-commerce consumer decision support tool. *Procedia Computer Science*, *192*, 4991-5002.

Baier, D., & Stüber, E. (2010). Acceptance of recommendations to buy in online retailing. *Journal of Retailing and Consumer Services*, *17*(3), 173-180. https://doi.org/https://doi.org/10.1016/j.jretconser.2010.03.005

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. *Journal of Public Policy & Marketing*, *38*(4), 500-515. https://doi.org/10.1177/0743915619858057

Bawden, D., & Robinson, L. (2020). Information Overload: An Overview. In *Oxford Encyclopedia of Political Decision Making*. Oxford: Oxford University Press. https://doi.org/10.1093/acrefore/9780190228637.013.1360

Beckers, J., & Cant, J. (2023). Half a decade in two years: household freight after COVID-19. *Transport Reviews*, 1-22. https://doi.org/10.1080/01441647.2023.2266859

Beckers, J., Cárdenas, I., & Verhetsel, A. (2018). Identifying the geography of online shopping adoption in Belgium. *Journal of Retailing and Consumer Services*, *45*, 33-41. https://doi.org/https://doi.org/10.1016/j.jretconser.2018.08.006

Bei, L.-T., & Widdows, R. (1999). Product Knowledge and Product Involvement as Moderators of the Effects of Information on Purchase Decisions: A Case Study Using the Perfect Information Frontier Approach. *Journal of Consumer Affairs*, *33*(1), 165-186. https://doi.org/https://doi.org/10.1111/j.1745-6606.1999.tb00765.x

Beierle, F., Aizawa, A., Collins, A., & Beel, J. (2020). Choice overload and recommendation effectiveness in related-article recommendations. *International Journal on Digital Libraries*, *21*(3), 231-246. https://doi.org/10.1007/s00799-019-00270-7

Besedeš, T., Deck, C., Sarangi, S., & Shor, M. (2015). Reducing Choice Overload without Reducing Choices. *The Review of Economics and Statistics*, *97*(4), 793-802. https://doi.org/10.1162/REST_a_00506

Bettman, J. R., Luce, M. F., & Payne, J. W. (2008). Consumer decision making: A choice goals approach. In *Handbook of consumer psychology.* (pp. 589-610). Taylor & Francis Group/Lawrence Erlbaum Associates.

Bhatti, H. Y., Bint E. Riaz, M., Nauman, S., & Ashfaq, M. (2022). Browsing or buying: A serial mediation analysis of consumer's online purchase intentions in times of COVID-19 pandemic [Original Research]. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1008983

Bigras, É., Léger, P.-M., & Sénécal, S. (2019). Recommendation Agent Adoption: How Recommendation Presentation Influences Employees' Perceptions, Behaviors, and Decision Quality. *Applied Sciences*, *9*(20), 4244. https://www.mdpi.com/2076-3417/9/20/4244

Biondi, F. N., Balasingam, B., & Ayare, P. (2020). On the Cost of Detection Response Task Performance on Cognitive Load. *Human Factors*, *63*(5), 804-812. https://doi.org/10.1177/0018720820931628

Blackwell, R. D., Miniard, P. W., & Engel, J. F. (2001). *Consumer Behavior* (9 ed.). Harcourt College Publishers. (Pennsylvania State University)

Bloch, P. H. (1986). THE PRODUCT ENTHUSIAST: IMPLICATIONS FOR MARKETING STRATEGY. *Journal of Consumer Marketing*, *3*(3), 51-62. https://doi.org/10.1108/eb008170

Bloch, P. H. G., Bruce D. (1984). The Leisure Experience and Consumer Products: Ari Investigation of Underlying Satisfactions. *NA Advances in Consumer Research*, *11*, 197-202.

Blut, M., Ghiassaleh, A., & Wang, C. (2023). Testing the performance of online recommendation agents: A meta-analysis. *Journal of Retailing*. https://doi.org/https://doi.org/10.1016/j.jretai.2023.08.001

Bollen, D., Knijnenburg, B. P., Willemsen, M. C., & Graus, M. (2010). *Understanding choice overload in recommender systems* Proceedings of the fourth ACM conference on Recommender systems, Barcelona, Spain. https://doi.org/10.1145/1864708.1864724

Brehm, J. W. (1966). *A theory of psychological reactance*. Academic Press.

Brehm, S. S., & Brehm, J. W. (1981). *Psychological reactance : a theory of freedom and control*. Academic Press New York.

Broniarczyk, S. M., & Griffin, J. G. (2014). Decision difficulty in the age of consumer empowerment. *Journal of Consumer Psychology*, *24*(4), 608-625. https://doi.org/10.1016/j.jcps.2014.05.003

Brown, C. L., & Krishna, A. (2004). The Skeptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice. *Journal of Consumer Research*, *31*(3), 529-539. https://doi.org/10.1086/425087

Brucks, M. (1985). The Effects of Product Class Knowledge on Information Search Behavior. *Journal of Consumer Research*, *12*(1), 1-16. http://www.jstor.org/stable/2489377

Buboltz Jr, W. C., Williams, D. J., Thomas, A., Seemann, E. A., Soper, B., & Woller, K. (2003). Personality and psychological reactance: extending the nomological net.

Personality and Individual Differences, *34*(7), 1167-1177. https://doi.org/https://doi.org/10.1016/S0191-8869(02)00107-1

Cacioppo, J., Petty, R., & Kao, C. (1984). The efficient assessment of NFC. *Journal of personality assessment*, *48*, 306-307. https://doi.org/10.1207/s15327752jpa4803_13

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, *42*(1), 116-131. https://doi.org/10.1037/0022-3514.42.1.116

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin*, *119*(2), 197-253. https://doi.org/10.1037/0033-2909.119.2.197

Calvo, L., Christel, I., Terrado, M., Cucchietti, F., & Pérez-Montoro, M. (2022). Users' Cognitive Load: A Key Aspect to Successfully Communicate Visual Climate Information [Article]. *Bulletin of the American Meteorological Society*, *103*(1), E1-E16. https://doi.org/10.1175/BAMS-D-20-0166.1

Campos, P. G., Bellogín, A., Díez, F., & Chavarriaga, J. E. (2010). *Simple time-biased KNN-based recommendations* Proceedings of the Workshop on Context-Aware Movie Recommendation, Barcelona, Spain. https://doi.org/10.1145/1869652.1869655

Chen, C. C., Shih, S.-Y., & Lee, M. (2016). Who should you follow? Combining learning to rank with social influence for informative friend recommendation. *Decision Support Systems*, *90*, 33-45. https://doi.org/https://doi.org/10.1016/j.dss.2016.06.017

Chen, M. (2018). Improving website structure through reducing information overload. *Decision Support Systems*, *110*, 84-94. https://doi.org/https://doi.org/10.1016/j.dss.2018.03.009

Chen, S., & Chaiken, S. (1999). The heuristic-systematic model in its broader context. In *Dual-process theories in social psychology.* (pp. 73-96). The Guilford Press.

Chen, S., Qiu, H., Zhao, S., Han, Y., He, W., Siponen, M., Mou, J., & Xiao, H. (2022). When more is less: The other side of artificial intelligence recommendation. *Journal of Management Science and Engineering*, *7*(2), 213-232. https://doi.org/https://doi.org/10.1016/j.jmse.2021.08.001

Chen, Y.-C., Shang, R.-A., & Kao, C.-Y. (2009). The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment. *Electron. Commer. Res. Appl.*, *8*(11), 48-58.

Chen, Z., Jin, J., Daly, I., Zuo, C., Wang, X., & Cichocki, A. (2020). Effects of Visual Attention on Tactile P300 BCI [Article]. *Computational Intelligence & Neuroscience*, 1-11. https://doi.org/10.1155/2020/6549189

Chernev, A., Bockenholt, U., & Goodman, J. (2010). Choice Overload: Is There Anything to It. *Journal of Consumer Research*, *37*, 426-428.

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, *25*(2), 333-358. https://doi.org/10.1016/j.jcps.2014.08.002

Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer Services*, *61*, 102528. https://doi.org/https://doi.org/10.1016/j.jretconser.2021.102528

Clarkson, J. J., Tormala, Z. L., & Rucker, D. D. (2008). A new look at the consequences of attitude certainty: The amplification hypothesis. *Journal of Personality and Social Psychology*, *95*(4), 810-825. https://doi.org/10.1037/a0013192

Collins, D., & Geist, M. (2023). Chapter 1: Introduction to Research Handbook on Digital Trade

In *Research Handbook on Digital Trade* (pp. 1-7). Edward Elgar Publishing. https://doi.org/10.4337/9781800884953.00006

Collins, L., & Collins, D. (2021). Managing the Cognitive Loads Associated with Judgment and Decision-Making in a Group of Adventure Sports Coaches: A Mixed-Method Investigation. *Journal of Adventure Education and Outdoor Learning*, *21*(1), 1-16. http://proxy2.hec.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1292642&lang=fr&site=ehost-live

http://dx.doi.org/10.1080/14729679.2019.1686041

Conner, B. P., Manogharan, G. P., & Meyers, K. L. (2015). An assessment of implementation of entry-level 3D printers from the perspective of small businesses. *Rapid Prototyping Journal*, *21*(5), 582-597. https://doi.org/10.1108/RPJ-09-2014-0132

Crocoll, W. M., & Coury, B. G. (1990). Status or Recommendation: Selecting the Type of Information for Decision Aiding. *Proceedings of the Human Factors Society Annual Meeting*, *34*(19), 1524-1528. https://doi.org/10.1177/154193129003401922

Curşeu, P. L. (2006). Need for cognition and rationality in decision-making. *Studia Psychologica*, *48*(2), 141.

Dabholkar, P. A., & Sheng, X. (2012). Consumer participation in using online recommendation agents: effects on satisfaction, trust, and purchase intentions. *The Service Industries Journal*, *32*(9), 1433-1449. https://doi.org/10.1080/02642069.2011.624596

de Bont, C. J. P. M., & Schoormans, J. P. L. (1995). The effects of product expertise on consumer evaluations of new-product concepts. *Journal of Economic Psychology*, *16*(4), 599-615. https://doi.org/https://doi.org/10.1016/0167-4870(95)00030-4

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments [Article]. *European Economic Review*, *78*, 97-119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Dellaert, B. G., Baker, T., & Johnson, E. J. (2017). Partitioning sorted sets: overcoming choice overload while maintaining decision quality. *Columbia Business School Research Paper*(18-2).

Dellaert, B. G. C., & Häubl, G. (2012). Searching in Choice Mode: Consumer Decision Processes in Product Search with Recommendations. *Journal of Marketing Research*, *49*(2), 277-288. https://doi.org/10.1509/jmr.09.0481

Deng, L., & Poole, M. S. (2010). Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order. *MIS Quarterly*, *34*(4), 711-730. https://doi.org/10.2307/25750702

Dhar, R. K. (1996). The Effect of Decision Strategy on Deciding to Defer Choice. *Journal of Behavioral Decision Making*, *9*, 265-281.

Di Flumeri, G., De Crescenzio, F., Berberian, B., Ohneiser, O., Kramer, J., Arico, P., Borghini, G., Babiloni, F., Bagassi, S., & Piastra, S. (2019). Brain-Computer Interface-Based Adaptive Automation to Prevent Out-Of-The-Loop Phenomenon in Air Traffic Controllers Dealing With Highly Automated Systems. *Front Hum Neurosci*, *13*, 296. https://doi.org/10.3389/fnhum.2019.00296

Diehl, K. (2005). When Two Rights Make a Wrong: Searching Too Much in Ordered Environments. *Journal of Marketing Research*, *42*(3), 313-322. https://doi.org/10.1509/jmkr.2005.42.3.313

Diehl, K., & Poynor, C. (2010). Great Expectations?! Assortment Size, Expectations, and Satisfaction. *Journal of Marketing Research*, *47*(2), 312-322. https://doi.org/10.1509/jmkr.47.2.312

Ding, G.-J., Hwang, T. K. P., & Kuo, P.-C. (2020, 2020//). Progressive Disclosure Options for Improving Choice Overload on Home Screen. Advances in Usability, User Experience, Wearable and Assistive Technology, Cham.

Divyaa, L. R., & Nargis, P. (2019). Towards generating scalable personalized recommendations: Integrating social trust, social bias, and geo-spatial clustering. *Decision Support Systems*, *122*, 113066. https://doi.org/https://doi.org/10.1016/j.dss.2019.05.006

Donkers, B., Dellaert, B. G. C., Waisman, R. M., & Häubl, G. (2020). Preference Dynamics in Sequential Consumer Choice with Defaults. *Journal of Marketing Research*, *57*(6), 1096-1112. https://doi.org/10.1177/0022243720956642

Drichoutis, A. C., & Nayga, R. M. (2020). Economic Rationality under Cognitive Load. *Economic Journal*, *130*(632), 2382-2409. https://doi.org/10.1093/ej/ueaa052

Edmunds, A., & Morris, A. (2000). The problem of information overload in business organisations: a review of the literature. *International Journal of Information Management*, *20*(1), 17-28. https://doi.org/https://doi.org/10.1016/S0268-4012(99)00051-1

Eldenfria, A., & Al-Samarraie, H. (2019). Towards an Online Continuous Adaptation Mechanism (OCAM) for Enhanced Engagement: An EEG Study [Article]. *International Journal of Human-Computer Interaction*, *35*(20), 1960-1974. https://doi.org/10.1080/10447318.2019.1595303

Emami, Z., & Chau, T. (2020). The effects of visual distractors on cognitive load in a motor imagery brain-computer interface. *Behav Brain Res*, *378*, 112240. https://doi.org/10.1016/j.bbr.2019.112240

Engel, M. M., Utomo, W. H., & Purnomo, H. D. (2017). Fuzzy Multi Attribute Decision Making Simple Additive Weighting (MADM SAW) for Information Retrieval (IR) in E Commerce Recommendation. *International Journal of Computer Science and Software Engineering*, *6*(6), 136-145.

Eppler, M. J., & Mengis, J. (2004). The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines. *The Information Society*, *20*(5), 325-344. https://doi.org/10.1080/01972240490507974

Ersner-Hershfield, H., Wimmer, G. E., & Knutson, B. (2009). Saving for the future self: neural measures of future self-continuity predict temporal discounting. *Soc Cogn Affect Neurosci*, *4*(1), 85-92. https://doi.org/10.1093/scan/nsn042

Fabius, V., Kohli, S., & Timelin, B. M. V., Sofia (2020, July 30, 2020). *How COVID-19 is changing consumer behavior-now and forever*. McKinsey & Company. https://www.mckinsey.com/industries/retail/our-insights/how-covid-19-is-changing-consumer-behavior-now-and-forever

Fagerstrøm, A., & Ghinea, G. (2010). Web 2.0's Marketing Impact on Low-Involvement Consumers. *Journal of Interactive Advertising*, *10*(2), 67-71. https://doi.org/10.1080/15252019.2010.10722171

Fasolo, B., McClelland, G. H., & Todd, P. M. (2007). Escaping the tyranny of choice: when fewer attributes make choice easier. *Marketing Theory*, *7*(1), 13-26. https://doi.org/10.1177/1470593107073842

Fehrenbacher, D. D., & Djamasbi, S. (2017). Information systems and task demand: An exploratory pupillometry study of computerized decision making. *Decision Support Systems*, *97*, 1-11. https://doi.org/https://doi.org/10.1016/j.dss.2017.02.007

Fernandez Rojas, R., Debie, E., Fidock, J., Barlow, M., Kasmarik, K., Anavatti, S., Garratt, M., & Abbass, H. (2020). Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments. *Frontiers in Neuroscience*, *14*, 40. https://doi.org/10.3389/fnins.2020.00040

Fishel, S. R., Muth, E. R., & Hoover, A. W. (2007). Establishing Appropriate Physiological Baseline Procedures for Real-Time Physiological Measurement. *Journal of Cognitive Engineering and Decision Making*, *1*(3), 286-308. https://doi.org/10.1518/155534307X255636

Fitzsimons, G. J., & Lehmann, D. R. (2004). Reactance to Recommendations: When Unsolicited Advice Yields Contrary Responses. *Marketing Science*, *23*(1), 82-94. https://doi.org/10.1287/mksc.1030.0033

Fridman, L., Reimer, B., Mehler, B., & Freeman, W. T. (2018). *Cognitive Load Estimation in the Wild* Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, Montreal QC, Canada. https://doi.org/10.1145/3173574.3174226

Gantner, Z., Rendle, S., & Schmidt-Thieme, L. (2010). *Factorization models for context-/time-aware movie recommendations* Proceedings of the Workshop on Context-Aware Movie Recommendation, Barcelona, Spain. https://doi.org/10.1145/1869652.1869654

Garcia Esparza, S., O'Mahony, M. P., & Smyth, B. (2012). Mining the real-time web: A novel approach to product recommendation. *Knowledge-Based Systems*, *29*, 3-11. https://doi.org/https://doi.org/10.1016/j.knosys.2011.07.007

Gershoff, A. D., Mukherjee, A., & Mukhopadhyay, A. (2003). Consumer Acceptance of Online Agent Advice: Extremity and Positivity Effects. *Journal of Consumer Psychology*, *13*(1), 161-170. https://doi.org/https://doi.org/10.1207/S15327663JCP13-1&2_14

Gevins, A., & Smith, M. E. (2000). Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. *Cereb Cortex*, *10*(9), 829-839. https://doi.org/10.1093/cercor/10.9.829

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. *Theoretical issues in ergonomics science*, *4*(1-2), 113-131.

Ghosh, R. (2022). *E-Commerce Sales Soar Past $1 Trillion: 4 Solid Stocks to Buy* NASDAQ. https://www.nasdaq.com/articles/e-commerce-sales-soar-past-%241-trillion%3a-4-solid-stocks-to-buy

Goodman, J. K., Broniarczyk, S. M., Griffin, J. G., & McAlister, L. (2013). Help or hinder? When recommendation signage expands consideration sets and heightens decision difficulty. *Journal of Consumer Psychology*, *23*(2), 165-174. https://doi.org/https://doi.org/10.1016/j.jcps.2012.06.003

Gourville, J. T., & Soman, D. (2005). Overchoice and Assortment Type: When and Why Variety Backfires. *Marketing Science*, *24*(3), 382-395. https://doi.org/10.1287/mksc.1040.0109

Gredin, N. V., Broadbent, D. P., Findon, J. L., Williams, A. M., & Bishop, D. T. (2020). The impact of task load on the integration of explicit contextual priors and visual information during anticipation [Article]. *Psychophysiology*, *57*(6), 1-13. https://doi.org/10.1111/psyp.13578

Gregor, S. (2006). The Nature of Theory in Information Systems. *MIS Quarterly*, *30*(3), 611-642. https://doi.org/10.2307/25148742

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly*, *37*(2), 337-355. https://doi.org/10.25300/misq/2013/37.2.01

Greifeneder, R., Scheibehenne, B., & Kleber, N. (2009). Less may be more when choosing is difficult: Choice complexity and too much choice. *Acta psychologica*, *133*, 45-50. https://doi.org/10.1016/j.actpsy.2009.08.005

Grimes, M., & Valacich, J. (2015). *Mind over mouse: The effect of cognitive load on mouse movement behavior* Thirty Sixth International Conference on Information Systems, Fort Worth.

Guan, K., Zhang, Z., Chai, X., Tian, Z., Liu, T., & Niu, H. (2022). EEG Based Dynamic Functional Connectivity Analysis in Mental Workload Tasks With Different Types of Information. *IEEE Trans Neural Syst Rehabil Eng*, *30*, 632-642. https://doi.org/10.1109/TNSRE.2022.3156546

Guo, R., & Li, H. (2022). Can the amount of information and information presentation reduce choice overload? An empirical study of online hotel booking. *Journal of Travel & Tourism Marketing*, *39*(1), 87-108. https://doi.org/10.1080/10548408.2022.2044970

Gupta, P., & Harris, J. (2010). How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. *Journal of Business Research*, *63*(9), 1041-1049. https://doi.org/https://doi.org/10.1016/j.jbusres.2009.01.015

Hadar, L., & Sood, S. (2014). When Knowledge Is Demotivating: Subjective Knowledge and Choice Overload. *Psychological Science*, *25*(9), 1739-1747. http://www.jstor.org/stable/24543909

Hadar, L., Sood, S., & Fox, C. R. (2013). Subjective Knowledge in Consumer Financial Decisions. *Journal of Marketing Research*, *50*(3), 303-316. https://doi.org/10.1509/jmr.10.0518

Harris, J., & Gupta, P. (2008). 'You should buy this one!' The influence of online recommendations on product attitudes and choice confidence. *International Journal of Electronic Marketing and Retailing*, *2*(2), 176-189. https://doi.org/10.1504/IJEMR.2008.019816

Hassan, L. M., Shiu, E., & McGowan, M. (2019). Relieving the regret for maximizers. *European Journal of Marketing*, *54*(2), 282-304. https://doi.org/10.1108/EJM-03-2018-0200

Häubl, G., Dellaert, B., & Usta, M. (2010). Ironic Effects of Personalized Product Recommendations on Subjective Decision Outcomes. *Proceedings of the Society for Consumer Psychology Winter Conference*.

Häubl, G., & Trifts, V. (2000). Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. *Marketing Science*, *19*(1), 4-21. https://doi.org/10.1287/mksc.19.1.4.15178

Haynes, G. A. (2009). Testing the boundaries of the choice overload phenomenon: The effect of number of options and time pressure on decision difficulty and satisfaction. *Psychology & Marketing*, *26*(3), 204-212. https://doi.org/https://doi.org/10.1002/mar.20269

Hdioud, F., Frikh, B., & Ouhbi, B. (2013). *Multi-Criteria Recommender Systems based on Multi-Attribute Decision Making* International Conference on Information Integration and Web-based Applications & Services,

Heitmann, M., Lehmann, D. R., & Herrmann, A. (2007). Choice Goal Attainment and Decision and Consumption Satisfaction. *Journal of Marketing Research*, *44*(2), 234-250. https://doi.org/10.1509/jmkr.44.2.234

Herrmann, A., Heitmann, M., & R, L. (2007). Choice Goal Attainment and Decision and Consumption Satisfaction. *Journal of Marketing Research*, *44*, 234-250. https://doi.org/10.1509/jmkr.44.2.234

Hevner, A. (2007). A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems*, *19*.

Hevner, A., Park, J., & March, S. T. (2004). Design Science in Information Systems Research. *MIS Quarterly*, *28*(1), 75-105.

Ho, E. H., Hagmann, D., & Loewenstein, G. (2021). Measuring Information Preferences. *Management Science*, *67*(1), 126-145. https://doi.org/10.1287/mnsc.2019.3543

Hoch, S. J., & Deighton, J. (1989). Managing what consumers learn from experience. *Journal of marketing*, *53*(2), 1-20. https://doi.org/10.2307/1251410

Hong, S.-m., & Page, S. (1989). A psychological reactance scale: Development, factor structure and reliability. *Psychological Reports*, *64*(3, Pt 2), 1323-1326. https://doi.org/10.2466/pr0.1989.64.3c.1323

Hu, H.-f., & Krishen, A. S. (2019). When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective. *Journal of Business Research*, *100*, 27-37. https://doi.org/https://doi.org/10.1016/j.jbusres.2019.03.011

Huang, Z., Zeng, D., & Chen, H. (2007). A Comparison of Collaborative-Filtering Recommendation Algorithms for E-commerce. *IEEE Intelligent Systems*, *22*(5), 68-78. https://doi.org/10.1109/MIS.2007.4338497

Huber, F., Köcher, S., Vogel, J., & Meyer, F. (2012). Dazing Diversity: Investigating the Determinants and Consequences of Decision Paralysis. *Psychology & Marketing*, *29*(6), 467-478. https://doi.org/https://doi.org/10.1002/mar.20535

Huffman, C., & Kahn, B. E. (1998). Variety for sale: Mass customization or mass confusion? *Journal of Retailing*, *74*(4), 491-513. https://doi.org/https://doi.org/10.1016/S0022-4359(99)80105-5

Huseynov, F., Huseynov, S. Y., & Özkan, S. (2014). The influence of knowledge-based e-commerce product recommender agents on online consumer decision-making. *Information Development*, *32*(1), 81-90. https://doi.org/10.1177/0266666914528929

Hutchinson, C. F., & Herrmann, S. M. (2008). Land use and Management. In C. F. Hutchinson & S. M. Herrmann (Eds.), *The Future of Arid Lands — Revisited: A Review of 50 Years of Drylands Research* (pp. 103-128). Springer Netherlands. https://doi.org/10.1007/978-1-4020-6689-4_7

Imai, K., Keele, L., Tingley, D., & Yamamoto, T. (2010). Causal mediation analysis using R. Advances in social science research using R,

Itani, O. S., & Hollebeek, L. D. (2021). Consumers' health-locus-of-control and social distancing in pandemic-based e-tailing services. *Journal of Services Marketing*, *35*(8), 1073-1091. https://doi.org/10.1108/JSM-10-2020-0410

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: can one desire too much of a good thing? *J Pers Soc Psychol*, *79*(6), 995-1006. https://doi.org/10.1037//0022-3514.79.6.995

Jacoby, J., Speller, D., & Berning, C. (1974). Brand Choice Behavior as a Function of Information Load. *Journal of Consumer Research*, *1*, 33-42. https://doi.org/10.1086/208579

Jacoby, J., Speller, D. E., & Kohn, C. A. (1974). Brand Choice Behavior as a Function of Information Load. *Journal of Marketing Research*, *11*(1), 63-69. https://doi.org/10.2307/3150994

Jiang, Y., Shang, J., & Liu, Y. (2010). Maximizing customer satisfaction through an online recommendation system: A novel associative classification model. *Decision Support Systems*, *48*(3), 470-479. https://doi.org/https://doi.org/10.1016/j.dss.2009.06.006

Jiang, Z., & Benbasat, I. (2005). Virtual Product Experience: Effects of Visual and Functional Control of Products on Perceived Diagnosticity and Flow in Electronic Shopping. *J. of Management Information Systems*, *21*, 111-148. https://doi.org/10.2139/ssrn.1400827

Jin, Y., Cardoso, B., & Verbert, K. (2017, 2017). How do different levels of user control affect cognitive load and acceptance of recommendations? CEUR Workshop Proceedings,

Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. *Management Science*, *31*(4), 395-414.

Johnson, E. J., Shu, S. B., Dellaert, B. G. C., Fox, C., Goldstein, D. G., Häubl, G., Larrick, R. P., Payne, J. W., Peters, E., Schkade, D., Wansink, B., & Weber, E. U. (2012). Beyond nudges: Tools of a choice architecture. *Marketing Letters: A Journal of Research in Marketing*, *23*(2), 487-504. https://doi.org/10.1007/s11002-012-9186-1

Jugovac, M., & Jannach, D. (2017). Interacting with Recommenders—Overview and Research Directions. *ACM Trans. Interact. Intell. Syst.*, *7*(3), Article 10. https://doi.org/10.1145/3001837

Kahn, B. E. (2017). Using Visual Design to Improve Customer Perceptions of Online Assortments. *Journal of Retailing*, *93*(1), 29-42. https://doi.org/https://doi.org/10.1016/j.jretai.2016.11.004

Kalanthroff, E., Cohen, N., & Henik, A. (2013). Stop feeling: inhibition of emotional interference following stop-signal trials [Original Research]. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00078

Kamal, A., & Burkell, J. (2011). Addressing Uncertainty: When Information is Not Enough / Faire face à l'incertitude : quand l'information ne suffit pas. *Canadian Journal of Information and Library Science*, *35*, 384-396. https://doi.org/10.1353/ils.2011.0030

Karran, A. J., Demazure, T., Hudon, A., Senecal, S., & Léger, P. M. (2022). Designing for Confidence: The Impact of Visualizing Artificial Intelligence Decisions. *Front Neurosci*, *16*, 883385. https://doi.org/10.3389/fnins.2022.883385

Karran, A. J., Demazure, T., Leger, P.-M., Labonte-LeMoyne, E., Senecal, S., Fredette, M., & Babin, G. (2019). Toward a Hybrid Passive BCI for the Modulation of Sustained Attention Using EEG and fNIRS [Original Research]. *Frontiers in Human Neuroscience*, *13*. https://doi.org/10.3389/fnhum.2019.00393

Kean Yew, J., & Kamarulzaman, Y. (2020). Effects of Personal Factors, Perceived Benefits, and Shopping Orientation on Online Shopping Behavior. *International Journal of Economics, Management and Accounting*, *28*, 327-360.

Khan, K., Hussainy, S. K., Hameed, I., & Riaz, K. (2021). Too Much Choice and Consumer Decision Making: The Moderating Role of Consumer Involvement. *JISR management and social sciences & economics*, *19*(1), 17-29. https://doi.org/10.31384/jisrmsse/2021.19.1.2

Kim, H. J., Lee, H., & Hong, H. (2020). Scale Development and Validation for Psychological Reactance to Health Promotion Messages. *Sustainability*, *12*(14), 5816. https://www.mdpi.com/2071-1050/12/14/5816

Kim, H. M., & Kramer, T. (2006). The Moderating Effects of Need for Cognition and Cognitive Effort on Responses to Multi-Dimensional Prices. *Marketing Letters*, *17*(3), 193-203. http://www.jstor.org/stable/40216676

Kim, S.-Y., Levine, T., & Allen, M. (2013). Comparing Separate Process and Intertwined Models for Reactance. *Communication Studies*, *64*(3), 273-295. https://doi.org/10.1080/10510974.2012.755639

Kirby-Hawkins, E., Birkin, M., & Clarke, G. (2018). An investigation into the geography of corporate e-commerce sales in the UK grocery market. *Environment and Planning B: Urban Analytics and City Science*, *46*(6), 1148-1164. https://doi.org/10.1177/2399808318755147

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. *Journal of Experimental Psychology*, *55*(4), 352-358. https://doi.org/10.1037/h0043688

Knijnenburg, B. P., Willemsen, M. C., & Hirtbach, S. (2010, 2010//). Receiving Recommendations and Providing Feedback: The User-Experience of a Recommender System. E-Commerce and Web Technologies, Berlin, Heidelberg.

Köcher, S., Jugovac, M., Jannach, D., & Holzmüller, H. H. (2019). New Hidden Persuaders: An Investigation of Attribute-Level Anchoring Effects of Product Recommendations. *Journal of Retailing*, *95*(1), 24-41. https://doi.org/https://doi.org/10.1016/j.jretai.2018.10.004

Kodali, S. (2019). *The State of Retailing Online 2019*. Forrester.

Koenig, A. (1995). Patterns and Antipatterns. *Journal of Object Oriented Programming*, *8*(1), 46-48.

Köhler, C. F., Breugelmans, E., & Dellaert, B. G. C. (2011). Consumer Acceptance of Recommendations by Interactive Decision Aids: The Joint Role of Temporal Distance and Concrete Versus Abstract Communications. *Journal of Management Information Systems*, *27*(4), 231-260. https://doi.org/10.2753/MIS0742-1222270408

Konstan, J. A., & Riedl, J. (2012). Recommender systems: from algorithms to user experience. *User Modeling and User-Adapted Interaction*, *22*(1), 101-123. https://doi.org/10.1007/s11257-011-9112-x

Köten, E. E. (2023). The impact of internet platform usage on firms' exports: New evidence for Turkish firms. *The World Economy*, *n/a*(n/a). https://doi.org/https://doi.org/10.1111/twec.13483

Krol, L. R., & Zander, T. O. (2017). Passive BCI-Based Neuroadaptive Systems. Graz Brain-Computer Interface Conference 2017,

Kuechler, W., & Vaishnavi, V. (2008a). The emergence of design research in information systems in North America. *Journal of Design Research*, *7*, 1. https://doi.org/10.1504/JDR.2008.019897

Kuechler, W., & Vaishnavi, V. (2008b). On theory development in design science research: anatomy of a research project. *EJIS*, *17*, 489-504.

Kuksov, D., & Villas-Boas, J. M. (2009). When More Alternatives Lead to Less Choice. *Marketing Science*, *29*(3), 507-524. https://doi.org/10.1287/mksc.1090.0535

Kuksov, D., & Villas-Boas, J. M. (2010). When more alternatives lead to less choice. *Marketing Science*, *29*(3), 507-524. https://doi.org/10.1287/mksc.1090.0535

Kurien, R., Paila, A. R., & Nagendra, A. (2014). Application of Paralysis Analysis Syndrome in Customer Decision Making. *Procedia Economics and Finance*, *11*, 323-334. https://doi.org/https://doi.org/10.1016/S2212-5671(14)00200-7

Kuvaas, B., & Kaufmann, G. (2004). Impact of mood, framing, and need for cognition on decision makers' recall and confidence. *Journal of Behavioral Decision Making*, *17*(1), 59-74. https://doi.org/https://doi.org/10.1002/bdm.461

Kwon, S. J., & Chung, N. (2010). The moderating effects of psychological reactance and product involvement on online shopping recommendation mechanisms based on a causal map. *Electronic Commerce Research and Applications*, *9*(6), 522-536. https://doi.org/https://doi.org/10.1016/j.elerap.2010.04.004

Lajos, J., Chattopadhyay, A., & Sengupta, K. (2009). When Electronic Recommendation Agents Backfire: Negative Effects on Choice Satisfaction, Attitudes, and Purchase Intentions.

Laroche, M., Kim, C., & Zhou, L. (1996). Brand familiarity and confidence as determinants of purchase intention: An empirical test in a multiple brand context. *Journal of Business Research*, *37*(2), 115-120. https://doi.org/https://doi.org/10.1016/0148-2963(96)00056-2

Leary, M. R., & Hoyle, R. H. (2009). *Handbook of individual differences in social behavior*. The Guilford Press.

Lee, B.-K., & Lee, W.-N. (2004). The effect of information overload on consumer choice quality in an on-line environment [https://doi.org/10.1002/mar.20000]. *Psychology & Marketing*, *21*(3), 159-183. https://doi.org/https://doi.org/10.1002/mar.20000

Lee, G., Lee, J., & Sanford, C. (2010). The roles of self-concept clarity and psychological reactance in compliance with product and service recommendations. *Computers in Human Behavior*, *26*(6), 1481-1487. https://doi.org/https://doi.org/10.1016/j.chb.2010.05.001

Lee, G., & Lee, W. J. (2009). Psychological reactance to online recommendation services. *Information & Management*, *46*(8), 448-452. https://doi.org/https://doi.org/10.1016/j.im.2009.07.005

Lee, K. C., & Kwon, S. (2008). Online shopping recommendation mechanism and its influence on consumer decisions and behaviors: A causal map approach. *Expert Systems with Applications*, *35*(4), 1567-1574. https://doi.org/https://doi.org/10.1016/j.eswa.2007.08.109

Lee, Y. E., & Benbasat, I. (2011). Research Note—The Influence of Trade-off Difficulty Caused by Preference Elicitation Methods on User Acceptance of Recommendation Agents Across Loss and Gain Conditions. *Information Systems Research*, *22*(4), 867-884. https://doi.org/10.1287/isre.1100.0334

Leninkumar, V. (2017). The Relationship between Customer Satisfaction and Customer Trust on Customer Loyalty. *International Journal of Academic Research in Business and Social Sciences*, *7*(4), 450-465. https://EconPapers.repec.org/RePEc:hur:ijarbs:v:7:y:2017:i:4:p:450-465

Levin, I. P., Huneke, M. E., & Jasper, J. D. (2000). Information Processing at Successive Stages of Decision Making: Need for Cognition and Inclusion–Exclusion Effects. *Organizational Behavior and Human Decision Processes*, *82*(2), 171-193. https://doi.org/https://doi.org/10.1006/obhd.2000.2881

Li, Y., Chen, W., & Yan, H. (2017). *Learning Graph-based Embedding For Time-Aware Product Recommendation* Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, Singapore, Singapore. https://doi.org/10.1145/3132847.3133060

Liang, T.-P., Lai, H.-J., & Ku, Y.-C. (2006). Personalized Content Recommendation and User Satisfaction: Theoretical Synthesis and Empirical Findings. *Journal of Management Information Systems*, *23*(3), 45-70. https://doi.org/10.2753/MIS0742-1222230303

Liberman, V., & Tversky, A. (1993). On the evaluation of probability judgments: Calibration, resolution, and monotonicity. *Psychological Bulletin*, *114*(1), 162-173. https://doi.org/10.1037/0033-2909.114.1.162

Linden, G., Smith, B., & York, J. (2003). *Amazon.com Recommendations* (IEEE Internet Computing, Issue. I. C. Society. https://www.cs.umd.edu/~samir/498/Amazon-Recommendations.pdf

Lins de Holanda Coelho, G., P, H. P. H., & L, J. W. (2020). The Very Efficient Assessment of Need for Cognition: Developing a Six-Item Version. *Assessment*, *27*(8), 1870-1885. https://doi.org/10.1177/1073191118793208

Liu, L., Zheng, Y., & Chen, R. (2015). Better with more choices? Impact of choice set size on variety seeking. *Acta Psychologica Sinica*, *47*(1), 66-78.

Liu, S., Kaikati, A. M., & Arnold, M. J. (2023). To touch or not to touch: Examining the role of choice set size. *Psychology & Marketing*, *40*(3), 567-578. https://doi.org/10.1002/mar.21754

Lops, P., de Gemmis, M., & Semeraro, G. (2011). Content-based Recommender Systems: State of the Art and Trends. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender Systems Handbook* (pp. 73-105). Springer US. https://doi.org/10.1007/978-0-387-85820-3_3

Lurie, N. H. (2004). Decision Making in Information-Rich Environments: The Role of Information Structure. *Journal of Consumer Research*, *30*(4), 473-486. https://doi.org/10.1086/380283

MacKenzie, I., Meyer, C., & Noble, S. (2013). *How retailers can keep up with consumers* (McKinsey & Company). M. Company. https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers#/download/%2F~%2Fmedia%2Fmckinsey%2Findustries%2Fretail%2Four%20insights%2Fhow%20retailers%20can%20keep%20up%20with%20consumers%2Fhow_retailers_can_keep_up_with_consumers_v2.pdf%3FshouldIndex%3Dfalse

Madrian, B. C., & Shea, D. F. (2001). The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior*. *The Quarterly Journal of Economics*, *116*(4), 1149-1187. https://doi.org/10.1162/003355301753265543

Maheswarappa, S. S., Sivakumaran, B., & Kumar, A. G. (2017). Returns to search when consumers use and do not use recommendation agents. *Asia Pacific Journal of Marketing and Logistics*, *29*(4), 813-836. https://doi.org/10.1108/APJML-10-2016-0188

Malhotra, N. K. (1982). Information load and consumer decision making. *Journal of Consumer Research*, *8*(4), 419-430.

Malone, T., & Lusk, J. L. (2019). Mitigating Choice Overload: An Experiment in the U.S. Beer Market. *Journal of Wine Economics*, *14*(1), 48-70. https://doi.org/10.1017/jwe.2018.34

Manfredo, M. J., & Bright, A. D. (1991). A model for assessing the effects of communication on recreationists. *Journal of Leisure Research*, *23*(1), 1-20. https://doi.org/10.1080/00222216.1991.11969840

Manolică, A., Guță, A.-S., Roman, T., & Dragăn, L. M. (2021). Is Consumer Overchoice a Reason for Decision Paralysis? *Sustainability*, *13*(11).

Marchand, A., & Marx, P. (2020). Automated Product Recommendations with Preference-Based Explanations. *Journal of Retailing*, *96*(3), 328-343. https://doi.org/https://doi.org/10.1016/j.jretai.2020.01.001

McKenny, J. L., & Keen, P. G. W. (1974, May 1974). How Managers' Minds Work. *Harvard Business Review*, 79-90.

Mcquarrie, E. F., & Munson, J. M. (1992). A Revised Product Involvement Inventory: Improved Usability and Validity. *ACR North American Advances*.

Melovic, B., Cirovic, D., Dudic, B., Vulic, T. B., & Gregus, M. (2020). The analysis of marketing factors influencing consumers' preferences and acceptance of organic food products—Recommendations for the optimization of the offer in a developing market. *Foods*, *9*(3), 259.

Mild, A., & Reutterer, T. (2003). An improved collaborative filtering approach for predicting cross-category purchases based on binary market basket data. *Journal of Retailing and Consumer Services*, *10*(3), 123-133.

Miri Ashtiani, S. N., & Daliri, M. R. (2023). Identification of cognitive load-dependent activation patterns using working memory task-based fMRI at various levels of difficulty. *Scientific Reports*, *13*(1), 16476.

Mishra, S. N., & Kumar, S. (2023, 28-30 April 2023). A Product based Recommendation System for E-Commerce Sites. 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES),

Misuraca, R., Ceresia, F., Teuscher, U., & Faraci, P. (2019). The Role of the Brand on Choice Overload. *Mind & Society*, *18*(1), 57-76. https://doi.org/10.1007/s11299-019-00210-7

Misuraca, R., Teuscher, U., & Faraci, P. (2016). Is more choice always worse? Age differences in the overchoice effect. *Journal of Cognitive Psychology*, *28*(2), 242-255. https://doi.org/10.1080/20445911.2015.1118107

Mitchell, A. A., & Dacin, P. A. (1996). The Assessment of Alternative Measures of Consumer Expertise. *Journal of Consumer Research*, *23*(3), 219-239. https://doi.org/10.1086/209479

Mogilner, C., Rudnick, T., & Iyengar, S. S. (2008). The Mere Categorization Effect: How the Presence of Categories Increases Choosers' Perceptions of Assortment Variety and Outcome Satisfaction. *Journal of Consumer Research*, *35*(2), 202-215. https://doi.org/10.1086/588698

Moorman, C., Diehl, K., Brinberg, D., Kidwell, B., Bettman, J., Chartrand, T., Levav, J., Lynch, J., Mela, C., & Rose, R. (2004). Subjective Knowledge, Search Locations, and Consumer Choice. *Journal of Consumer Research - J CONSUM RES*, *31*. https://doi.org/10.1086/425102

Nagar, K., & Gandotra, P. (2016). Exploring Choice Overload, Internet Shopping Anxiety, Variety Seeking and Online Shopping Adoption Relationship: Evidence from Online Fashion Stores. *Global Business Review*, *17*(4), 851-869. https://doi.org/10.1177/0972150916645682

Naiseh, M., Jiang, N., Ma, J., & Ali, R. (2020). Explainable Recommendations in Intelligent Systems: Delivery Methods, Modalities and Risks. In *Research Challenges in Information Science* (pp. 212-228). https://doi.org/10.1007/978-3-030-50316-1_13

Nataraajan, R., & Angur, M. G. (1998). *Perceived control in consumer choice: A closer look*. Association for Consumer Research.

Nesterkin, D. A. (2013). Organizational change and psychological reactance. *Journal of Organizational Change Management*, *26*(3), 573-594. https://doi.org/10.1108/09534811311328588

Nguyen, J., Le, Q. V., & Ha, J. T. (2021). Impacts of Health and Safety Concerns on E-Commerce and Service Reconfiguration During the COVID-19 Pandemic: Insights from an Emerging Economy. *Service Science*, *13*(4), 227-242. https://doi.org/10.1287/serv.2021.0279

NielsenIQ. (2019). *Bursting with new products, there's never been a better time for breakthrough innovation* NielsenIQ. https://nielseniq.com/global/en/insights/analysis/2019/bursting-with-new-products-theres-never-been-a-better-time-for-breakthrough-innovation/

Nilashi, M., Jannach, D., Ibrahim, O., Dalvi, M., & Ahmadi, H. (2016). Recommendation, transparency, and website quality for trust-building in recommendation agents. *Electronic Commerce Research and Applications*, *19*. https://doi.org/10.1016/j.elerap.2016.09.003

Nunes, I., & Jannach, D. (2017). A systematic review and taxonomy of explanations in decision support and recommender systems. *User Modeling and User-Adapted Interaction*, *27*(3), 393-444. https://doi.org/10.1007/s11257-017-9195-0

Okfalisa, O., Rusnedy, H., Iswavigra, D. U., Pranggono, B., Haerani, E. H., & Saktioto, S. (2020). Decision Support System for Smartphone Recommendation: The Comparison of Fuzzy Ahp and Fuzzy Anp in Multi-Attribute Decision Making. *Sinergi*, *25*(1). https://doi.org/10.22441/sinergi.2021.1.013

Oppewal, H., & Koelemeijer, K. (2005). More choice is better: Effects of assortment size and composition on assortment evaluation. *International Journal of Research in Marketing*, *22*(1), 45-60. https://doi.org/https://doi.org/10.1016/j.ijresmar.2004.03.002

Özkan, E., & Tolon, M. (2015). The Effects of Information Overload on Consumer Confusion: An Examination on User Generated Content. *Bogazici Journal*, *29*, 27-51. https://doi.org/10.21773/boun.29.1.2

Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. *Educational Psychologist*, *38*(1), 63-71. https://doi.org/10.1207/S15326985EP3801_8

Padmala, S., Bauer, A., & Pessoa, L. (2011). Negative Emotion Impairs Conflict-Driven Executive Control [Original Research]. *Frontiers in Psychology*, *2*. https://doi.org/10.3389/fpsyg.2011.00192

Park, C. W., & Lessig, V. P. (1981). Familiarity and its impact on consumer decision biases and heuristics. *Journal of Consumer Research*, *8*(2), 223-230. https://doi.org/10.1086/208859

Patharia, I., & Jain, T. (2023). Antecedents of Electronic Shopping Cart Abandonment during Online Purchase Process. *Business Perspectives and Research*, 22785337221148810. https://doi.org/10.1177/22785337221148810

Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance*, *16*(2), 366-387. https://doi.org/https://doi.org/10.1016/0030-5073(76)90022-2

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker* [doi:10.1017/CBO9781139173933]. Cambridge University Press. https://doi.org/10.1017/CBO9781139173933

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*, 45. https://doi.org/10.2753/MIS0742-1222240302

Peng, M., Xu, Z., & Huang, H. (2021). How Does Information Overload Affect Consumers' Online Decision Process? An Event-Related Potentials Study. *Front Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.695852

Pereira, R. E. (2001). Influence of Query-Based Decision Aids on Consumer Decision Making in Electronic Commerce. *Information Resources Management Journal (IRMJ)*, *14*(1), 31-48. https://doi.org/10.4018/irmj.2001010104

Perry, N. C., Wiggins, M. W., Childs, M., & Fogarty, G. (2012). Can reduced processing decision support interfaces improve the decision-making of less-experienced incident commanders? [Article]. *Decision Support Systems*, *52*(2), 497-504. https://doi.org/10.1016/j.dss.2011.10.010

Petrocelli, J. V., Tormala, Z. L., & Rucker, D. D. (2007). Unpacking attitude certainty: attitude clarity and attitude correctness. *Journal of Pers Soc Psychol*, *92*(1), 30-41. https://doi.org/10.1037/0022-3514.92.1.30

Petty, R. E., Brinol, P., Loersch, C., & McCaslin, M. J. (2009). The need for cognition. In *Handbook of individual differences in social behavior.* (pp. 318-329). The Guilford Press.

Petty, R. E., Briñol, P., & Tormala, Z. L. (2002). Thought confidence as a determinant of persuasion: The self-validation hypothesis. *Journal of Personality and Social Psychology*, *82*(5), 722-741. https://doi.org/10.1037/0022-3514.82.5.722

Petty, R. E., Briñol, P., Tormala, Z. L., & Wegener, D. T. (2007). *The Role of Meta-Cognition in Social Judgment* (A. W. H. Kruglanski, E. T. , Ed. 2 ed.). Social Psychology: Handbook of Basic Principles, The Guilford Press.

Petty, R. E., & Cacioppo, J. T. (2012). *Communication and persuasion: Central and peripheral routes to attitude change*. Springer Science & Business Media.

Pratiwi, D., Putri, J., & Agushinta R, D. (2014). Decision Support System to Majoring High School Student Using Simple Additive Weighting Method. *International Journal of Computer Trends and Technology*, *10*, 153-159. https://doi.org/10.14445/22312803/IJCTT-V10P126

Punj, G. (2012). Consumer Decision Making on the Web: A Theoretical Analysis and Research Guidelines. *Psychology & Marketing*, *29*(10), 791-803. https://doi.org/https://doi.org/10.1002/mar.20564

Rahinel, R., Otto, A. S., Grossman, D. M., & Clarkson, J. J. (2021). Exposure to brands makes preferential decisions easier. *Journal of Consumer Research*, *48*(4), 541-561. https://doi.org/10.1093/jcr/ucab025

Rains, S. A. (2013). The Nature of Psychological Reactance Revisited: A Meta-Analytic Review. *Human Communication Research*, *39*(1), 47-73. https://doi.org/https://doi.org/10.1111/j.1468-2958.2012.01443.x

Reed, A. E., Mikels, J. A., & Löckenhoff, C. E. (2012). Choosing with confidence: Self-efficacy and preferences for choice. *Judgment and Decision Making*, *7*(2), 173-180.

Reutkaja, E. I., S. S , Fasolo, B., & R., M. (2021). Cognitive and Affective Consequences of Information and Choice Overload. In R. Viale (Ed.), *Routledge Handbook of Bounded Rationality* (pp. pp. 625-636).

Reutskaja, E., Cheek, N. N., Iyengar, S., & Schwartz, B. (2021). Choice Deprivation, Choice Overload, and Satisfaction with Choices Across Six Nations. *Journal of International Marketing*, *30*(3), 18-34. https://doi.org/10.1177/1069031X211073821

Reutskaja, E., Iyengar, S., Fasolo, B., & Misuraca, R. (2020). Cognitive and affective consequences of information and choice overload. In R. Viale, (ed.) (Ed.), *Routledge Handbook of Bounded Rationality* (pp. 625-636). Routledge International Handbooks.

Ricci, F., Rokach, L., & Shapira, B. (2022). Recommender Systems: Techniques, Applications, and Challenges. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender Systems Handbook* (pp. 1-35). Springer US. https://doi.org/10.1007/978-1-0716-2197-4_1

Richins, M. L., & Bloch, P. H. (1991). Post-purchase product satisfaction: Incorporating the effects of involvement and time. *Journal of Business Research*, *23*(2), 145-158. https://doi.org/https://doi.org/10.1016/0148-2963(91)90025-S

Roberts, J. H., & Lattin, J. M. (1991). Development and Testing of a Model of Consideration Set Composition. *Journal of Marketing Research*, *28*(4), 429-440. https://doi.org/10.2307/3172783

Robinette, P., Li, W., Allen, R., Howard, A., & Wagner, A. (2016). *Overtrust of Robots in Emergency Evacuation Scenarios*. https://doi.org/10.1109/HRI.2016.7451740

Roetzel, P. G. (2019). Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. *Business Research*, *12*(2), 479-522. https://doi.org/10.1007/s40685-018-0069-z

Ron-Angevin, R., Garcia, L., Fernández-Rodríguez, Á., Saracco, J., André, J. M., & Lespinet-Najib, V. (2019). Impact of Speller Size on a Visual P300 Brain-Computer Interface (BCI) System under Two Conditions of Constraint for Eye Movement [Article]. *Computational Intelligence & Neuroscience*, 1-16. https://doi.org/10.1155/2019/7876248

Rose, J. M. (2005). Decision Aids and Experiential Learning [Article]. *Behavioral Research in Accounting*, *17*, 175-189. https://doi.org/10.2308/bria.2005.17.1.175

Rose, J. M., Roberts, F. D., & Rose, A. M. (2004). Affective responses to financial data and multimedia: the effects of information load and cognitive load. *International Journal of Accounting Information Systems*, *5*(1), 5-24. https://doi.org/https://doi.org/10.1016/j.accinf.2004.02.005

Rosenberg, B. D., & Siegel, J. T. (2018). A 50-year review of psychological reactance theory: Do not read this article. *Motivation Science*, *4*(4), 281-300. https://doi.org/10.1037/mot0000091

Salem, M., Lakatos, G., Amirabdollahian, F., & Dautenhahn, K. (2015). *Would You Trust a (Faulty) Robot? Effects of Error, Task Type and Personality on Human-Robot Cooperation and Trust* Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction, Portland, Oregon, USA. https://doi.org/10.1145/2696454.2696497

Santoso, P. A., Wibawa, A. P., & Pujianto, U. (2018). Internship recommendation system using simple additive weighting. *Bulletin of Social Informatics Theory and Application*, *2*(1), 15-21. https://doi.org/10.31763/businta.v2i1.102

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2000). *Analysis of Recommendation Algorithms for E-Commerce* (GroupLens Research Group / Army HPC Research Center, Issue. G. R. G. A. H. R. Center.

Scheibehenne, B., Greifeneder, R., & Todd, P. (2010). Can There Ever be Too Many Options? A Meta-analytic Review of Choice Overload. *Journal of Consumer Research*, *37*, 409-425. https://doi.org/10.1086/651235

Schulz, E., Bhui, R., Love, B. C., Brier, B., Todd, M. T., & Gershman, S. J. (2019). Structured, uncertainty-driven exploration in real-world consumer choice. *Proceedings of the National Academy of Sciences*, *116*(28), 13903-13908. https://doi.org/10.1073/pnas.1821028116

Schwartz, B. (2016). *The Paradox of Choice: Why More Is Less* (E. Press, Ed. 2nd ed.).

Sela, A., & Berger, J. (2012). How Attribute Quantity Influences Option Choice. *Journal of Marketing Research*, *49*(6), 942-953. https://doi.org/10.1509/jmr.11.0142

Sela, A., Berger, J., & Liu, W. (2009). Variety, Vice, and Virtue: How Assortment Size Influences Option Choice. *Journal of Consumer Research*, *35*(6), 941-951. https://doi.org/10.1086/593692

Senecal, S., Kalczynski, P. J., & Nantel, J. (2005). Consumers' decision-making process and their online shopping behavior: a clickstream analysis. *Journal of Business Research*, *58*(11), 1599-1608. https://doi.org/https://doi.org/10.1016/j.jbusres.2004.06.003

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. *Journal of Retailing*, *80*(2), 159-169. https://doi.org/https://doi.org/10.1016/j.jretai.2004.04.001

Shang, Q., Chen, J., Fu, H., Wang, C., Pei, G., & Jin, J. (2023). "Guess You Like It" - How personalized recommendation timing and product type influence consumers' acceptance: An ERP study. *Neurosci Letters*, *807*, 137261. https://doi.org/10.1016/j.neulet.2023.137261

Shanteau, J. (1992). Competence in experts: The role of task characteristics. *Organizational Behavior and Human Decision Processes*, *53*(2), 252-266. https://doi.org/https://doi.org/10.1016/0749-5978(92)90064-E

Sharma, J., Sharma, K., Garg, K., & Sharma, A. K. (2021). Product Recommendation System a Comprehensive Review. *IOP Conference Series: Materials Science and Engineering*, *1022*(1), 12-21. https://doi.org/10.1088/1757-899X/1022/1/012021

Shen, A. (2014). Recommendations as personalized marketing: insights from customer experiences. *Journal of Services Marketing*, *28*(5), 414-427. https://doi.org/10.1108/JSM-04-2013-0083

Shen, L., & Dillard, J. (2005). Psychometric Properties of the Hong Psychological Reactance Scale. *Journal of personality assessment*, *85*, 74-81. https://doi.org/10.1207/s15327752jpa8501_07

Shen, L., & Dillard, J. P. (2005). Psychometric properties of the Hong psychological reactance scale. *J Pers Assess*, *85*(1), 74-81. https://doi.org/10.1207/s15327752jpa8501_07

Sheng, X., Li, J., & Zolfagharian, M. A. (2014). Consumer initial acceptance and continued use of recommendation agents: literature review and proposed conceptual framework. *International Journal of Electronic Marketing and Retailing*, *6*(2), 112-127. https://doi.org/10.1504/IJEMR.2014.066467

Shields, G. S., Moons, W. G., Tewell, C. A., & Yonelinas, A. P. (2016). The effect of negative affect on cognition: Anxiety, not anger, impairs executive function. *Emotion*, *16*(6), 792-797. https://doi.org/10.1037/emo0000151

Simon, H. A. (1959). Theories of Decision-Making in Economics and Behavioral Science. *The American Economic Review*, *49*(3), 253-283. http://www.jstor.org/stable/1809901

Simon, H. A. (1996). *The sciences of the artificial*. MIT press.

Sirois, S., & Brisson, J. (2014). Pupillometry. *Wiley Interdisciplinary Reviews: Cognitive Science*, *5*(6), 679-692.

Slama, M. E., & Tashchian, A. (1985). Selected socioeconomic and demographic characteristics associated with purchasing involvement. *Journal of marketing*, *49*(1), 72-82.

Smith, S. M., & Levin, I. P. (1996). Need for Cognition and Choice Framing Effects. *Journal of Behavioral Decision Making*, *9*(4), 283-290. https://doi.org/https://doi.org/10.1002/(SICI)1099-0771(199612)9:4<283::AID-BDM241>3.0.CO;2-7

Soliha, E., Marlien, R. A., Widyasari, S., Riva'i, A. R., & Nurul, K. (2019). Image, Consumer Product Knowledge, Satisfaction and Loyalty Testing Their Relationships in the Rural Bank Sector. *International Journal of Economics and Management Systems 40*(42), 1267-1274.

Spuler, M. (2017). A high-speed brain-computer interface (BCI) using dry EEG electrodes. *PLoS ONE*, *12*(2), e0172400. https://doi.org/10.1371/journal.pone.0172400

Stanton, J. V., & Cook, L. A. (2019). Product knowledge and information processing of organic foods. *Journal of Consumer Marketing*, *36*(1), 240-252. https://doi.org/10.1108/JCM-07-2017-2275

Steindl, C., Jonas, E., Sittenthaler, S., Traut-Mattausch, E., & Greenberg, J. (2015). Understanding Psychological Reactance: New Developments and Findings. *Zeitschrift für Psychologie*, *223*(4), 205-214. https://doi.org/10.1027/2151-2604/a000222

Sun, P., Yang, J., & Zhi, Y. (2019). Multi-attribute decision-making method based on Taylor expansion. *International Journal of Distributed Sensor Networks*, *15*(3). https://doi.org/10.1177/1550147719836078

Swaminathan, V. (2003). The Impact of Recommendation Agents on Consumer Evaluation and Choice: The Moderating Role of Category Risk, Product Complexity, and Consumer Knowledge. *Journal of Consumer Psychology*, *13*(1), 93-101. https://doi.org/https://doi.org/10.1207/S15327663JCP13-1&2_08

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257-285. https://doi.org/https://doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2011). CHAPTER TWO - Cognitive Load Theory. In J. P. Mestre & B. H. Ross (Eds.), *Psychology of Learning and Motivation* (Vol. 55, pp. 37-76). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. (1998). Cognitive Architecture and Instructional Design. *Educational Psychology Review*, *10*, 251. https://doi.org/https://doi.org/10.1023/a:1022193728205

Szász, L., Bálint, C., Csíki, O., Nagy, B. Z., Rácz, B.-G., Csala, D., & Harris, L. C. (2022). The impact of COVID-19 on the evolution of online retail: The pandemic as a window of opportunity. *Journal of Retailing and Consumer Services*, *69*, 103089. https://doi.org/https://doi.org/10.1016/j.jretconser.2022.103089

Tadson, B., Boasen, J., Courtemanche, F., Beauchemin, N., Karran, A.-J., Léger, P.-M., & Sénécal, S. (2023). Neuro-Adaptive Interface System to Evaluate Product Recommendations in the Context of E-Commerce. Design Science Research for a New Society: Society 5.0, Pretoria, South Africa.

Takemura, K. (1985). Ishikettei sutorateji jikko ni okeru meta ninchi katei moderu [Metacognition process model in the implementation of decision-making strategy]. *Doshisha Psychological Review*, *32*, pp 16-22.

Takemura, K. (2001). Contingent Decision Making in the Social World: The “Mental Ruler” Model. In C. M. Allwood & M. Selart (Eds.), *Decision Making: Social and Creative Dimensions* (pp. 153-173). Springer Netherlands. https://doi.org/10.1007/978-94-015-9827-9_8

Takemura, K. (2014). Behavioral Decision Theories that Explain Decision-Making Processes. In K. Takemura (Ed.), *Behavioral Decision Theory: Psychological and Mathematical Descriptions of Human Choice Behavior* (pp. 143-164). Springer Japan. https://doi.org/10.1007/978-4-431-54580-4_12

Taylor-West, P., Fulford, H., Reed, G., Story, V., & Saker, J. (2008). Familiarity, expertise and involvement: key consumer segmentation factors. *Journal of Consumer Marketing*, *25*(6), 361-368. https://doi.org/10.1108/07363760810902495

Thomas, M., & Menon, G. (2007). When Internal Reference Prices and Price Expectations Diverge: The Role of Confidence. *Journal of Marketing Research*, *44*(3), 401-409. https://doi.org/10.1509/jmkr.44.3.401

Thorpe, A., Friedman, J., Evans, S., Nesbitt, K., & Eidels, A. (2022). Mouse Movement Trajectories as an Indicator of Cognitive Workload. *International Journal of Human–Computer Interaction*, *38*(15), 1464-1479.

Tian, Y., Beier, M. E., & Fischer-Baum, S. (2022). The domain-specificity of serial order working memory. *Memory & Cognition*, *50*(5), 941-961. https://doi.org/10.3758/s13421-021-01260-4

Tintarev, N., & Masthoff, J. (2012). Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction*, *22*(4), 399-439. https://doi.org/10.1007/s11257-011-9117-5

Todd, P., & Benbasat, I. (1994). The Influence of Decision Aids on Choice Strategies: An Experimental Analysis of the Role of Cognitive Effort. *Organizational Behavior and Human Decision Processes*, *60*(1), 36-74. https://doi.org/https://doi.org/10.1006/obhd.1994.1074

Toffler, A. (1970). *Future shock* (Bantam, Ed.). Random House.

Tokushige, H., Narumi, T., Ono, S., Fuwamoto, Y., Tanikawa, T., & Hirose, M. (2017). *Trust Lengthens Decision Time on Unexpected Recommendations in Human-agent Interaction* Proceedings of the 5th International Conference on Human Agent Interaction, Bielefeld, Germany. https://doi.org/10.1145/3125739.3125751

Torres, F., Gendreau, M., & Rei, W. (2022). Crowdshipping: An open VRP variant with stochastic destinations. *Transportation Research Part C: Emerging Technologies*, *140*, 103677. https://doi.org/https://doi.org/10.1016/j.trc.2022.103677

Townsend, C., & Kahn, B. E. (2014). The “Visual Preference Heuristic”: The Influence of Visual versus Verbal Depiction on Assortment Processing, Perceived Variety, and Choice Overload. *Journal of Consumer Research*, *40*(5), 993-1015. https://doi.org/10.1086/673521

Tsekouras, D., Li, T., & Benbasat, I. (2022). Scratch my back and I'll scratch yours: The impact of user effort and recommendation agent effort on perceived recommendation agent quality. *Information & Management*, *59*(1), 103571. https://doi.org/https://doi.org/10.1016/j.im.2021.103571

Urbany, J. E., Dickson, P. R., & Wilkie, W. L. (1989). Buyer Uncertainty and Information Search. *Journal of Consumer Research*, *16*(2), 208-215. https://doi.org/10.1086/209209

van der Merwe, A., Gerber, A., & Smuts, H. (2020). Guidelines for Conducting Design Science Research in Information Systems. In *ICT Education* (pp. 163-178). https://doi.org/10.1007/978-3-030-35629-3_11

Velasco-Álvarez, F., Fernández-Rodríguez, Á., Vizcaíno-Martín, F.-J., Díaz-Estrella, A., & Ron-Angevin, R. (2021). Brain–Computer Interface (BCI) Control of a Virtual Assistant in a Smartphone to Manage Messaging Applications [Article]. *Sensors (14248220)*, *21*(11), 3716-3716. https://doi.org/10.3390/s21113716

Verhagen, T., & Bloemers, D. (2018). Exploring the cognitive and affective bases of online purchase intentions: a hierarchical test across product types. *Electronic Commerce Research*, *18*(3), 537-561. https://doi.org/10.1007/s10660-017-9270-y

Verplanken, B. (1993). Need for Cognition and External Information Search: Responses to Time Pressure during Decision-Making. *Journal of Research in Personality*, *27*(3), 238-252. https://doi.org/https://doi.org/10.1006/jrpe.1993.1017

Vogrincic-Haselbacher, C., Krueger, J. I., Lurger, B., Dinslaken, I., Anslinger, J., Caks, F., Florack, A., Brohmer, H., & Athenstaedt, U. (2021). Not Too Much and Not

Too Little: Information Processing for a Good Purchase Decision [Original Research]. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.642641

Wang, S., Gwizdka, J., & Chaovalitwongse, W. A. (2016). Using Wireless EEG Signals to Assess Memory Workload in the N-Back Task. *IEEE Transactions on Human-Machine Systems*, *46*(3), 424-435. https://doi.org/10.1109/THMS.2015.2476818

Wang, W., & Benbasat, I. (2007). Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs. *J. of Management Information Systems*, *23*, 217-246. https://doi.org/10.2753/MIS0742-1222230410

Weber, P., Rupprecht, F., Wiesen, S., Hamann, B., & Ebert, A. (2021). Assessing cognitive load via pupillometry. Advances in Artificial Intelligence and Applied Cognitive Computing: Proceedings from ICAI'20 and ACC'20,

Wegener, D. T., & Petty, R. E. (2001). Understanding effects of mood through the elaboration likelihood and flexible correction models. In *Theories of mood and cognition: A user's guidebook.* (pp. 177-210). Lawrence Erlbaum Associates Publishers.

Wen, N., & Lurie, N. H. (2019). More Than Aesthetic: Visual Boundaries and Perceived Variety [Article]. *Journal of Retailing*, *95*(3), 86-98. https://doi.org/10.1016/j.jretai.2019.03.001

Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D. R., Matz, S., Nave, G., Parker, J. R., Puntoni, S., Zheng, Y., & Zwebner, Y. (2020). Autonomy in consumer choice. *Marketing Letters*, *31*(4), 429-439. https://doi.org/10.1007/s11002-020-09521-z

Whang, C., & Im, H. (2021). "I Like Your Suggestion!" the role of humanlikeness and parasocial relationship on the website versus voice shopper's perception of recommendations. *Psychology & Marketing*, *38*. https://doi.org/10.1002/mar.21437

Wheeler, P., & Arunachalam, V. (2009). The effects of multimedia on cognitive aspects of decision-making. *International Journal of Accounting Information Systems*, *10*(2), 97-116. https://doi.org/https://doi.org/10.1016/j.accinf.2008.10.004

Wheeler, S. C., Petty, R. E., & Bizer, G. Y. (2005). Self-schema matching and attitude change: Situational and dispositional determinants of message elaboration. *Journal of Consumer Research*, *31*(4), 787-797.

Whelan, R. R. (2007). Neuroimaging of cognitive load in instructional multimedia. *Educational Research Review*, *2*(1), 1-12.

Willemsen, M., Knijnenburg, B., Graus, M., Velter-Bremmers, L., & Fu, K. (2011). Using latent features diversification to reduce choice difficulty in recommendation lists. CEUR Workshop Proceedings,

Willemsen, M. C., Graus, M. P., & Knijnenburg, B. P. (2016). Understanding the role of latent feature diversification on choice difficulty and satisfaction. *User Modeling* *and User-Adapted Interaction*, *26*(4), 347-389. https://doi.org/10.1007/s11257-016-9178-6

Woller, K. M. P., Buboltz, W. C., & Loveland, J. M. (2007). Psychological Reactance: Examination across Age, Ethnicity, and Gender. *The American Journal of Psychology*, *120*(1), 15-24. https://doi.org/10.2307/20445379

Wolpaw, J. R., Millán, J. d. R., & Ramsey, N. F. (2020). Chapter 2 - Brain-computer interfaces: Definitions and principles. In N. F. Ramsey & J. d. R. Millán (Eds.), *Handbook of Clinical Neurology* (Vol. 168, pp. 15-23). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-444-63934-9.00002-0

Wu, C.-H., Parker, S. K., & de Jong, J. P. J. (2011). Need for Cognition as an Antecedent of Individual Innovation Behavior. *Journal of Management*, *40*(6), 1511-1534. https://doi.org/10.1177/0149206311429862

Xiao, B., & Benbasat, I. (2007). E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact. *MIS Quarterly*, *31*(1), 137-209. https://doi.org/10.2307/25148784

Xiao, B., & Benbasat, I. (2014). Research on the Use, Characteristics, and Impact of e-Commerce Product Recommendation Agents: A Review and Update for 2007–2012. In F. J. Martínez-López (Ed.), *Handbook of Strategic e-Business Management* (pp. 403-431). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-39747-9_18

Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. *Decision Support Systems*, *110*, 46-57. https://doi.org/https://doi.org/10.1016/j.dss.2018.03.005

Xu, J., Benbasat, I., & Cenfetelli, R. T. (2020). The Relative Effect of the Convergence of Product Recommendations from Various Online Sources. *Journal of Management Information Systems*, *37*(3), 788-819. https://doi.org/10.1080/07421222.2020.1790192

Yan, Q., Zhang, L., Li, Y., Wu, S., Sun, T., Wang, L., & Chen, H. (2016). Effects of product portfolios and recommendation timing in the efficiency of personalized recommendation. *Journal of Consumer Behaviour*, *15*(6), 516-526. https://doi.org/https://doi.org/10.1002/cb.1588

Yangyang Miao, m. c., Shugeng Chen, t. c., Xinru Zhang, z. c., Jing Jin, j. g. c., Ren Xu, x. g. a., Ian Daly, i. d. e. a. u., Jie Jia, s. c., Xingyu Wang, x. e. e. c., Andrzej Cichocki, a. c. r. j., & Tzyy-Ping Jung, t. u. e. (2020). BCI-Based Rehabilitation on the Stroke in Sequela Stage. *Neural Plasticity*, *2020*. https://doi.org/10.1155/2020/8882764

Yanping, W., & Yan, C. (2012, 20-21 Oct. 2012). Psychology reactance to online recommendations: The influence of time pressure. 2012 3rd International Conference on System Science, Engineering Design and Manufacturing Informatization, Yi, Y. (1990). A Critical Review of Consumer Satisfaction. In V. A. Zeithaml (Ed.), *Review of Marketing* (pp. 68-123). American Marketing Association.

Yoon, V. Y., Hostler, R. E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. *Decision Support Systems*, *55*(4), 883-893. https://doi.org/https://doi.org/10.1016/j.dss.2012.12.024

Yuan, Z.-m., Huang, C., Sun, X.-y., Li, X.-x., & Xu, D.-r. (2015). A microblog recommendation algorithm based on social tagging and a temporal interest evolution model. *Frontiers of Information Technology & Electronic Engineering*, *16*(7), 532-540. https://doi.org/10.1631/FITEE.1400368

Zaichkowsky, J. (2012). Consumer involvement: Review, update and links to decision neuroscience. *Handbook of Developments in Consumer Behaviour*, 523-546. https://doi.org/10.4337/9781849802444.00022

Zeithaml, V. A., Bitner, M. J., & Gremler, D. D. (2006). *Services marketing : integrating customer focus across the firm* (4th ed. ed.). McGraw-Hill/Irwin. http://catdir.loc.gov/catdir/enhancements/fy0619/2004065642-d.html

http://catdir.loc.gov/catdir/enhancements/fy0619/2004065642-t.html

http://catdir.loc.gov/catdir/enhancements/fy0737/2004065642-b.html

Zhang, H., Zhao, L., & Gupta, S. (2018). The role of online product recommendations on customer decision making and loyalty in social shopping communities. *International Journal of Information Management*, *38*, 150-166. https://doi.org/10.1016/j.ijinfomgt.2017.07.006

Zhang, N., & Xu, H. (2019). Reconciling the paradoxical findings of choice overload through an analytical lens. *MIS Quarterly (Forthcoming)*.

Zhou, Y., Huang, S., Xu, Z., Wang, P., Wu, X., & Zhang, D. (2022). Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review. *IEEE Transactions on Cognitive and Developmental Systems*, *14*(3), 799-818. https://doi.org/10.1109/TCDS.2021.3090217

Zhu, D. H., Chang, Y., Luo, J., & Li, X. (2014). Understanding the adoption of location-based recommendation agents among active users of social networking sites. *Information Processing & Management*, *50*, 675–682. https://doi.org/10.1016/j.ipm.2014.04.010

Zhu, D. H., Wang, Y. W., & Chang, Y. P. (2018). The influence of online cross-recommendation on consumers' instant cross-buying intention. *Internet Research*, *28*(3), 604-622. https://doi.org/10.1108/IntR-05-2017-0211

Chapter 4 – Conclusion

4.1 Reminder of Research Context and Objectives

The objective of this article-based thesis was to address the discrepancies in the existing literature concerning the effectiveness of currently utilized recommendations that aim to mitigate the impact of choice overload, which grows in prevalence in today's online shopping environment. We achieved this by targeting two specific narratives underscored in the scientific discourse.

First, we endeavoured the development of a neuro-adaptive interface to attend to the need highlighted by researchers for improved assessment tools to evaluate the effects of product recommendations in the context of choice overload.

To achieve this initial subgoal, we applied a DSR methodology and proceeded to daily to weekly iterations of various subcomponents of the solution, which were executed over a period of 8 months and included 42 formative testing participants. The aspired design theory components included the following predominant testable propositions (Gregor, 2006):

- The interface simulates an online decision-making context and is susceptible of inducing choice overload.
- Provided recommendations are personalized, according to users' individual preferences.
- When applicable, recommendations are provided based on a real-time neurophysiological detection of cognitive load, measured through EEG.

Secondly, we applied this newly created artifact in an investigation aimed at assessing the effects of this novel approach of providing users with product recommendations based on cognitive load in an online decision-making simulation. This investigation served as empirical evidence for a more tailored display of recommendations, thereby providing a solution the limitations of currently employed indiscriminate recommendations and their limitations, commonly discussed by scholars and practitioners.

The study included 55 participants, aged 19 to 50 (28 female; 27 male), recruited mostly through HEC's research panel. The experiment followed a within-subjects study design and exposed participants to three recommendations display conditions: (a) control (no recommendations), (b) static (presented perpetually), and (c) neuro-adaptive (presented only if choice overload is detected). It was conducted in a controlled laboratory setting, operating in a Faraday cage to purge the EEG measures of all external, confounding electrical signal. It began by inviting participants to complete a pre-experiment questionnaire (Appendix E), followed by an EEG N-Back calibration task (Karran et al., 2019; Kirchner, 1958; Wang et al., 2016), pursued with the experimental tasks, and concluded with a post-experiment questionnaire (Appendix E).

The experimental trials were designed to simulate an online decision-making process that had the potential to induce choice overload. Participants were exposed to an assortment of 24 laptops (Greifeneder et al., 2009; Iyengar & Lepper, 2000) and 8 attributes per laptop (Greifeneder et al., 2009), and were tasked to select a single product based on their personal preferences. A total of three trials was presented in each condition, for a total of nine trials per participant. After each trial, participants were also prompted to complete a post-trial questionnaire (Appendix E).

Below is a summary of all assessed measures:

- Mediating variable: perceived choice overload.
- Dependent variables: perceptual measures of choice satisfaction and choice confidence, as well as performance metrics of decision quality and decision time.
- Moderating variables: behavioural measure of compliance with recommendations, and self-reported metrics of consumer product involvement, product expertise, psychological reactance and need for cognition.

In the subsequent sections, we present a recapitulation of the research questions that served as the foundational basis for this thesis, followed by a breakdown of main results and a discussion of the empirical findings and contributions derived from this research.

4.2 Reminder of Research Questions and Main Findings

Guided by the twofold research objective of this thesis, the research questions targeted two main goals: the creation of the artifact and its application in a research study. This first aim was therefore considered in this opening research question:

RQ1. *How can we address the aforementioned call to research*[14] *by following a DSR approach while leveraging cognitive neuroscience to develop a real-time neuro-adaptive interface for e-commerce evaluation?*

The successful development and implementation of the artifact serve as the main results derived from this research question. The proof-of-concept demonstration of the artifact operating reliably and as intended based on the sought-out design requirements allowed us to conclude the formative testing cycles associated with the development and establish the validity and quality of the system (Gregor & Hevner, 2013).

Following the first article (Chapter 2), the artifact was thus ready for real-world application in a research investigation. The second article (Chapter 3) proceeded to this practical application, thereby concluding the summative testing phase outlined in the methodological framework of **Figure 1** (Chapter 1), and validated the remaining components of utility and efficacy in the appropriate functioning of the artifact in real-world operations (Gregor & Hevner, 2013).

The results of the remaining research questions were provided by the second article of this thesis, which allowed us to deliver empirical evidence to support our overarching idea, where we posited for the advantageous effects of neuro-adaptive recommendations on decisional outcomes, compared to traditional recommendations or the absence thereof. Following is a summary of the main findings, addressing each of our subsequent research questions:

[14] This formulation was preserved, based on the original research question from the article. The call for research being referenced is the need for reliable evaluation tools to assess the effects of recommendations in instances of choice overload (Aljukhadar et al., 2012; Appiah Kusi et al., 2022; Häubl & Trifts, 2000; Yan et al., 2016).

RQ2. *To what extent does a neuro-adaptive interface which detects cognitive load and provides recommendations accordingly impact users' decision-making in an online shopping experience?*

Our findings suggest that both static and neuro-adaptive recommendations are similarly and significantly beneficial at enhancing choice confidence and decision quality, compared to when no recommendations are presented. Occasionally, neuro-adaptive recommendations exhibited significantly superior results in a few experimental trials. Choice satisfaction and decision times, however, were not directly influenced by the manipulation of recommendations display conditions, but rather through a mediation, as uncovered through the remaining research question below.

RQ3. *To what extent consumers' perceptions and individual characteristics influence their decision-making outcomes when provided with recommendations from a neuro-adaptive system?*

In terms of users' perceptions, the results indicated that, contrary to what we postulated, both static and neuro-adaptive recommendations increased perceptions choice overload, instead of alleviating them. However, most decisional outcomes were positively impacted by this rise: choice satisfaction increased through full mediation, and choice confidence heightened with a partial, complementary mediation. Only decision times were negatively impacted, as they grew significantly in relation to the increase in perceived choice overload, thereby also fully mediated. Notably though, when accounting for the mediator, significantly higher levels of choice confidence were unveiled, when recommendations were neuro-adaptive, compared to when they were static.

On the other hand, through findings regarding individual characteristics, we discover that all evaluated moderators impacted choice overload and most decisional outcomes to varying degrees. Other than the moderating effect of compliance with recommendations, which amplified the positive effects of recommendations for all concerned variables – apart from increasing choice overload, – the rest of the moderators manifested themselves prevailingly through interaction effects. Specifically, consumers scoring low on levels of product involvement, expertise, and need for cognition exhibited significantly disfavoured decisional outcomes when no recommendations are presented. However, these effects were not observed when recommendations were presented (be it statically or neuro-adaptively), which suggests that recommendations democratized decisional outcomes across different types of users.

Interestingly, individual characteristics also unveil additional benefits of neuro-adaptive recommendations. They demonstrate advantageous results in significantly improving choice satisfaction and confidence for users with low product expertise and involvement. They also benefit individuals with high need for cognition and high reactance by resulting in significantly higher choice satisfaction among the former and significantly reduced decision times among the latter. Furthermore, neuro-adaptive recommendations mitigated some of the drawbacks of standard recommendations for certain types of individuals. For instance, users with low product expertise and psychological reactance scores did not experience higher choice overload perceptions with neuro-adaptive recommendations, unlike they did in the case of static recommendations. Additionally, as opposed to static recommendations, neuro-adaptive ones did not increase decision times among users with higher psychological reactance.

4.3 Theoretical Contributions and Practical Implications

4.3.1 Theoretical Contributions

Congruent with the articles that compose this thesis, the theoretical contributions are derived from two inferences: the development of the neuro-adaptive artifact, and the evaluation of neuro-adaptive recommendations.

The BCI system we developed has direct implications for DSR in IS. The proof-of-concept of our novel application of neuro-adaptive technology in the field of e-commerce can now be formalized into a prescriptive (type Λ or lambda) design theory (Gregor & Hevner, 2013; Kuechler & Vaishnavi, 2008b; Simon, 1996). As per Gregor and Hevner (2013), a prescriptive theory comprises “how-to” knowledge gained from the instantiation of a DSR artifact, specifying how future researchers may practically undertake analogous developments. In other words, the prescriptive theory derived from our artifact may now serve as guidance in the choice of requirements, functionalities, and design decisions to achieve the construction of similar neuro-adaptive systems using the DSR framework.

The investigation we undertook, on the other hand, contributes to the state of the art by empirically supporting our proposed neuro-adaptive approach to recommendations, which yielded similar results, and occasionally outperformed canonical, static recommendations (see **Appendix F**). We therefore contributed to the sought-out research gap, devising a more personalized and interactive solution to standard recommendations.

This research also contributes by shedding light on the contradictory conclusions surrounding the benefits of recommendations (Bollen et al., 2010; Willemsen et al., 2011). Our findings show that this form of decisional aid does, in fact, result in higher choice overload and decision time, but nonetheless optimizes other decisional outcomes, namely choice satisfaction, choice confidence, and decision quality. Partially supporting both sides of the debate, we therefore advocate for a more nuanced perspective on the effect of recommendations in the context of choice overload.

Lastly, our conceptual framework integrated various theoretical perspectives, from which we may now gain a more holistic understanding of individual factors and their effects on decision-making in a context of choice overload. The significant results obtained from our moderation analyses may prompt future research to revisit current assessment models to integrate constructs whose collective significance may have been overlooked.

4.3.2 Practical Implications

The practical contributions of this thesis also span across the artifact development and the subsequent empirical study.

The instantiation of the neuro-adaptive artifact in the field of e-commerce has important implications for stakeholders, particularly researchers, as well as industry practitioners in marketing, IS, user experience, etc. They now have access to a novel, robust system, that comprises a more effective assessment tool to evaluate the effects of product recommendations in an online shopping experience, within controlled experimental settings. We were, in fact, the first to use this tool in its first research application.

Moreover, the design decisions that guided the development of the system anticipated for its versatility and customizability to accommodate various e-commerce evaluation needs. For instance, in the context of our research, we selected a cognitive load classification index. However, the latter could be replaced within the MATLAB's real-time processing block, to assess other cognitive factors, such as fatigue or attention. Similarly, the interface adaptation logic may be modified through the JSON rules engine, depending on the researchers' needs. Lastly, both the interface design and adaptation elements are entirely customizable through simple web development, using HTML, CSS, and Javascript. Through variations of the signal, adaptation elements, and interface design, practicing professionals may apply this artifact in a wide range of empirical studies.

The experimental article provides practical contributions that also serve both scholars and industry professionals, such as online retailers, marketers, consumer behaviour, and user experience researchers. Through an empirical quantitative study, we have demonstrated that displaying recommendations generally results in beneficial outcomes for online decision-makers. This decisional aid is especially beneficial when participants comply with the proposed product suggestions, which underlines the relevance for online retailers to further explore means of enticing users to accept the decisional assistance, in order to reap higher levels of choice satisfaction, confidence and decision quality.

Secondly, the results derived from our moderating constructs could help guide design decisions when dealing with specific client niches or types of products. Namely, upon conducting research on the individual characteristics of their target audience, online merchants could predict the perceptions and behaviours of their customers in response to recommendations or an absence thereof. For example, antique furniture, hobby products and video game consumers are generally highly involved (Bloch, 1986; Bloch, 1984; Taylor-West et al., 2008), so because they respond similarly to the presence and absence of recommendations, there may be no need to invest in complex recommendations systems for this clientele. Conversely, recommendations may be beneficial in instances where consumers typically possess low levels of product expertise, such as in the presence of organic food items (Stanton & Cook, 2019) or household cleaners and laundry detergents (Blackwell et al., 2001).

Lastly, our experiment shows that adding a dimension of personalization to the display of product recommendations, basing them on the occurrence of choice overload, is a promising undertaking, as it provides the most beneficial outcomes for decision-makers and, therefore, online merchants. The research therefore provides the groundwork to encourage practitioners and researchers to devise ways of achieving this enhanced personalization, without relying on neuro-adaptive technology. A few preliminary ideas and techniques to attain this are proposed in the following section.

4.4 Limitations and Future Work

Despite the neuro-adaptive system operating reliably and fulfilling our evaluation needs, a few limitations could nonetheless be revisited.

First and foremost, despite numerous iterative cycles, the cognitive load classification index still allows room for optimization to better suit the context and particularities of our interface stimuli. Secondly, adaptation conditions are not centralized within the rules agent of the web application that runs the interface, which necessitates a more cumbersome approach and a two-step adaptation logic (discussed in the Design and Development section of the article). Likewise, the identification and input of recommendations for every individual must currently be performed manually, which leaves higher potential for transcription errors. An improvement avenue for future iterations would thus consist of consolidating both of these components within the same web application for a more seamless integration of all the subcomponents of the solution.

Regarding our empirical study, future work could potentially revisit the stimuli displayed on the user interface. The design of our interface intentionally purged the stimuli of any superfluous or bias-encouraging elements, such as images and brand names. Despite being favourable at the current initial stages of experimentation, such a design is not representative of e-commerce website designs currently deployed in the real-world. Future work could thus attempt to replicate our results on an interface design that is more congruent with current industry practices.

Lately, research has also raised awareness about cultural and sociodemographic differences in response to choice overload. Specifically, consumers in individualistic cultures, such as those representing our North American sample group, place greater value on their freedom of choice and have therefore shown to exert more cognitive and emotional effort in choosing products, compared to users from collectivistic cultures (Herrmann et al., 2007). In the same vein, Reutskaja et al. (2021) posit that certain individuals are less prone to experience choice overload, as they are more accustomed to experiencing choice deprivation, as in countries like Brazil, Russia, China, Japan, and India. Future studies may therefore explore these cultural differences in consumers' responses to choice overload.

Last, but not least, a commonly discussed limitation of neuro-adaptive technology is its real-world usability outside of the controlled laboratory environment. Indeed, the goal of this research was to investigate whether personalizing recommendations based on cognitive load yielded beneficial results. Having obtained promising empirical evidence in support of this approach, new research gaps may now be filled by exploring less invasive methods of obtaining reliable measures of cognitive load in real-time.

For instance, future studies may involve a combination of modalities, such as EEG signals and other physiological measures like oculometry (Fehrenbacher & Djamasbi, 2017). This could lead to a less invasive method of identifying cognitive load, and eventually transition to a cognitive load assessment based on pupil dilation observed through a webcam. Alternatively, proxy techniques of assessing excessive cognitive load could be explored, such as on-screen behavioural indicators, like mouse movements and trajectories (Grimes & Valacich, 2015; Thorpe et al., 2022) or clicking behaviour (Beierle et al., 2020). Combining both pupillometry and on-screen behaviour approaches may also enhance their reliability for a more accurate prediction of choice overload.

References

Beierle, F., Aizawa, A., Collins, A., & Beel, J. (2020). Choice overload and recommendation effectiveness in related-article recommendations. International Journal on Digital Libraries, 21(3), 231-246. https://doi.org/10.1007/s00799-019-00270-7

Blackwell, R. D., Miniard, P. W., & Engel, J. F. (2001). Consumer Behavior (9 ed.). Harcourt College Publishers. (Pennsylvania State University)

Bloch, P. H. (1986). THE PRODUCT ENTHUSIAST: IMPLICATIONS FOR MARKETING STRATEGY. Journal of Consumer Marketing, 3(3), 51-62. https://doi.org/10.1108/eb008170

Bloch, P. H. G., Bruce D. (1984). The Leisure Experience and Consumer Products: Ari Investigation of Underlying Satisfactions. NA Advances in Consumer Research, 11, 197-202.

Bollen, D., Knijnenburg, B. P., Willemsen, M. C., & Graus, M. (2010). Understanding choice overload in recommender systems Proceedings of the fourth ACM conference on Recommender systems, Barcelona, Spain. https://doi.org/10.1145/1864708.1864724

Brehm, S. S., & Brehm, J. W. (1981). Psychological reactance : a theory of freedom and control. Academic Press New York.

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. Journal of Personality and Social Psychology, 42(1), 116-131. https://doi.org/10.1037/0022-3514.42.1.116

Ding, G.-J., Hwang, T. K. P., & Kuo, P.-C. (2020, 2020//). Progressive Disclosure Options for Improving Choice Overload on Home Screen. Advances in Usability, User Experience, Wearable and Assistive Technology, Cham.

Fehrenbacher, D. D., & Djamasbi, S. (2017). Information systems and task demand: An exploratory pupillometry study of computerized decision making [Article]. Decision Support Systems, 97, 1-11. https://doi.org/10.1016/j.dss.2017.02.007

Fitzsimons, G. J., & Lehmann, D. R. (2004). Reactance to Recommendations: When Unsolicited Advice Yields Contrary Responses. Marketing Science, 23(1), 82-94. https://doi.org/10.1287/mksc.1030.0033

Gregor, S. (2006). The Nature of Theory in Information Systems. MIS Quarterly, 30(3), 611-642. https://doi.org/10.2307/25148742

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. MIS Quarterly, 37(2), 337-355. https://doi.org/10.25300/misq/2013/37.2.01

Greifeneder, R., Scheibehenne, B., & Kleber, N. (2009). Less may be more when choosing is difficult: Choice complexity and too much choice. Acta psychologica, 133, 45-50. https://doi.org/10.1016/j.actpsy.2009.08.005

Grimes, M., & Valacich, J. (2015). Mind over mouse: The effect of cognitive load on mouse movement behavior Thirty Sixth International Conference on Information Systems, Fort Worth.

Gupta, P., & Harris, J. (2010). How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. Journal of Business Research, 63(9), 1041-1049. https://doi.org/https://doi.org/10.1016/j.jbusres.2009.01.015

Herrmann, A., Heitmann, M., & R, L. (2007). Choice Goal Attainment and Decision and Consumption Satisfaction. Journal of Marketing Research, 44, 234-250. https://doi.org/10.1509/jmkr.44.2.234

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: can one desire too much of a good thing? J Pers Soc Psychol, 79(6), 995-1006. https://doi.org/10.1037//0022-3514.79.6.995

Karran, A. J., Demazure, T., Leger, P.-M., Labonte-LeMoyne, E., Senecal, S., Fredette, M., & Babin, G. (2019). Toward a Hybrid Passive BCI for the Modulation of Sustained Attention Using EEG and fNIRS [Original Research]. Frontiers in Human Neuroscience, 13. https://doi.org/10.3389/fnhum.2019.00393

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. Journal of Experimental Psychology, 55(4), 352-358. https://doi.org/10.1037/h0043688

Kuechler, W., & Vaishnavi, V. (2008). On theory development in design science research: anatomy of a research project. EJIS, 17, 489-504.

Lee, K. C., & Kwon, S. (2008). Online shopping recommendation mechanism and its influence on consumer decisions and behaviors: A causal map approach. Expert

Systems with Applications, 35(4), 1567-1574. https://doi.org/https://doi.org/10.1016/j.eswa.2007.08.109

Maheswarappa, S. S., Sivakumaran, B., & Kumar, A. G. (2017). Returns to search when consumers use and do not use recommendation agents. Asia Pacific Journal of Marketing and Logistics, 29(4), 813-836. https://doi.org/10.1108/APJML-10-2016-0188

Petty, R. E., Briñol, P., Tormala, Z. L., & Wegener, D. T. (2007). The Role of Meta-Cognition in Social Judgment (A. W. H. Kruglanski, E. T. , Ed. 2 ed.). Social Psychology: Handbook of Basic Principles, The Guilford Press.

Reutskaja, E., Cheek, N. N., Iyengar, S., & Schwartz, B. (2021). Choice Deprivation, Choice Overload, and Satisfaction with Choices Across Six Nations. Journal of International Marketing, 30(3), 18-34. https://doi.org/10.1177/1069031X211073821

Shen, L., & Dillard, J. P. (2005). Psychometric properties of the Hong psychological reactance scale. J Pers Assess, 85(1), 74-81. https://doi.org/10.1207/s15327752jpa8501_07

Stanton, J. V., & Cook, L. A. (2019). Product knowledge and information processing of organic foods. Journal of Consumer Marketing, 36(1), 240-252. https://doi.org/10.1108/JCM-07-2017-2275

Taylor-West, P., Fulford, H., Reed, G., Story, V., & Saker, J. (2008). Familiarity, expertise and involvement: key consumer segmentation factors. Journal of Consumer Marketing, 25(6), 361-368. https://doi.org/10.1108/07363760810902495

Thorpe, A., Friedman, J., Evans, S., Nesbitt, K., & Eidels, A. (2022). Mouse Movement Trajectories as an Indicator of Cognitive Workload. International Journal of Human–Computer Interaction, 38(15), 1464-1479.

Tokushige, H., Narumi, T., Ono, S., Fuwamoto, Y., Tanikawa, T., & Hirose, M. (2017). Trust Lengthens Decision Time on Unexpected Recommendations in Human-agent Interaction Proceedings of the 5th International Conference on Human Agent Interaction, Bielefeld, Germany. https://doi.org/10.1145/3125739.3125751

Wang, S., Gwizdka, J., & Chaovalitwongse, W. A. (2016). Using Wireless EEG Signals to Assess Memory Workload in the N-Back Task. IEEE Transactions on Human-Machine Systems, 46(3), 424-435. https://doi.org/10.1109/THMS.2015.2476818

Wheeler, S. C., Petty, R. E., & Bizer, G. Y. (2005). Self-schema matching and attitude change: Situational and dispositional determinants of message elaboration. Journal of Consumer Research, 31(4), 787-797.

Willemsen, M., Knijnenburg, B., Graus, M., Velter-Bremmers, L., & Fu, K. (2011). Using latent features diversification to reduce choice difficulty in recommendation lists. CEUR Workshop Proceedings,

Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. Decision Support Systems, 110, 46-57. https://doi.org/https://doi.org/10.1016/j.dss.2018.03.005

Bibliography

Adabi, A., and de Alfaro, L.: 'Toward a Social Graph Recommendation Algorithm: Do We Trust Our Friends in Movie Recommendations?', in Editor (Ed.)^(Eds.): 'Book Toward a Social Graph Recommendation Algorithm: Do We Trust Our Friends in Movie Recommendations?' (Springer Berlin Heidelberg, 2012, edn.), pp. 637-647

Addepalli, S. L., Addepalli, S. G., Kherajani, M., Jeshnani, H., & Khedkar, S. (2016). A proposed framework for measuring customer satisfaction and product recommendation for ecommerce. International Journal of Computer Applications, 138(3), 30-35.

Adriyendi, M.: 'Multi-Attribute Decision Making Using Simple Additive Weighting and Weighted Product in Food Choice', International Journal of Information Engineering and Electronic Business, 2015, 7, (6), pp. 8-14

Aertsens, J., Mondelaers, K., Verbeke, W., Buysse, J., & Van Huylenbroeck, G. (2011). The influence of subjective and objective knowledge on attitude, motivations and consumption of organic food. British Food Journal, 113(11), 1353-1378. https://doi.org/10.1108/00070701111179988

Aksoy, L., Bloom, P. N., Lurie, N. H., & Cooil, B. (2006). Should Recommendation Agents Think Like People? Journal of Service Research, 8(4), 297-315. https://doi.org/10.1177/1094670506286326

Aksoy, L., Cooil, B., & Lurie, N. H. (2011). Decision Quality Measures in Recommendation Agents Research. Journal of Interactive Marketing, 25(2), 110-122. https://doi.org/https://doi.org/10.1016/j.intmar.2011.01.001

Alba, J. W., & Hutchinson, J. W. (2000). Knowledge calibration: What consumers know and what they think they know. Journal of Consumer Research, 27(2), 123-156. https://doi.org/10.1086/314317

Aljanabi, A. R. A., & Al-Hadban, W. K. H. M. (2023). The impact of information factors on green consumer behaviour: The moderating role of information overload. Information Development, 02666669231207590. https://doi.org/10.1177/02666669231207590

Aljukhadar, M., Senecal, S., & Daoust, C.-E. (2010). Information Overload and Usage of Recommendations.

Aljukhadar, M., Senecal, S., & Daoust, C.-E. (2012). Using Recommendation Agents to Cope with Information Overload. International Journal of Electronic Commerce, 17(2), 41-70. http://www.jstor.org/stable/41739511

Aljukhadar, M., Trifts, V., & Senecal, S. (2017). Consumer self-construal and trust as determinants of the reactance to a recommender advice. Psychology and Marketing, 34, 708-719. https://doi.org/10.1002/mar.21017

Allen, P. M., Edwards, J. A., Snyder, F. J., Makinson, K. A., & Hamby, D. M. (2014). The Effect of Cognitive Load on Decision Making with Graphically Displayed Uncertainty Information [Article]. Risk Analysis: An International Journal, 34(8), 1495-1505. https://doi.org/https://doi.org/10.1111/risa.12161

Al-Samarraie, H., Eldenfria, A., Zaqout, F., & Price, M. L. (2019). How reading in single- and multiple-column types influence our cognitive load: an EEG study. The Electronic Library, 37(4), 593-606. https://doi.org/10.1108/EL-01-2019-0006

Aminudin, N., Huda, M., Kilani, A., Embong, W. H. W., Mohamed, A. M., Basiron, B., Ihwani, S. S., Noor, S. S. M., Jasmi, K. A., & Safar, J. (2018). Higher education selection using simple additive weighting. International Journal of Engineering and Technology (UAE), 7(2.27), 211-217.

Andersone, I. (2022). Marketing Decision Making by Generations: Problems and Solutions. Regional Formation and Development Studies, 11(3), 18-23. https://doi.org/10.15181/rfds.v11i3.606

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., & Yang, H. (2018). Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. Customer Needs and Solutions, 5(1), 28-37. https://doi.org/10.1007/s40547-017-0085-8

Andreessen, L. M., Gerjets, P., Meurers, D., & Zander, T. O. (2021). Toward neuroadaptive support technologies for improving digital reading: a passive BCI-based assessment of mental workload imposed by text difficulty and presentation speed during reading [Article]. User Modeling & User-Adapted Interaction, 31(1), 75-104. https://doi.org/10.1007/s11257-020-09273-5

Andrews, D. (2016). Product information and consumer choice confidence in multi-item sales promotions. Journal of Retailing and Consumer Services, 28, 45-53. https://doi.org/https://doi.org/10.1016/j.jretconser.2015.07.011

Angela Chang, C. c., & Kukar-Kinney, M. (2011). The effects of shopping aid usage on consumer purchase decision and decision satisfaction. Asia Pacific Journal of Marketing and Logistics, 23(5), 745-754. https://doi.org/10.1108/13555851111183110

Antonenko, P. P., Paas, F., Grabner, R., & Gog, T. (2010). Using Electroencephalography to Measure Cognitive Load. Educational Psychology Review, 22, 425-438. https://doi.org/https://doi.org/10.1007/s10648-010-9130-y

Appelt, K. C., Milch, K. F., Handgraaf, M. J. J., & Weber, E. U. (2011). The Decision Making Individual Differences Inventory and guidelines for the study of individual differences in judgment and decision-making research. Judgment and Decision Making, 6(3), 252-262. https://doi.org/10.1017/S1930297500001455

Appiah Kusi, G., Azmira Rumki, Z., Hammond Quarcoo, F., Otchere, E., & Fu, G. (2022). The Role of Information Overload on Consumers' Online Shopping Behavior. Journal of Business and Management Studies, 4(4), 162-178. https://doi.org/10.32996/jbms

Aricò, P., Borghini, G., Di Flumeri, G., Sciaraffa, N., & Babiloni, F. (2018). Passive BCI beyond the lab: current trends and future directions. Physiol Meas, 39(8), 08tr02. https://doi.org/10.1088/1361-6579/aad57e

Ariga, A. (2018, 31 Jan.-3 Feb. 2018). Is Choice Overload Replicable? 2018 10th International Conference on Knowledge and Smart Technology (KST),

Arora, P., & Narula, S. (2018). Linkages Between Service Quality, Customer Satisfaction and Customer Loyalty: A Literature Review. IUP Journal of Marketing Management, 17(4), 30.

Bączkiewicz, A. (2021). MCDM based e-commerce consumer decision support tool. Procedia Computer Science, 192, 4991-5002.

Baier, D., & Stüber, E. (2010). Acceptance of recommendations to buy in online retailing. Journal of Retailing and Consumer Services, 17(3), 173-180. https://doi.org/https://doi.org/10.1016/j.jretconser.2010.03.005

Ball, N.L.: 'Design Science II: The Impact of Design Science on E-Commerce Research and Practice', Communications of the Association for Information Systems, 2001, 7

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. Journal of Public Policy & Marketing, 38(4), 500-515. https://doi.org/10.1177/0743915619858057

Bawden, D., & Robinson, L. (2020). Information Overload: An Overview. In Oxford Encyclopedia of Political Decision Making. Oxford: Oxford University Press. https://doi.org/10.1093/acrefore/9780190228637.013.1360

Beckers, J., & Cant, J. (2023). Half a decade in two years: household freight after COVID-19. Transport Reviews, 1-22. https://doi.org/10.1080/01441647.2023.2266859

Beckers, J., Cárdenas, I., & Verhetsel, A. (2018). Identifying the geography of online shopping adoption in Belgium. Journal of Retailing and Consumer Services, 45, 33-41. https://doi.org/https://doi.org/10.1016/j.jretconser.2018.08.006

Bei, L.-T., & Widdows, R. (1999). Product Knowledge and Product Involvement as Moderators of the Effects of Information on Purchase Decisions: A Case Study Using the Perfect Information Frontier Approach. Journal of Consumer Affairs, 33(1), 165-186. https://doi.org/https://doi.org/10.1111/j.1745-6606.1999.tb00765.x

Beierle, F., Aizawa, A., Collins, A., & Beel, J. (2020). Choice overload and recommendation effectiveness in related-article recommendations. International Journal on Digital Libraries, 21(3), 231-246. https://doi.org/10.1007/s00799-019-00270-7

Besedeš, T., Deck, C., Sarangi, S., & Shor, M. (2015). Reducing Choice Overload without Reducing Choices. The Review of Economics and Statistics, 97(4), 793-802. https://doi.org/10.1162/REST_a_00506

Bettman, J. R., Luce, M. F., & Payne, J. W. (2008). Consumer decision making: A choice goals approach. In Handbook of consumer psychology. (pp. 589-610). Taylor & Francis Group/Lawrence Erlbaum Associates.

Bhatti, H. Y., Bint E. Riaz, M., Nauman, S., & Ashfaq, M. (2022). Browsing or buying: A serial mediation analysis of consumer's online purchase intentions in times of

COVID-19 pandemic [Original Research]. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.1008983

Bigras, É., Léger, P.-M., & Sénécal, S. (2019). Recommendation Agent Adoption: How Recommendation Presentation Influences Employees' Perceptions, Behaviors, and Decision Quality. Applied Sciences, 9(20), 4244. https://www.mdpi.com/2076-3417/9/20/4244

Biondi, F. N., Balasingam, B., & Ayare, P. (2020). On the Cost of Detection Response Task Performance on Cognitive Load. Human Factors, 63(5), 804-812. https://doi.org/10.1177/0018720820931628

Blackwell, R. D., Miniard, P. W., & Engel, J. F. (2001). Consumer Behavior (9 ed.). Harcourt College Publishers. (Pennsylvania State University)

Bloch, P. H. (1986). THE PRODUCT ENTHUSIAST: IMPLICATIONS FOR MARKETING STRATEGY. Journal of Consumer Marketing, 3(3), 51-62. https://doi.org/10.1108/eb008170

Bloch, P. H. G., Bruce D. (1984). The Leisure Experience and Consumer Products: Ari Investigation of Underlying Satisfactions. NA Advances in Consumer Research, 11, 197-202.

Blut, M., Ghiassaleh, A., & Wang, C. (2023). Testing the performance of online recommendation agents: A meta-analysis. Journal of Retailing. https://doi.org/https://doi.org/10.1016/j.jretai.2023.08.001

Bollen, D., Knijnenburg, B. P., Willemsen, M. C., & Graus, M. (2010). Understanding choice overload in recommender systems Proceedings of the fourth ACM conference on Recommender systems, Barcelona, Spain. https://doi.org/10.1145/1864708.1864724

Brehm, J. W. (1966). A theory of psychological reactance. Academic Press.

Brehm, S. S., & Brehm, J. W. (1981). Psychological reactance : a theory of freedom and control. Academic Press New York.

Broniarczyk, S. M., & Griffin, J. G. (2014). Decision difficulty in the age of consumer empowerment. Journal of Consumer Psychology, 24(4), 608-625. https://doi.org/10.1016/j.jcps.2014.05.003

Brown, C. L., & Krishna, A. (2004). The Skeptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice. Journal of Consumer Research, 31(3), 529-539. https://doi.org/10.1086/425087

Brucks, M. (1985). The Effects of Product Class Knowledge on Information Search Behavior. Journal of Consumer Research, 12(1), 1-16. http://www.jstor.org/stable/2489377

Buboltz Jr, W. C., Williams, D. J., Thomas, A., Seemann, E. A., Soper, B., & Woller, K. (2003). Personality and psychological reactance: extending the nomological net. Personality and Individual Differences, 34(7), 1167-1177. https://doi.org/https://doi.org/10.1016/S0191-8869(02)00107-1

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. Journal of Personality and Social Psychology, 42(1), 116-131. https://doi.org/10.1037/0022-3514.42.1.116

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. Psychological Bulletin, 119(2), 197-253. https://doi.org/10.1037/0033-2909.119.2.197

Cacioppo, J., Petty, R., & Kao, C. (1984). The efficient assessment of NFC. Journal of personality assessment, 48, 306-307. https://doi.org/10.1207/s15327752jpa4803_13

Calvo, L., Christel, I., Terrado, M., Cucchietti, F., & Pérez-Montoro, M. (2022). Users' Cognitive Load: A Key Aspect to Successfully Communicate Visual Climate Information [Article]. Bulletin of the American Meteorological Society, 103(1), E1-E16. https://doi.org/10.1175/BAMS-D-20-0166.1

Campos, P. G., Bellogín, A., Díez, F., & Chavarriaga, J. E. (2010). Simple time-biased KNN-based recommendations Proceedings of the Workshop on Context-Aware Movie Recommendation, Barcelona, Spain. https://doi.org/10.1145/1869652.1869655

Chen, C. C., Shih, S.-Y., & Lee, M. (2016). Who should you follow? Combining learning to rank with social influence for informative friend recommendation. Decision Support Systems, 90, 33-45. https://doi.org/https://doi.org/10.1016/j.dss.2016.06.017

Chen, M. (2018). Improving website structure through reducing information overload. Decision Support Systems, 110, 84-94. https://doi.org/https://doi.org/10.1016/j.dss.2018.03.009

Chen, S., Qiu, H., Zhao, S., Han, Y., He, W., Siponen, M., Mou, J., & Xiao, H. (2022). When more is less: The other side of artificial intelligence recommendation. Journal of Management Science and Engineering, 7(2), 213-232. https://doi.org/https://doi.org/10.1016/j.jmse.2021.08.001

Chen, Y.-C., Shang, R.-A., & Kao, C.-Y. (2009). The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment. Electron. Commer. Res. Appl., 8(11), 48-58.

Chen, Z., Jin, J., Daly, I., Zuo, C., Wang, X., & Cichocki, A. (2020). Effects of Visual Attention on Tactile P300 BCI [Article]. Computational Intelligence & Neuroscience, 1-11. https://doi.org/10.1155/2020/6549189

Chernev, A., Bockenholt, U., & Goodman, J. (2010). Choice Overload: Is There Anything to It. Journal of Consumer Research, 37, 426-428.

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. Journal of Consumer Psychology, 25(2), 333-358. https://doi.org/10.1016/j.jcps.2014.08.002

Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. Journal of Retailing and Consumer Services, 61, 102528. https://doi.org/https://doi.org/10.1016/j.jretconser.2021.102528

Clarkson, J. J., Tormala, Z. L., & Rucker, D. D. (2008). A new look at the consequences of attitude certainty: The amplification hypothesis. Journal of Personality and Social Psychology, 95(4), 810-825. https://doi.org/10.1037/a0013192

Collins, D., & Geist, M. (2023). Chapter 1: Introduction to Research Handbook on Digital Trade

Collins, L., & Collins, D. (2021). Managing the Cognitive Loads Associated with Judgment and Decision-Making in a Group of Adventure Sports Coaches: A Mixed-Method Investigation. Journal of Adventure Education and Outdoor Learning, 21(1), 1-16. http://proxy2.hec.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=EJ1292642&lang=fr&site=ehost-live

Conner, B. P., Manogharan, G. P., & Meyers, K. L. (2015). An assessment of implementation of entry-level 3D printers from the perspective of small businesses. Rapid Prototyping Journal, 21(5), 582-597. https://doi.org/10.1108/RPJ-09-2014-0132

Crocoll, W. M., & Coury, B. G. (1990). Status or Recommendation: Selecting the Type of Information for Decision Aiding. Proceedings of the Human Factors Society Annual Meeting, 34(19), 1524-1528. https://doi.org/10.1177/154193129003401922

Curşeu, P. L. (2006). Need for cognition and rationality in decision-making. Studia Psychologica, 48(2), 141.

Dabholkar, P. A., & Sheng, X. (2012). Consumer participation in using online recommendation agents: effects on satisfaction, trust, and purchase intentions. The Service Industries Journal, 32(9), 1433-1449. https://doi.org/10.1080/02642069.2011.624596

de Bont, C. J. P. M., & Schoormans, J. P. L. (1995). The effects of product expertise on consumer evaluations of new-product concepts. Journal of Economic Psychology, 16(4), 599-615. https://doi.org/https://doi.org/10.1016/0167-4870(95)00030-4

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments [Article]. European Economic Review, 78, 97-119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Dellaert, B. G. C., & Häubl, G. (2012). Searching in Choice Mode: Consumer Decision Processes in Product Search with Recommendations. Journal of Marketing Research, 49(2), 277-288. https://doi.org/10.1509/jmr.09.0481

Dellaert, B. G., Baker, T., & Johnson, E. J. (2017). Partitioning sorted sets: overcoming choice overload while maintaining decision quality. Columbia Business School Research Paper(18-2).

Deng, L., & Poole, M. S. (2010). Affect in Web Interfaces: A Study of the Impacts of Web Page Visual Complexity and Order. MIS Quarterly, 34(4), 711-730. https://doi.org/10.2307/25750702

Dhar, R. K. (1996). The Effect of Decision Strategy on Deciding to Defer Choice. Journal of Behavioral Decision Making, 9, 265-281.

Di Flumeri, G., De Crescenzio, F., Berberian, B., Ohneiser, O., Kramer, J., Arico, P., Borghini, G., Babiloni, F., Bagassi, S., & Piastra, S. (2019). Brain-Computer Interface-Based Adaptive Automation to Prevent Out-Of-The-Loop Phenomenon in Air Traffic Controllers Dealing With Highly Automated Systems. Front Hum Neurosci, 13, 296. https://doi.org/10.3389/fnhum.2019.00296

Diehl, K. (2005). When Two Rights Make a Wrong: Searching Too Much in Ordered Environments. Journal of Marketing Research, 42(3), 313-322. https://doi.org/10.1509/jmkr.2005.42.3.313

Diehl, K., & Poynor, C. (2010). Great Expectations?! Assortment Size, Expectations, and Satisfaction. Journal of Marketing Research, 47(2), 312-322. https://doi.org/10.1509/jmkr.47.2.312

Ding, G.-J., Hwang, T. K. P., & Kuo, P.-C. (2020, 2020//). Progressive Disclosure Options for Improving Choice Overload on Home Screen. Advances in Usability, User Experience, Wearable and Assistive Technology, Cham.

Divyaa, L. R., & Nargis, P. (2019). Towards generating scalable personalized recommendations: Integrating social trust, social bias, and geo-spatial clustering. Decision Support Systems, 122, 113066. https://doi.org/https://doi.org/10.1016/j.dss.2019.05.006

Donkers, B., Dellaert, B. G. C., Waisman, R. M., & Häubl, G. (2020). Preference Dynamics in Sequential Consumer Choice with Defaults. Journal of Marketing Research, 57(6), 1096-1112. https://doi.org/10.1177/0022243720956642

Drichoutis, A. C., & Nayga, R. M. (2020). Economic Rationality under Cognitive Load. Economic Journal, 130(632), 2382-2409. https://doi.org/10.1093/ej/ueaa052

Edmunds, A., & Morris, A. (2000). The problem of information overload in business organisations: a review of the literature. International Journal of Information

Management, 20(1), 17-28. https://doi.org/https://doi.org/10.1016/S0268-4012(99)00051-1

Eldenfria, A., & Al-Samarraie, H. (2019). Towards an Online Continuous Adaptation Mechanism (OCAM) for Enhanced Engagement: An EEG Study [Article]. International Journal of Human-Computer Interaction, 35(20), 1960-1974. https://doi.org/10.1080/10447318.2019.1595303

Emami, Z., & Chau, T. (2020). The effects of visual distractors on cognitive load in a motor imagery brain-computer interface. Behav Brain Res, 378, 112240. https://doi.org/10.1016/j.bbr.2019.112240

Engel, M. M., Utomo, W. H., & Purnomo, H. D. (2017). Fuzzy Multi Attribute Decision Making Simple Additive Weighting (MADM SAW) for Information Retrieval (IR) in E Commerce Recommendation. International Journal of Computer Science and Software Engineering, 6(6), 136-145.

Eppler, M. J., & Mengis, J. (2004). The Concept of Information Overload: A Review of Literature from Organization Science, Accounting, Marketing, MIS, and Related Disciplines. The Information Society, 20(5), 325-344. https://doi.org/10.1080/01972240490507974

Ersner-Hershfield, H., Wimmer, G. E., & Knutson, B. (2009). Saving for the future self: neural measures of future self-continuity predict temporal discounting. Soc Cogn Affect Neurosci, 4(1), 85-92. https://doi.org/10.1093/scan/nsn042

Fabius, V., Kohli, S., & Timelin, B. M. V., Sofia (2020, July 30, 2020). How COVID-19 is changing consumer behavior-now and forever. McKinsey & Company. https://www.mckinsey.com/industries/retail/our-insights/how-covid-19-is-changing-consumer-behavior-now-and-forever

Fagerstrøm, A., & Ghinea, G. (2010). Web 2.0's Marketing Impact on Low-Involvement Consumers. Journal of Interactive Advertising, 10(2), 67-71. https://doi.org/10.1080/15252019.2010.10722171

Fasolo, B., McClelland, G. H., & Todd, P. M. (2007). Escaping the tyranny of choice: when fewer attributes make choice easier. Marketing Theory, 7(1), 13-26. https://doi.org/10.1177/1470593107073842

Fehrenbacher, D. D., & Djamasbi, S. (2017). Information systems and task demand: An exploratory pupillometry study of computerized decision making. Decision Support Systems, 97, 1-11. https://doi.org/https://doi.org/10.1016/j.dss.2017.02.007

Fernandez Rojas, R., Debie, E., Fidock, J., Barlow, M., Kasmarik, K., Anavatti, S., Garratt, M., & Abbass, H. (2020). Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments. Frontiers in Neuroscience, 14, 40. https://doi.org/10.3389/fnins.2020.00040

Fishel, S. R., Muth, E. R., & Hoover, A. W. (2007). Establishing Appropriate Physiological Baseline Procedures for Real-Time Physiological Measurement. Journal of Cognitive Engineering and Decision Making, 1(3), 286-308. https://doi.org/10.1518/155534307X255636

Fitzsimons, G. J., & Lehmann, D. R. (2004). Reactance to Recommendations: When Unsolicited Advice Yields Contrary Responses. Marketing Science, 23(1), 82-94. https://doi.org/10.1287/mksc.1030.0033

Fridman, L., Reimer, B., Mehler, B., & Freeman, W. T. (2018). Cognitive Load Estimation in the Wild Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, Montreal QC, Canada. https://doi.org/10.1145/3173574.3174226

Gantner, Z., Rendle, S., & Schmidt-Thieme, L. (2010). Factorization models for context-/time-aware movie recommendations Proceedings of the Workshop on Context-Aware Movie Recommendation, Barcelona, Spain. https://doi.org/10.1145/1869652.1869654

Garcia Esparza, S., O'Mahony, M. P., & Smyth, B. (2012). Mining the real-time web: A novel approach to product recommendation. Knowledge-Based Systems, 29, 3-11. https://doi.org/https://doi.org/10.1016/j.knosys.2011.07.007

Gershoff, A. D., Mukherjee, A., & Mukhopadhyay, A. (2003). Consumer Acceptance of Online Agent Advice: Extremity and Positivity Effects. Journal of Consumer Psychology, 13(1), 161-170. https://doi.org/https://doi.org/10.1207/S15327663JCP13-1&2_14

Gevins, A., & Smith, M. E. (2000). Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. Cereb Cortex, 10(9), 829-839. https://doi.org/10.1093/cercor/10.9.829

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical issues in ergonomics science, 4(1-2), 113-131.

Ghosh, R. (2022). E-Commerce Sales Soar Past $1 Trillion: 4 Solid Stocks to Buy NASDAQ. https://www.nasdaq.com/articles/e-commerce-sales-soar-past-%241-trillion%3a-4-solid-stocks-to-buy

Goodman, J. K., Broniarczyk, S. M., Griffin, J. G., & McAlister, L. (2013). Help or hinder? When recommendation signage expands consideration sets and heightens decision difficulty. Journal of Consumer Psychology, 23(2), 165-174. https://doi.org/https://doi.org/10.1016/j.jcps.2012.06.003

Gourville, J. T., & Soman, D. (2005). Overchoice and Assortment Type: When and Why Variety Backfires. Marketing Science, 24(3), 382-395. https://doi.org/10.1287/mksc.1040.0109

Gredin, N. V., Broadbent, D. P., Findon, J. L., Williams, A. M., & Bishop, D. T. (2020). The impact of task load on the integration of explicit contextual priors and visual information during anticipation [Article]. Psychophysiology, 57(6), 1-13. https://doi.org/10.1111/psyp.13578

Gregor, S. (2006). The Nature of Theory in Information Systems. MIS Quarterly, 30(3), 611-642. https://doi.org/10.2307/25148742

Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. MIS Quarterly, 37(2), 337-355. https://doi.org/10.25300/misq/2013/37.2.01

Gregor, S.: ‘The Nature of Theory in Information Systems’, MIS Quarterly, 2006, 30, (3), pp. 611-642

Greifeneder, R., Scheibehenne, B., & Kleber, N. (2009). Less may be more when choosing is difficult: Choice complexity and too much choice. Acta psychologica, 133, 45-50. https://doi.org/10.1016/j.actpsy.2009.08.005

Grimes, M., & Valacich, J. (2015). Mind over mouse: The effect of cognitive load on mouse movement behavior Thirty Sixth International Conference on Information Systems, Fort Worth.

Guan, K., Zhang, Z., Chai, X., Tian, Z., Liu, T., & Niu, H. (2022). EEG Based Dynamic Functional Connectivity Analysis in Mental Workload Tasks With Different Types of Information. IEEE Trans Neural Syst Rehabil Eng, 30, 632-642. https://doi.org/10.1109/TNSRE.2022.3156546

Guarnieri, R., Zhao, M., Taberna, G.A., Ganzetti, M., Swinnen, S.P., and Mantini, D.: 'RT-NET: real-time reconstruction of neural activity using high-density electroencephalography', Neuroinformatics, 2021, 19, (2), pp. 251-266

Guo, R., & Li, H. (2022). Can the amount of information and information presentation reduce choice overload? An empirical study of online hotel booking. Journal of Travel & Tourism Marketing, 39(1), 87-108. https://doi.org/10.1080/10548408.2022.2044970

Gupta, P., & Harris, J. (2010). How e-WOM recommendations influence product consideration and quality of choice: A motivation to process information perspective. Journal of Business Research, 63(9), 1041-1049. https://doi.org/https://doi.org/10.1016/j.jbusres.2009.01.015

Hadar, L., & Sood, S. (2014). When Knowledge Is Demotivating: Subjective Knowledge and Choice Overload. Psychological Science, 25(9), 1739-1747. http://www.jstor.org/stable/24543909

Hadar, L., Sood, S., & Fox, C. R. (2013). Subjective Knowledge in Consumer Financial Decisions. Journal of Marketing Research, 50(3), 303-316. https://doi.org/10.1509/jmr.10.0518

Harris, J., & Gupta, P. (2008). 'You should buy this one!' The influence of online recommendations on product attitudes and choice confidence. International Journal of Electronic Marketing and Retailing, 2(2), 176-189. https://doi.org/10.1504/IJEMR.2008.019816

Hassan, L. M., Shiu, E., & McGowan, M. (2019). Relieving the regret for maximizers. European Journal of Marketing, 54(2), 282-304. https://doi.org/10.1108/EJM-03-2018-0200

Häubl, G., & Trifts, V. (2000). Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids. Marketing Science, 19(1), 4-21. https://doi.org/10.1287/mksc.19.1.4.15178

Häubl, G., Dellaert, B., & Usta, M. (2010). Ironic Effects of Personalized Product Recommendations on Subjective Decision Outcomes. Proceedings of the Society for Consumer Psychology Winter Conference.

Haynes, G. A. (2009). Testing the boundaries of the choice overload phenomenon: The effect of number of options and time pressure on decision difficulty and satisfaction. Psychology & Marketing, 26(3), 204-212. https://doi.org/https://doi.org/10.1002/mar.20269

Hdioud, F., Frikh, B., & Ouhbi, B. (2013). Multi-Criteria Recommender Systems based on Multi-Attribute Decision Making International Conference on Information Integration and Web-based Applications & Services,

Heitmann, M., Lehmann, D. R., & Herrmann, A. (2007). Choice Goal Attainment and Decision and Consumption Satisfaction. Journal of Marketing Research, 44(2), 234-250. https://doi.org/10.1509/jmkr.44.2.234

Hevner, A. (2007). A Three Cycle View of Design Science Research. Scandinavian Journal of Information Systems, 19.

Hevner, A., Park, J., & March, S. T. (2004). Design Science in Information Systems Research. MIS Quarterly, 28(1), 75-105.

Hevner, A.: 'A Three Cycle View of Design Science Research', Scandinavian Journal of Information Systems, 2007, 19

Ho, E. H., Hagmann, D., & Loewenstein, G. (2021). Measuring Information Preferences. Management Science, 67(1), 126-145. https://doi.org/10.1287/mnsc.2019.3543

Hoch, S. J., & Deighton, J. (1989). Managing what consumers learn from experience. Journal of marketing, 53(2), 1-20. https://doi.org/10.2307/1251410

Hong, S.-m., & Page, S. (1989). A psychological reactance scale: Development, factor structure and reliability. Psychological Reports, 64(3, Pt 2), 1323-1326. https://doi.org/10.2466/pr0.1989.64.3c.1323

Hu, H.-f., & Krishen, A. S. (2019). When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective. Journal of Business Research, 100, 27-37. https://doi.org/https://doi.org/10.1016/j.jbusres.2019.03.011

Huang, Z., Zeng, D., & Chen, H. (2007). A Comparison of Collaborative-Filtering Recommendation Algorithms for E-commerce. IEEE Intelligent Systems, 22(5), 68-78. https://doi.org/10.1109/MIS.2007.4338497

Huber, F., Köcher, S., Vogel, J., & Meyer, F. (2012). Dazing Diversity: Investigating the Determinants and Consequences of Decision Paralysis. Psychology & Marketing, 29(6), 467-478. https://doi.org/https://doi.org/10.1002/mar.20535

Huffman, C., & Kahn, B. E. (1998). Variety for sale: Mass customization or mass confusion? Journal of Retailing, 74(4), 491-513. https://doi.org/https://doi.org/10.1016/S0022-4359(99)80105-5

Huseynov, F., Huseynov, S. Y., & Özkan, S. (2014). The influence of knowledge-based e-commerce product recommender agents on online consumer decision-making. Information Development, 32(1), 81-90. https://doi.org/10.1177/0266666914528929

Hutchinson, C. F., & Herrmann, S. M. (2008). Land use and Management. In C. F. Hutchinson & S. M. Herrmann (Eds.), The Future of Arid Lands — Revisited: A Review of 50 Years of Drylands Research (pp. 103-128). Springer Netherlands. https://doi.org/10.1007/978-1-4020-6689-4_7

Imai, K., Keele, L., Tingley, D., & Yamamoto, T. (2010). Causal mediation analysis using R. Advances in social science research using R

In Research Handbook on Digital Trade (pp. 1-7). Edward Elgar Publishing. https://doi.org/10.4337/9781800884953.00006

Itani, O. S., & Hollebeek, L. D. (2021). Consumers' health-locus-of-control and social distancing in pandemic-based e-tailing services. Journal of Services Marketing, 35(8), 1073-1091. https://doi.org/10.1108/JSM-10-2020-0410

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: can one desire too much of a good thing? J Pers Soc Psychol, 79(6), 995-1006. https://doi.org/10.1037//0022-3514.79.6.995

Jacoby, J., Speller, D. E., & Kohn, C. A. (1974). Brand Choice Behavior as a Function of Information Load. Journal of Marketing Research, 11(1), 63-69. https://doi.org/10.2307/3150994

Jiang, Y., Shang, J., & Liu, Y. (2010). Maximizing customer satisfaction through an online recommendation system: A novel associative classification model. Decision Support Systems, 48(3), 470-479. https://doi.org/https://doi.org/10.1016/j.dss.2009.06.006

Jiang, Z., & Benbasat, I. (2005). Virtual Product Experience: Effects of Visual and Functional Control of Products on Perceived Diagnosticity and Flow in Electronic Shopping. J. of Management Information Systems, 21, 111-148. https://doi.org/10.2139/ssrn.1400827

Jin, Y., Cardoso, B., & Verbert, K. (2017). How do different levels of user control affect cognitive load and acceptance of recommendations? CEUR Workshop Proceedings,

Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. Management Science, 31(4), 395-414.

Johnson, E. J., Shu, S. B., Dellaert, B. G. C., Fox, C., Goldstein, D. G., Häubl, G., Larrick, R. P., Payne, J. W., Peters, E., Schkade, D., Wansink, B., & Weber, E. U. (2012). Beyond nudges: Tools of a choice architecture. Marketing Letters: A Journal of Research in Marketing, 23(2), 487-504. https://doi.org/10.1007/s11002-012-9186-1

Jones, D., and Gregor, S.: 'The Anatomy of a Design Theory', Journal of the Association for Information Systems, 2007, 8, (5), pp. 312-335

Jugovac, M., & Jannach, D. (2017). Interacting with Recommenders—Overview and Research Directions. ACM Trans. Interact. Intell. Syst., 7(3), Article 10. https://doi.org/10.1145/3001837

Kahn, B. E. (2017). Using Visual Design to Improve Customer Perceptions of Online Assortments. Journal of Retailing, 93(1), 29-42. https://doi.org/https://doi.org/10.1016/j.jretai.2016.11.004

Kalanthroff, E., Cohen, N., & Henik, A. (2013). Stop feeling: inhibition of emotional interference following stop-signal trials [Original Research]. Frontiers in Human Neuroscience, 7. https://doi.org/10.3389/fnhum.2013.00078

Kamal, A., & Burkell, J. (2011). Addressing Uncertainty: When Information is Not Enough / Faire face à l'incertitude : quand l'information ne suffit pas. Canadian Journal of Information and Library Science, 35, 384-396. https://doi.org/10.1353/ils.2011.0030

Karmokar, S., and Singh, H.: 'Improving the Website Design Process for SMEs: A Design Science Perspective'2012 pp. Pages

Karran, A. J., Demazure, T., Hudon, A., Senecal, S., & Léger, P. M. (2022). Designing for Confidence: The Impact of Visualizing Artificial Intelligence Decisions. Front Neurosci, 16, 883385. https://doi.org/10.3389/fnins.2022.883385

Karran, A. J., Demazure, T., Leger, P.-M., Labonte-LeMoyne, E., Senecal, S., Fredette, M., & Babin, G. (2019). Toward a Hybrid Passive BCI for the Modulation of Sustained Attention Using EEG and fNIRS [Original Research]. Frontiers in Human Neuroscience, 13. https://doi.org/10.3389/fnhum.2019.00393

Kean Yew, J., & Kamarulzaman, Y. (2020). Effects of Personal Factors, Perceived Benefits, and Shopping Orientation on Online Shopping Behavior. International Journal of Economics, Management and Accounting, 28, 327-360.

Khan, K., Hussainy, S. K., Hameed, I., & Riaz, K. (2021). Too Much Choice and Consumer Decision Making: The Moderating Role of Consumer Involvement. JISR management and social sciences & economics, 19(1), 17-29. https://doi.org/10.31384/jisrmsse/2021.19.1.2

Khorshidtalab, A., and Salami, M.J.E.: 'EEG signal classification for real-time brain-computer interface applications: A review', in Editor (Ed.)^(Eds.): 'Book EEG signal classification for real-time brain-computer interface applications: A review' (2011, edn.), pp. 1-7

Kim, H. J., Lee, H., & Hong, H. (2020). Scale Development and Validation for Psychological Reactance to Health Promotion Messages. Sustainability, 12(14), 5816. https://www.mdpi.com/2071-1050/12/14/5816

Kim, H. M., & Kramer, T. (2006). The Moderating Effects of Need for Cognition and Cognitive Effort on Responses to Multi-Dimensional Prices. Marketing Letters, 17(3), 193-203. http://www.jstor.org/stable/40216676

Kim, S.-Y., Levine, T., & Allen, M. (2013). Comparing Separate Process and Intertwined Models for Reactance. Communication Studies, 64(3), 273-295. https://doi.org/10.1080/10510974.2012.755639

Kirby-Hawkins, E., Birkin, M., & Clarke, G. (2018). An investigation into the geography of corporate e-commerce sales in the UK grocery market. Environment and Planning B: Urban Analytics and City Science, 46(6), 1148-1164. https://doi.org/10.1177/2399808318755147

Kirchner, W. K. (1958). Age differences in short-term retention of rapidly changing information. Journal of Experimental Psychology, 55(4), 352-358. https://doi.org/10.1037/h0043688

Knijnenburg, B. P., Willemsen, M. C., & Hirtbach, S. (2010, 2010//). Receiving Recommendations and Providing Feedback: The User-Experience of a Recommender System. E-Commerce and Web Technologies, Berlin, Heidelberg.

Köcher, S., Jugovac, M., Jannach, D., & Holzmüller, H. H. (2019). New Hidden Persuaders: An Investigation of Attribute-Level Anchoring Effects of Product Recommendations. Journal of Retailing, 95(1), 24-41. https://doi.org/https://doi.org/10.1016/j.jretai.2018.10.004

Kodali, S.: 'The State of Retailing Online 2019', in Forrester 'The State of Retailing Online 2019' (Forrester, 2019, edn.), pp. 25

Koenig, A. (1995). Patterns and Antipatterns. Journal of Object Oriented Programming, 8(1), 46-48.

Köhler, C. F., Breugelmans, E., & Dellaert, B. G. C. (2011). Consumer Acceptance of Recommendations by Interactive Decision Aids: The Joint Role of Temporal Distance and Concrete Versus Abstract Communications. Journal of Management Information Systems, 27(4), 231-260. https://doi.org/10.2753/MIS0742-1222270408

Konstan, J. A., & Riedl, J. (2012). Recommender systems: from algorithms to user experience. User Modeling and User-Adapted Interaction, 22(1), 101-123. https://doi.org/10.1007/s11257-011-9112-x

Köten, E. E. (2023). The impact of internet platform usage on firms' exports: New evidence for Turkish firms. The World Economy, n/a(n/a). https://doi.org/https://doi.org/10.1111/twec.13483

Krol, L. R., & Zander, T. O. (2017). Passive BCI-Based Neuroadaptive Systems. Graz Brain-Computer Interface Conference 2017,

Kuechler, W., & Vaishnavi, V. (2008a). The emergence of design research in information systems in North America. Journal of Design Research, 7, 1. https://doi.org/10.1504/JDR.2008.019897

Kuechler, W., and Vaishnavi, V.: 'On theory development in design science research: anatomy of a research project', EJIS, 2008, 17, pp. 489-504

Kuksov, D., & Villas-Boas, J. M. (2009). When More Alternatives Lead to Less Choice. Marketing Science, 29(3), 507-524. https://doi.org/10.1287/mksc.1090.0535

Kurien, R., Paila, A. R., & Nagendra, A. (2014). Application of Paralysis Analysis Syndrome in Customer Decision Making. Procedia Economics and Finance, 11, 323-334. https://doi.org/https://doi.org/10.1016/S2212-5671(14)00200-7

Kuvaas, B., & Kaufmann, G. (2004). Impact of mood, framing, and need for cognition on decision makers' recall and confidence. Journal of Behavioral Decision Making, 17(1), 59-74. https://doi.org/https://doi.org/10.1002/bdm.461

Kwon, S. J., & Chung, N. (2010). The moderating effects of psychological reactance and product involvement on online shopping recommendation mechanisms based on a causal map. Electronic Commerce Research and Applications, 9(6), 522-536. https://doi.org/https://doi.org/10.1016/j.elerap.2010.04.004

Lajos, J., Chattopadhyay, A., & Sengupta, K. (2009). When Electronic Recommendation Agents Backfire: Negative Effects on Choice Satisfaction, Attitudes, and Purchase Intentions.

Laroche, M., Kim, C., & Zhou, L. (1996). Brand familiarity and confidence as determinants of purchase intention: An empirical test in a multiple brand context. Journal of Business Research, 37(2), 115-120. https://doi.org/https://doi.org/10.1016/0148-2963(96)00056-2

Leary, M. R., & Hoyle, R. H. (2009). Handbook of individual differences in social behavior. The Guilford Press.

Lee, B.-K., & Lee, W.-N. (2004). The effect of information overload on consumer choice quality in an on-line environment [https://doi.org/10.1002/mar.20000]. Psychology & Marketing, 21(3), 159-183. https://doi.org/https://doi.org/10.1002/mar.20000

Lee, G., & Lee, W. J. (2009). Psychological reactance to online recommendation services. Information & Management, 46(8), 448-452. https://doi.org/https://doi.org/10.1016/j.im.2009.07.005

Lee, G., Lee, J., & Sanford, C. (2010). The roles of self-concept clarity and psychological reactance in compliance with product and service recommendations. Computers in Human Behavior, 26(6), 1481-1487. https://doi.org/https://doi.org/10.1016/j.chb.2010.05.001

Lee, K. C., & Kwon, S. (2008). Online shopping recommendation mechanism and its influence on consumer decisions and behaviors: A causal map approach. Expert Systems with Applications, 35(4), 1567-1574. https://doi.org/https://doi.org/10.1016/j.eswa.2007.08.109

Lee, Y. E., & Benbasat, I. (2011). Research Note—The Influence of Trade-off Difficulty Caused by Preference Elicitation Methods on User Acceptance of Recommendation Agents Across Loss and Gain Conditions. Information Systems Research, 22(4), 867-884. https://doi.org/10.1287/isre.1100.0334

Leninkumar, V. (2017). The Relationship between Customer Satisfaction and Customer Trust on Customer Loyalty. International Journal of Academic Research in

Business and Social Sciences, 7(4), 450-465. https://EconPapers.repec.org/RePEc:hur:ijarbs:v:7:y:2017:i:4:p:450-465

Levin, I. P., Huneke, M. E., & Jasper, J. D. (2000). Information Processing at Successive Stages of Decision Making: Need for Cognition and Inclusion–Exclusion Effects. Organizational Behavior and Human Decision Processes, 82(2), 171-193. https://doi.org/https://doi.org/10.1006/obhd.2000.2881

Li, Y., Chen, W., & Yan, H. (2017). Learning Graph-based Embedding For Time-Aware Product Recommendation Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, Singapore, Singapore. https://doi.org/10.1145/3132847.3133060

Liang, T.-P., Lai, H.-J., & Ku, Y.-C. (2006). Personalized Content Recommendation and User Satisfaction: Theoretical Synthesis and Empirical Findings. Journal of Management Information Systems, 23(3), 45-70. https://doi.org/10.2753/MIS0742-1222230303

Liberman, V., & Tversky, A. (1993). On the evaluation of probability judgments: Calibration, resolution, and monotonicity. Psychological Bulletin, 114(1), 162-173. https://doi.org/10.1037/0033-2909.114.1.162

Linden, G., Smith, B., & York, J. (2003). Amazon.com Recommendations (IEEE Internet Computing, Issue. I. C. Society. https://www.cs.umd.edu/~samir/498/Amazon-Recommendations.pdf

Linden, G., Smith, B., and York, J.: 'Amazon.com Recommendations', in Editor (Ed.)^(Eds.): 'Book Amazon.com Recommendations' (IEEE Computer Society, 2003, edn.), pp. 76-80

Lins de Holanda Coelho, G., P, H. P. H., & L, J. W. (2020). The Very Efficient Assessment of Need for Cognition: Developing a Six-Item Version. Assessment, 27(8), 1870-1885. https://doi.org/10.1177/1073191118793208

Liu, L., Zheng, Y., & Chen, R. (2015). Better with more choices? Impact of choice set size on variety seeking. Acta Psychologica Sinica, 47(1), 66-78.

Liu, S., Kaikati, A. M., & Arnold, M. J. (2023). To touch or not to touch: Examining the role of choice set size. Psychology & Marketing, 40(3), 567-578. https://doi.org/10.1002/mar.21754

Lops, P., de Gemmis, M., & Semeraro, G. (2011). Content-based Recommender Systems: State of the Art and Trends. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), Recommender Systems Handbook (pp. 73-105). Springer US. https://doi.org/10.1007/978-0-387-85820-3_3

Lurie, N. H. (2004). Decision Making in Information-Rich Environments: The Role of Information Structure. Journal of Consumer Research, 30(4), 473-486. https://doi.org/10.1086/380283

MacKenzie, I., Meyer, C., & Noble, S. (2013). How retailers can keep up with consumers (McKinsey & Company). M. Company. https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers#/download/%2F~%2Fmedia%2Fmckinsey%2Findustries%2Fretail%2Four%20insights%2Fhow%20retailers%20can%20keep%20up%20with%20consumers%2Fhow_retailers_can_keep_up_with_consumers_v2.pdf%3FshouldIndex%3Dfalse

Madrian, B. C., & Shea, D. F. (2001). The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior*. The Quarterly Journal of Economics, 116(4), 1149-1187. https://doi.org/10.1162/003355301753265543

Maheswarappa, S. S., Sivakumaran, B., & Kumar, A. G. (2017). Returns to search when consumers use and do not use recommendation agents. Asia Pacific Journal of Marketing and Logistics, 29(4), 813-836. https://doi.org/10.1108/APJML-10-2016-0188

Malhotra, N. K. (1982). Information load and consumer decision making. Journal of Consumer Research, 8(4), 419-430.

Malone, T., & Lusk, J. L. (2019). Mitigating Choice Overload: An Experiment in the U.S. Beer Market. Journal of Wine Economics, 14(1), 48-70. https://doi.org/10.1017/jwe.2018.34

Manfredo, M. J., & Bright, A. D. (1991). A model for assessing the effects of communication on recreationists. Journal of Leisure Research, 23(1), 1-20. https://doi.org/10.1080/00222216.1991.11969840

Manolică, A., Guță, A.-S., Roman, T., & Dragăn, L. M. (2021). Is Consumer Overchoice a Reason for Decision Paralysis? Sustainability, 13(11).

Marchand, A., & Marx, P. (2020). Automated Product Recommendations with Preference-Based Explanations. Journal of Retailing, 96(3), 328-343. https://doi.org/https://doi.org/10.1016/j.jretai.2020.01.001

McKenny, J. L., & Keen, P. G. W. (1974, May 1974). How Managers' Minds Work. Harvard Business Review, 79-90.

Mcquarrie, E. F., & Munson, J. M. (1992). A Revised Product Involvement Inventory: Improved Usability and Validity. ACR North American Advances.

Melovic, B., Cirovic, D., Dudic, B., Vulic, T. B., & Gregus, M. (2020). The analysis of marketing factors influencing consumers' preferences and acceptance of organic food products—Recommendations for the optimization of the offer in a developing market. Foods, 9(3), 259.

Mild, A., & Reutterer, T. (2003). An improved collaborative filtering approach for predicting cross-category purchases based on binary market basket data. Journal of Retailing and Consumer Services, 10(3), 123-133.

Miri Ashtiani, S. N., & Daliri, M. R. (2023). Identification of cognitive load-dependent activation patterns using working memory task-based fMRI at various levels of difficulty. Scientific Reports, 13(1), 16476.

Miron, A. M., & Brehm, J. W. (2006). Reaktanz theorie - 40 Jahre spärer. [Reactance Theory - 40 Years Later.]. Zeitschrift für Sozialpsychologie, 37(1), 9-18. https://doi.org/10.1024/0044-3514.37.1.9

Mishra, S. N., & Kumar, S. (2023, 28-30 April 2023). A Product based Recommendation System for E-Commerce Sites. 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES),

Misuraca, R., Ceresia, F., Teuscher, U., & Faraci, P. (2019). The Role of the Brand on Choice Overload. Mind & Society, 18(1), 57-76. https://doi.org/10.1007/s11299-019-00210-7

Misuraca, R., Teuscher, U., & Faraci, P. (2016). Is more choice always worse? Age differences in the overchoice effect. Journal of Cognitive Psychology, 28(2), 242-255. https://doi.org/10.1080/20445911.2015.1118107

Mitchell, A. A., & Dacin, P. A. (1996). The Assessment of Alternative Measures of Consumer Expertise. Journal of Consumer Research, 23(3), 219-239. https://doi.org/10.1086/209479

Mogilner, C., Rudnick, T., & Iyengar, S. S. (2008). The Mere Categorization Effect: How the Presence of Categories Increases Choosers' Perceptions of Assortment Variety and Outcome Satisfaction. Journal of Consumer Research, 35(2), 202-215. https://doi.org/10.1086/588698

Moorman, C., Diehl, K., Brinberg, D., Kidwell, B., Bettman, J., Chartrand, T., Levav, J., Lynch, J., Mela, C., & Rose, R. (2004). Subjective Knowledge, Search Locations, and Consumer Choice. Journal of Consumer Research - J CONSUM RES, 31. https://doi.org/10.1086/425102

Nagar, K., & Gandotra, P. (2016). Exploring Choice Overload, Internet Shopping Anxiety, Variety Seeking and Online Shopping Adoption Relationship: Evidence from Online Fashion Stores. Global Business Review, 17(4), 851-869. https://doi.org/10.1177/0972150916645682

Naiseh, M., Jiang, N., Ma, J., & Ali, R. (2020). Explainable Recommendations in Intelligent Systems: Delivery Methods, Modalities and Risks. In Research Challenges in Information Science (pp. 212-228). https://doi.org/10.1007/978-3-030-50316-1_13

NASDAQ. (2017). UK Online Shopping and E-Commerce Statistics for 2017 NASDAQ. https://www.nasdaq.com/articles/uk-online-shopping-and-e-commerce-statistics-2017-2017-03-14

Nataraajan, R., & Angur, M. G. (1998). Perceived control in consumer choice: A closer look. Association for Consumer Research.

Nesterkin, D. A. (2013). Organizational change and psychological reactance. Journal of Organizational Change Management, 26(3), 573-594. https://doi.org/10.1108/09534811311328588

Nguyen, J., Le, Q. V., & Ha, J. T. (2021). Impacts of Health and Safety Concerns on E-Commerce and Service Reconfiguration During the COVID-19 Pandemic: Insights from an Emerging Economy. Service Science, 13(4), 227-242. https://doi.org/10.1287/serv.2021.0279

NielsenIQ. (2019). Bursting with new products, there's never been a better time for breakthrough innovation NielsenIQ. https://nielseniq.com/global/en/insights/analysis/2019/bursting-with-new-products-theres-never-been-a-better-time-for-breakthrough-innovation/

Nilashi, M., Jannach, D., Ibrahim, O., Dalvi, M., & Ahmadi, H. (2016). Recommendation, transparency, and website quality for trust-building in recommendation agents. Electronic Commerce Research and Applications, 19. https://doi.org/10.1016/j.elerap.2016.09.003

Nunes, I., & Jannach, D. (2017). A systematic review and taxonomy of explanations in decision support and recommender systems. User Modeling and User-Adapted Interaction, 27(3), 393-444. https://doi.org/10.1007/s11257-017-9195-0

Okfalisa, O., Rusnedy, H., Iswavigra, D. U., Pranggono, B., Haerani, E. H., & Saktioto, S. (2020). Decision Support System for Smartphone Recommendation: The Comparison of Fuzzy Ahp and Fuzzy Anp in Multi-Attribute Decision Making. Sinergi, 25(1). https://doi.org/10.22441/sinergi.2021.1.013

Oppewal, H., & Koelemeijer, K. (2005). More choice is better: Effects of assortment size and composition on assortment evaluation. International Journal of Research in Marketing, 22(1), 45-60. https://doi.org/https://doi.org/10.1016/j.ijresmar.2004.03.002

Özkan, E., & Tolon, M. (2015). The Effects of Information Overload on Consumer Confusion: An Examination on User Generated Content. Bogazici Journal, 29, 27-51. https://doi.org/10.21773/boun.29.1.2

Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. Educational Psychologist, 38(1), 63-71. https://doi.org/10.1207/S15326985EP3801_8

Padmala, S., Bauer, A., & Pessoa, L. (2011). Negative Emotion Impairs Conflict-Driven Executive Control [Original Research]. Frontiers in Psychology, 2. https://doi.org/10.3389/fpsyg.2011.00192

Pandey, S., and Kumar, T.S.: ‘Customization of Recommendation System Using Collaborative Filtering Algorithm on Cloud Using Mahout’, IJRET: International Journal of Research in Engineering and Technology, 2014, 3, (7), pp. 39-43

Park, C. W., & Lessig, V. P. (1981). Familiarity and its impact on consumer decision biases and heuristics. Journal of Consumer Research, 8(2), 223-230. https://doi.org/10.1086/208859

Patharia, I., & Jain, T. (2023). Antecedents of Electronic Shopping Cart Abandonment during Online Purchase Process. Business Perspectives and Research, 22785337221148810. https://doi.org/10.1177/22785337221148810

Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. Organizational Behavior and Human Performance, 16(2), 366-387. https://doi.org/https://doi.org/10.1016/0030-5073(76)90022-2

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). The adaptive decision maker [doi:10.1017/CBO9781139173933]. Cambridge University Press. https://doi.org/10.1017/CBO9781139173933

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2008). A Design Science Research Methodology for Information Systems Research. Journal of Management Information Systems, 24, 45. https://doi.org/10.2753/MIS0742-1222240302

Peffers, K., Tuunanen, T., Rothenberger, M.A., and Chatterjee, S.: ‘A Design Science Research Methodology for Information Systems Research’, Journal of Management Information Systems, 2008, 24, pp. 45

Peng, M., Xu, Z., & Huang, H. (2021). How Does Information Overload Affect Consumers' Online Decision Process? An Event-Related Potentials Study. Front Neuroscience, 15. https://doi.org/10.3389/fnins.2021.695852

Pereira, R. E. (2001). Influence of Query-Based Decision Aids on Consumer Decision Making in Electronic Commerce. Information Resources Management Journal (IRMJ), 14(1), 31-48. https://doi.org/10.4018/irmj.2001010104

Perry, N. C., Wiggins, M. W., Childs, M., & Fogarty, G. (2012). Can reduced processing decision support interfaces improve the decision-making of less-experienced incident commanders? [Article]. Decision Support Systems, 52(2), 497-504. https://doi.org/10.1016/j.dss.2011.10.010

Petrocelli, J. V., Tormala, Z. L., & Rucker, D. D. (2007). Unpacking attitude certainty: attitude clarity and attitude correctness. Journal of Pers Soc Psychol, 92(1), 30-41. https://doi.org/10.1037/0022-3514.92.1.30

Petty, R. E., & Cacioppo, J. T. (2012). Communication and persuasion: Central and peripheral routes to attitude change. Springer Science & Business Media.

Petty, R. E., Briñol, P., & Tormala, Z. L. (2002). Thought confidence as a determinant of persuasion: The self-validation hypothesis. Journal of Personality and Social Psychology, 82(5), 722-741. https://doi.org/10.1037/0022-3514.82.5.722

Petty, R. E., Brinol, P., Loersch, C., & McCaslin, M. J. (2009). The need for cognition. In Handbook of individual differences in social behavior. (pp. 318-329). The Guilford Press.

Petty, R. E., Briñol, P., Tormala, Z. L., & Wegener, D. T. (2007). The Role of Meta-Cognition in Social Judgment (A. W. H. Kruglanski, E. T. , Ed. 2 ed.). Social Psychology: Handbook of Basic Principles, The Guilford Press.

Pratiwi, D., Putri, J., & Agushinta R, D. (2014). Decision Support System to Majoring High School Student Using Simple Additive Weighting Method. International Journal of Computer Trends and Technology, 10, 153-159. https://doi.org/10.14445/22312803/IJCTT-V10P126

Pratiwi, D., Putri, J., and Agushinta R, D.: 'Decision Support System to Majoring High School Student Using Simple Additive Weighting Method', International Journal of Computer Trends and Technology, 2014, 10, pp. 153-159

Punj, G. (2012). Consumer Decision Making on the Web: A Theoretical Analysis and Research Guidelines. Psychology & Marketing, 29(10), 791-803. https://doi.org/https://doi.org/10.1002/mar.20564

Rahinel, R., Otto, A. S., Grossman, D. M., & Clarkson, J. J. (2021). Exposure to brands makes preferential decisions easier. Journal of Consumer Research, 48(4), 541-561. https://doi.org/10.1093/jcr/ucab025

Rains, S. A. (2013). The Nature of Psychological Reactance Revisited: A Meta-Analytic Review. Human Communication Research, 39(1), 47-73. https://doi.org/https://doi.org/10.1111/j.1468-2958.2012.01443.x

Reed, A. E., Mikels, J. A., & Löckenhoff, C. E. (2012). Choosing with confidence: Self-efficacy and preferences for choice. Judgment and Decision Making, 7(2), 173-180.

Reutkaja, E. I., S. S , Fasolo, B., & R., M. (2021). Cognitive and Affective Consequences of Information and Choice Overload. In R. Viale (Ed.), Routledge Handbook of Bounded Rationality (pp. pp. 625-636).

Reutskaja, E., Cheek, N. N., Iyengar, S., & Schwartz, B. (2021). Choice Deprivation, Choice Overload, and Satisfaction with Choices Across Six Nations. Journal of International Marketing, 30(3), 18-34. https://doi.org/10.1177/1069031X211073821

Reutskaja, E., Iyengar, S., Fasolo, B., & Misuraca, R. (2020). Cognitive and affective consequences of information and choice overload. In R. Viale, (ed.) (Ed.), Routledge Handbook of Bounded Rationality (pp. 625-636). Routledge International Handbooks.

Ricci, F., Rokach, L., & Shapira, B. (2022). Recommender Systems: Techniques, Applications, and Challenges. In F. Ricci, L. Rokach, & B. Shapira (Eds.), Recommender Systems Handbook (pp. 1-35). Springer US. https://doi.org/10.1007/978-1-0716-2197-4_1

Richins, M. L., & Bloch, P. H. (1991). Post-purchase product satisfaction: Incorporating the effects of involvement and time. Journal of Business Research, 23(2), 145-158. https://doi.org/https://doi.org/10.1016/0148-2963(91)90025-S

Roberts, J. H., & Lattin, J. M. (1991). Development and Testing of a Model of Consideration Set Composition. Journal of Marketing Research, 28(4), 429-440. https://doi.org/10.2307/3172783

Robinette, P., Li, W., Allen, R., Howard, A., & Wagner, A. (2016). Overtrust of Robots in Emergency Evacuation Scenarios. https://doi.org/10.1109/HRI.2016.7451740

Roetzel, P. G. (2019). Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. Business Research, 12(2), 479-522. https://doi.org/10.1007/s40685-018-0069-z

Ron-Angevin, R., Garcia, L., Fernández-Rodríguez, Á., Saracco, J., André, J. M., & Lespinet-Najib, V. (2019). Impact of Speller Size on a Visual P300 Brain-Computer Interface (BCI) System under Two Conditions of Constraint for Eye Movement [Article]. Computational Intelligence & Neuroscience, 1-16. https://doi.org/10.1155/2019/7876248

Rose, J. M. (2005). Decision Aids and Experiential Learning [Article]. Behavioral Research in Accounting, 17, 175-189. https://doi.org/10.2308/bria.2005.17.1.175

Rose, J. M., Roberts, F. D., & Rose, A. M. (2004). Affective responses to financial data and multimedia: the effects of information load and cognitive load. International Journal of Accounting Information Systems, 5(1), 5-24. https://doi.org/https://doi.org/10.1016/j.accinf.2004.02.005

Rosenberg, B. D., & Siegel, J. T. (2018). A 50-year review of psychological reactance theory: Do not read this article. Motivation Science, 4(4), 281-300. https://doi.org/10.1037/mot0000091

Salem, M., Lakatos, G., Amirabdollahian, F., & Dautenhahn, K. (2015). Would You Trust a (Faulty) Robot? Effects of Error, Task Type and Personality on Human-Robot Cooperation and Trust Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction, Portland, Oregon, USA. https://doi.org/10.1145/2696454.2696497

Santoso, P. A., Wibawa, A. P., & Pujianto, U. (2018). Internship recommendation system using simple additive weighting. Bulletin of Social Informatics Theory and Application, 2(1), 15-21. https://doi.org/10.31763/businta.v2i1.102

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2000). Analysis of Recommendation Algorithms for E-Commerce (GroupLens Research Group / Army HPC Research Center, Issue. G. R. G. A. H. R. Center.

Scheibehenne, B., Greifeneder, R., & Todd, P. (2010). Can There Ever be Too Many Options? A Meta-analytic Review of Choice Overload. Journal of Consumer Research, 37, 409-425. https://doi.org/10.1086/651235

Schulz, E., Bhui, R., Love, B. C., Brier, B., Todd, M. T., & Gershman, S. J. (2019). Structured, uncertainty-driven exploration in real-world consumer choice. Proceedings of the National Academy of Sciences, 116(28), 13903-13908. https://doi.org/10.1073/pnas.1821028116

Schwartz, B. (2016). The Paradox of Choice: Why More Is Less (E. Press, Ed. 2nd ed.).

Sela, A., & Berger, J. (2012). How Attribute Quantity Influences Option Choice. Journal of Marketing Research, 49(6), 942-953. https://doi.org/10.1509/jmr.11.0142

Sela, A., Berger, J., & Liu, W. (2009). Variety, Vice, and Virtue: How Assortment Size Influences Option Choice. Journal of Consumer Research, 35(6), 941-951. https://doi.org/10.1086/593692

Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. Journal of Retailing, 80(2), 159-169. https://doi.org/https://doi.org/10.1016/j.jretai.2004.04.001

Senecal, S., Kalczynski, P. J., & Nantel, J. (2005). Consumers' decision-making process and their online shopping behavior: a clickstream analysis. Journal of Business Research, 58(11), 1599-1608. https://doi.org/https://doi.org/10.1016/j.jbusres.2004.06.003

Shang, Q., Chen, J., Fu, H., Wang, C., Pei, G., & Jin, J. (2023). "Guess You Like It" - How personalized recommendation timing and product type influence consumers' acceptance: An ERP study. Neurosci Lett, 807, 137261. https://doi.org/10.1016/j.neulet.2023.137261

Shanteau, J. (1992). Competence in experts: The role of task characteristics. Organizational Behavior and Human Decision Processes, 53(2), 252-266. https://doi.org/https://doi.org/10.1016/0749-5978(92)90064-E

Sharma, J., Sharma, K., Garg, K., & Sharma, A. K. (2021). Product Recommendation System a Comprehensive Review. IOP Conference Series: Materials Science and Engineering, 1022(1), 12-21. https://doi.org/10.1088/1757-899X/1022/1/012021

Shen, A. (2014). Recommendations as personalized marketing: insights from customer experiences. Journal of Services Marketing, 28(5), 414-427. https://doi.org/10.1108/JSM-04-2013-0083

Shen, L., & Dillard, J. P. (2005). Psychometric properties of the Hong psychological reactance scale. J Pers Assess, 85(1), 74-81. https://doi.org/10.1207/s15327752jpa8501_07

Sheng, X., Li, J., & Zolfagharian, M. A. (2014). Consumer initial acceptance and continued use of recommendation agents: literature review and proposed conceptual framework. International Journal of Electronic Marketing and Retailing, 6(2), 112-127. https://doi.org/10.1504/IJEMR.2014.066467

Shields, G. S., Moons, W. G., Tewell, C. A., & Yonelinas, A. P. (2016). The effect of negative affect on cognition: Anxiety, not anger, impairs executive function. Emotion, 16(6), 792-797. https://doi.org/10.1037/emo0000151

Sia, C., Shi, Y., Yan, J., and Chen, H.: 'Web personalization to build trust in E-commerce: A design science approach', World Academy of Science, Engineering and Technology, 2010, 64, pp. 325-329

Simon, H. A. (1959). Theories of Decision-Making in Economics and Behavioral Science. The American Economic Review, 49(3), 253-283. http://www.jstor.org/stable/1809901

Simon, H.A.: 'The Sciences of the Artificial' (The MIT Press, 1996. 1996)

Sirois, S., & Brisson, J. (2014). Pupillometry. Wiley Interdisciplinary Reviews: Cognitive Science, 5(6), 679-692.

Slama, M. E., & Tashchian, A. (1985). Selected socioeconomic and demographic characteristics associated with purchasing involvement. Journal of marketing, 49(1), 72-82.

Smith, S. M., & Levin, I. P. (1996). Need for Cognition and Choice Framing Effects. Journal of Behavioral Decision Making, 9(4), 283-290. https://doi.org/https://doi.org/10.1002/(SICI)1099-0771(199612)9:4<283::AID-BDM241>3.0.CO;2-7

Soliha, E., Marlien, R. A., Widyasari, S., Riva'i, A. R., & Nurul, K. (2019). Image, Consumer Product Knowledge, Satisfaction and Loyalty Testing Their Relationships in the Rural Bank Sector. International Journal of Economics and Management Systems 40(42), 1267-1274.

Spuler, M. (2017). A high-speed brain-computer interface (BCI) using dry EEG electrodes. PLoS ONE, 12(2), e0172400. https://doi.org/10.1371/journal.pone.0172400

Stanton, J. V., & Cook, L. A. (2019). Product knowledge and information processing of organic foods. Journal of Consumer Marketing, 36(1), 240-252. https://doi.org/10.1108/JCM-07-2017-2275

Steindl, C., Jonas, E., Sittenthaler, S., Traut-Mattausch, E., & Greenberg, J. (2015). Understanding Psychological Reactance: New Developments and Findings. Zeitschrift für Psychologie, 223(4), 205-214. https://doi.org/10.1027/2151-2604/a000222

Sun, P., Yang, J., & Zhi, Y. (2019). Multi-attribute decision-making method based on Taylor expansion. International Journal of Distributed Sensor Networks, 15(3). https://doi.org/10.1177/1550147719836078

Sun, P., Yang, J., and Zhi, Y.: 'Multi-attribute decision-making method based on Taylor expansion', International Journal of Distributed Sensor Networks, 2019, 15, (3)

Swaminathan, V. (2003). The Impact of Recommendation Agents on Consumer Evaluation and Choice: The Moderating Role of Category Risk, Product Complexity, and Consumer Knowledge. Journal of Consumer Psychology, 13(1), 93-101. https://doi.org/https://doi.org/10.1207/S15327663JCP13-1&2_08

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285. https://doi.org/https://doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2011). CHAPTER TWO - Cognitive Load Theory. In J. P. Mestre & B. H. Ross (Eds.), Psychology of Learning and Motivation (Vol. 55, pp. 37-76). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. (1998). Cognitive Architecture and Instructional Design. Educational Psychology Review, 10, 251. https://doi.org/https://doi.org/10.1023/a:1022193728205

Szász, L., Bálint, C., Csíki, O., Nagy, B. Z., Rácz, B.-G., Csala, D., & Harris, L. C. (2022). The impact of COVID-19 on the evolution of online retail: The pandemic as a window of opportunity. Journal of Retailing and Consumer Services, 69, 103089. https://doi.org/https://doi.org/10.1016/j.jretconser.2022.103089

Tadson, B., Boasen, J., Courtemanche, F., Beauchemin, N., Karran, A.-J., Léger, P.-M., & Sénécal, S. (2023, 2023//). Neuro-Adaptive Interface System to Evaluate Product Recommendations in the Context of E-Commerce. Design Science Research for a New Society: Society 5.0, Cham.

Takemura, K. (1985). Ishikettei sutorateji jikko ni okeru meta ninchi katei moderu [Metacognition process model in the implementation of decision-making strategy]. Doshisha Psychological Review, 32, pp 16-22.

Takemura, K. (2001). Contingent Decision Making in the Social World: The "Mental Ruler" Model. In C. M. Allwood & M. Selart (Eds.), Decision Making: Social and Creative Dimensions (pp. 153-173). Springer Netherlands. https://doi.org/10.1007/978-94-015-9827-9_8

Takemura, K. (2014). Behavioral Decision Theories that Explain Decision-Making Processes. In K. Takemura (Ed.), Behavioral Decision Theory: Psychological and Mathematical Descriptions of Human Choice Behavior (pp. 143-164). Springer Japan. https://doi.org/10.1007/978-4-431-54580-4_12

Taylor-West, P., Fulford, H., Reed, G., Story, V., & Saker, J. (2008). Familiarity, expertise and involvement: key consumer segmentation factors. Journal of Consumer Marketing, 25(6), 361-368. https://doi.org/10.1108/07363760810902495

Thomas, M., & Menon, G. (2007). When Internal Reference Prices and Price Expectations Diverge: The Role of Confidence. Journal of Marketing Research, 44(3), 401-409. https://doi.org/10.1509/jmkr.44.3.401

Thorpe, A., Friedman, J., Evans, S., Nesbitt, K., & Eidels, A. (2022). Mouse Movement Trajectories as an Indicator of Cognitive Workload. International Journal of Human–Computer Interaction, 38(15), 1464-1479.

Tian, Y., Beier, M. E., & Fischer-Baum, S. (2022). The domain-specificity of serial order working memory. Memory & Cognition, 50(5), 941-961. https://doi.org/10.3758/s13421-021-01260-4

Tintarev, N., & Masthoff, J. (2012). Evaluating the effectiveness of explanations for recommender systems. User Modeling and User-Adapted Interaction, 22(4), 399-439. https://doi.org/10.1007/s11257-011-9117-5

Todd, P., & Benbasat, I. (1994). The Influence of Decision Aids on Choice Strategies: An Experimental Analysis of the Role of Cognitive Effort. Organizational Behavior and Human Decision Processes, 60(1), 36-74. https://doi.org/https://doi.org/10.1006/obhd.1994.1074

Toffler, A. (1970). Future shock (Bantam, Ed.). Random House.

Tokushige, H., Narumi, T., Ono, S., Fuwamoto, Y., Tanikawa, T., & Hirose, M. (2017). Trust Lengthens Decision Time on Unexpected Recommendations in Human-agent Interaction Proceedings of the 5th International Conference on Human Agent Interaction, Bielefeld, Germany. https://doi.org/10.1145/3125739.3125751

Torres, F., Gendreau, M., & Rei, W. (2022). Crowdshipping: An open VRP variant with stochastic destinations. Transportation Research Part C: Emerging Technologies, 140, 103677. https://doi.org/https://doi.org/10.1016/j.trc.2022.103677

Townsend, C., & Kahn, B. E. (2014). The "Visual Preference Heuristic": The Influence of Visual versus Verbal Depiction on Assortment Processing, Perceived Variety, and Choice Overload. Journal of Consumer Research, 40(5), 993-1015. https://doi.org/10.1086/673521

Tsekouras, D., Li, T., & Benbasat, I. (2022). Scratch my back and I'll scratch yours: The impact of user effort and recommendation agent effort on perceived recommendation agent quality. Information & Management, 59(1), 103571. https://doi.org/https://doi.org/10.1016/j.im.2021.103571

Urbany, J. E., Dickson, P. R., & Wilkie, W. L. (1989). Buyer Uncertainty and Information Search. Journal of Consumer Research, 16(2), 208-215. https://doi.org/10.1086/209209

van der Merwe, A., Gerber, A., & Smuts, H. (2020). Guidelines for Conducting Design Science Research in Information Systems. In ICT Education (pp. 163-178). https://doi.org/10.1007/978-3-030-35629-3_11

Velasco-Álvarez, F., Fernández-Rodríguez, Á., Vizcaíno-Martín, F.-J., Díaz-Estrella, A., & Ron-Angevin, R. (2021). Brain–Computer Interface (BCI) Control of a Virtual Assistant in a Smartphone to Manage Messaging Applications [Article]. Sensors (14248220), 21(11), 3716-3716. https://doi.org/10.3390/s21113716

Verhagen, T., & Bloemers, D. (2018). Exploring the cognitive and affective bases of online purchase intentions: a hierarchical test across product types. Electronic Commerce Research, 18(3), 537-561. https://doi.org/10.1007/s10660-017-9270-y

Verplanken, B. (1993). Need for Cognition and External Information Search: Responses to Time Pressure during Decision-Making. Journal of Research in Personality, 27(3), 238-252. https://doi.org/https://doi.org/10.1006/jrpe.1993.1017

Vogrincic-Haselbacher, C., Krueger, J. I., Lurger, B., Dinslaken, I., Anslinger, J., Caks, F., Florack, A., Brohmer, H., & Athenstaedt, U. (2021). Not Too Much and Not Too Little: Information Processing for a Good Purchase Decision [Original Research]. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.642641

Wang, S., Gwizdka, J., & Chaovalitwongse, W. A. (2016). Using Wireless EEG Signals to Assess Memory Workload in the N-Back Task. IEEE Transactions on Human-Machine Systems, 46(3), 424-435. https://doi.org/10.1109/THMS.2015.2476818

Wang, W., & Benbasat, I. (2007). Recommendation Agents for Electronic Commerce: Effects of Explanation Facilities on Trusting Beliefs. J. of Management Information Systems, 23, 217-246. https://doi.org/10.2753/MIS0742-1222230410

Weber, P., Rupprecht, F., Wiesen, S., Hamann, B., & Ebert, A. (2021). Assessing cognitive load via pupillometry. Advances in Artificial Intelligence and Applied Cognitive Computing: Proceedings from ICAI’20 and ACC’20,

Wegener, D. T., & Petty, R. E. (2001). Understanding effects of mood through the elaboration likelihood and flexible correction models. In Theories of mood and cognition: A user's guidebook. (pp. 177-210). Lawrence Erlbaum Associates Publishers.

Wen, N., & Lurie, N. H. (2019). More Than Aesthetic: Visual Boundaries and Perceived Variety [Article]. Journal of Retailing, 95(3), 86-98. https://doi.org/10.1016/j.jretai.2019.03.001

Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D. R., Matz, S., Nave, G., Parker, J. R., Puntoni, S., Zheng, Y., & Zwebner, Y. (2020). Autonomy in consumer choice. Marketing Letters, 31(4), 429-439. https://doi.org/10.1007/s11002-020-09521-z

Whang, C., & Im, H. (2021). "I Like Your Suggestion!" the role of humanlikeness and parasocial relationship on the website versus voice shopper's perception of recommendations. Psychology & Marketing, 38. https://doi.org/10.1002/mar.21437

Wheeler, P., & Arunachalam, V. (2009). The effects of multimedia on cognitive aspects of decision-making. International Journal of Accounting Information Systems, 10(2), 97-116. https://doi.org/https://doi.org/10.1016/j.accinf.2008.10.004

Wheeler, S. C., Petty, R. E., & Bizer, G. Y. (2005). Self-schema matching and attitude change: Situational and dispositional determinants of message elaboration. Journal of Consumer Research, 31(4), 787-797.

Whelan, R. R. (2007). Neuroimaging of cognitive load in instructional multimedia. Educational Research Review, 2(1), 1-12.

Willemsen, M. C., Graus, M. P., & Knijnenburg, B. P. (2016). Understanding the role of latent feature diversification on choice difficulty and satisfaction. User Modeling and User-Adapted Interaction, 26(4), 347-389. https://doi.org/10.1007/s11257-016-9178-6

Willemsen, M., Knijnenburg, B., Graus, M., Velter-Bremmers, L., & Fu, K. (2011). Using latent features diversification to reduce choice difficulty in recommendation lists. CEUR Workshop Proceedings,

Woller, K. M. P., Buboltz, W. C., & Loveland, J. M. (2007). Psychological Reactance: Examination across Age, Ethnicity, and Gender. The American Journal of Psychology, 120(1), 15-24. https://doi.org/10.2307/20445379

Wolpaw, J. R., Millán, J. d. R., & Ramsey, N. F. (2020). Chapter 2 - Brain-computer interfaces: Definitions and principles. In N. F. Ramsey & J. d. R. Millán (Eds.), Handbook of Clinical Neurology (Vol. 168, pp. 15-23). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-444-63934-9.00002-0

Wolpaw, J.R., Millán, J.d.R., and Ramsey, N.F.: ‘Chapter 2 - Brain-computer interfaces: Definitions and principles’, in Ramsey, N.F., and Millán, J.d.R. (Eds.): ‘Handbook of Clinical Neurology’ (Elsevier, 2020), pp. 15-23

Wu, C.-H., Parker, S. K., & de Jong, J. P. J. (2011). Need for Cognition as an Antecedent of Individual Innovation Behavior. Journal of Management, 40(6), 1511-1534. https://doi.org/10.1177/0149206311429862

Xiao, B., & Benbasat, I. (2007). E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact. MIS Quarterly, 31(1), 137-209. https://doi.org/10.2307/25148784

Xiao, B., & Benbasat, I. (2014). Research on the Use, Characteristics, and Impact of e-Commerce Product Recommendation Agents: A Review and Update for 2007–2012. In F. J. Martínez-López (Ed.), Handbook of Strategic e-Business Management (pp. 403-431). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-39747-9_18

Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. Decision Support Systems, 110, 46-57. https://doi.org/https://doi.org/10.1016/j.dss.2018.03.005

Xu, J., Benbasat, I., & Cenfetelli, R. T. (2020). The Relative Effect of the Convergence of Product Recommendations from Various Online Sources. Journal of Management Information Systems, 37(3), 788-819. https://doi.org/10.1080/07421222.2020.1790192

Yan, Q., Zhang, L., Li, Y., Wu, S., Sun, T., Wang, L., & Chen, H. (2016). Effects of product portfolios and recommendation timing in the efficiency of personalized recommendation. Journal of Consumer Behaviour, 15(6), 516-526. https://doi.org/https://doi.org/10.1002/cb.1588

Yangyang Miao, m. c., Shugeng Chen, t. c., Xinru Zhang, z. c., Jing Jin, j. g. c., Ren Xu, x. g. a., Ian Daly, i. d. e. a. u., Jie Jia, s. c., Xingyu Wang, x. e. e. c., Andrzej Cichocki, a. c. r. j., & Tzyy-Ping Jung, t. u. e. (2020). BCI-Based Rehabilitation on the Stroke in Sequela Stage. Neural Plasticity, 2020. https://doi.org/10.1155/2020/8882764

a.c.r.j., and Tzyy-Ping Jung, t.u.e.: ‘BCI-Based Rehabilitation on the Stroke in Sequela Stage’, Neural Plasticity, 2020, 2020

Yanping, W., & Yan, C. (2012, 20-21 Oct. 2012). Psychology reactance to online recommendations: The influence of time pressure. 2012 3rd International Conference on System Science, Engineering Design and Manufacturing Informatization,

Yi, Y. (1990). A Critical Review of Consumer Satisfaction. In V. A. Zeithaml (Ed.), Review of Marketing (pp. 68-123). American Marketing Association.

Yoon, V. Y., Hostler, R. E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. Decision Support Systems, 55(4), 883-893. https://doi.org/https://doi.org/10.1016/j.dss.2012.12.024

Yuan, Z.-m., Huang, C., Sun, X.-y., Li, X.-x., & Xu, D.-r. (2015). A microblog recommendation algorithm based on social tagging and a temporal interest evolution model. Frontiers of Information Technology & Electronic Engineering, 16(7), 532-540. https://doi.org/10.1631/FITEE.1400368

Zaichkowsky, J. (2012). Consumer involvement: Review, update and links to decision neuroscience. Handbook of Developments in Consumer Behaviour, 523-546. https://doi.org/10.4337/9781849802444.00022

Zanetti, R., Arza, A., Aminifar, A., and Atienza, D.: 'Real-Time EEG-Based Cognitive Workload Monitoring on Wearable Devices', IEEE Trans Biomed Eng, 2022, 69, (1), pp. 265-277

Zeithaml, V. A., Bitner, M. J., & Gremler, D. D. (2006). Services marketing : integrating customer focus across the firm (4th ed. ed.). McGraw-Hill/Irwin. http://catdir.loc.gov/catdir/enhancements/fy0619/2004065642-d.html

Zhang, H., Zhao, L., & Gupta, S. (2018). The role of online product recommendations on customer decision making and loyalty in social shopping communities. International Journal of Information Management, 38, 150-166. https://doi.org/10.1016/j.ijinfomgt.2017.07.006

Zhang, N., & Xu, H. (2019). Reconciling the paradoxical findings of choice overload through an analytical lens. MIS Quarterly (Forthcoming).

Zhou, Y., Huang, S., Xu, Z., Wang, P., Wu, X., & Zhang, D. (2022). Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review. IEEE

Transactions on Cognitive and Developmental Systems, 14(3), 799-818. https://doi.org/10.1109/TCDS.2021.3090217

Zhu, D. H., Chang, Y., Luo, J., & Li, X. (2014). Understanding the adoption of location-based recommendation agents among active users of social networking sites. Information Processing & Management, 50, 675–682. https://doi.org/10.1016/j.ipm.2014.04.010

Zhu, D. H., Wang, Y. W., & Chang, Y. P. (2018). The influence of online cross-recommendation on consumers' instant cross-buying intention. Internet Research, 28(3), 604-622. https://doi.org/10.1108/IntR-05-2017-0211

Appendices

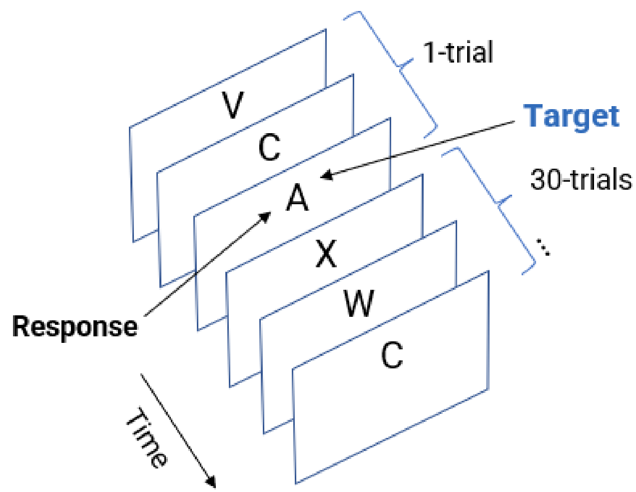
Appendix A

Demonstration of the baseline and N-Back EEG calibration tasks, and EEG cognitive load classification index.

Baseline task interface

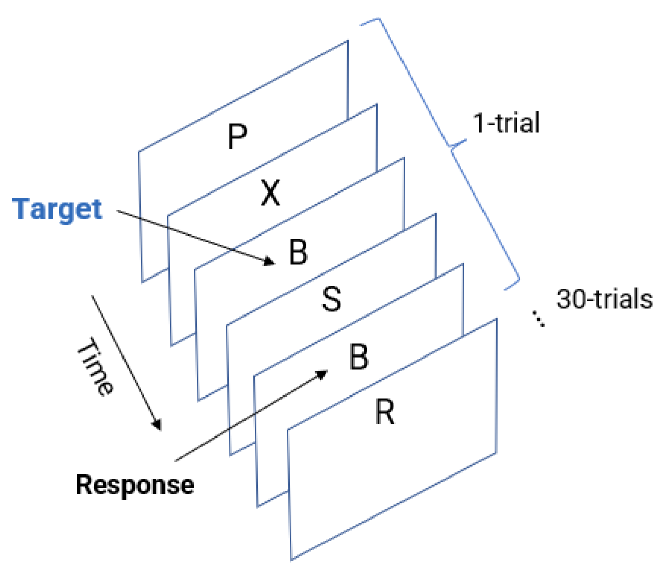
N-Back task

0-Back:



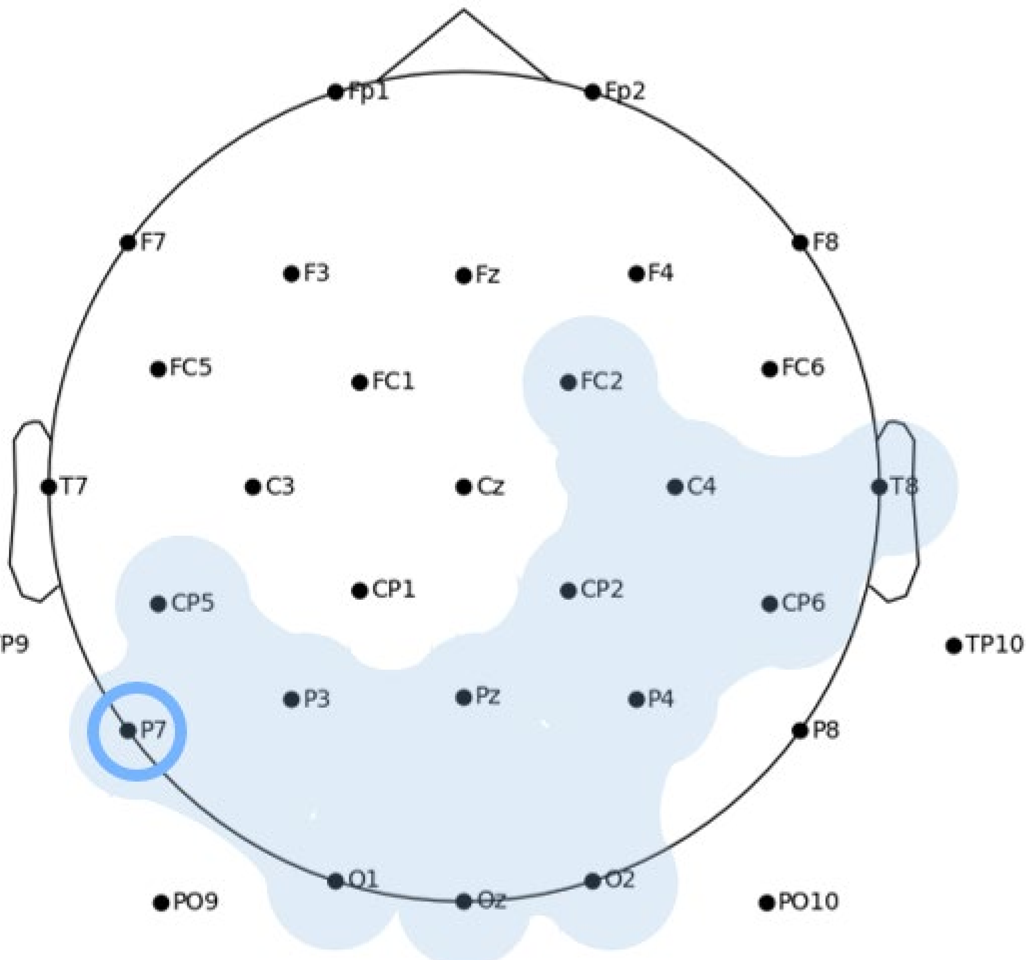
0-Back = Low CL (0)

2-Back:



2-Back = High CL (2)

Cognitive load classification target electrode and formula



$$\frac{\text{Alpha power}}{(\text{Theta} + \text{Alpha} + \text{Beta})}$$

Cognitive load thresholds

The cumulative average was taken over 60 seconds, aimed to adjust to the progression of the task.

The 1.25 coefficient is an adjustment for the specificity of the experimental tasks.

$$\text{Cumul Avg} \left[\frac{\text{mean of 0-Back}}{\text{mean of N-Back}} \right] 1.25$$

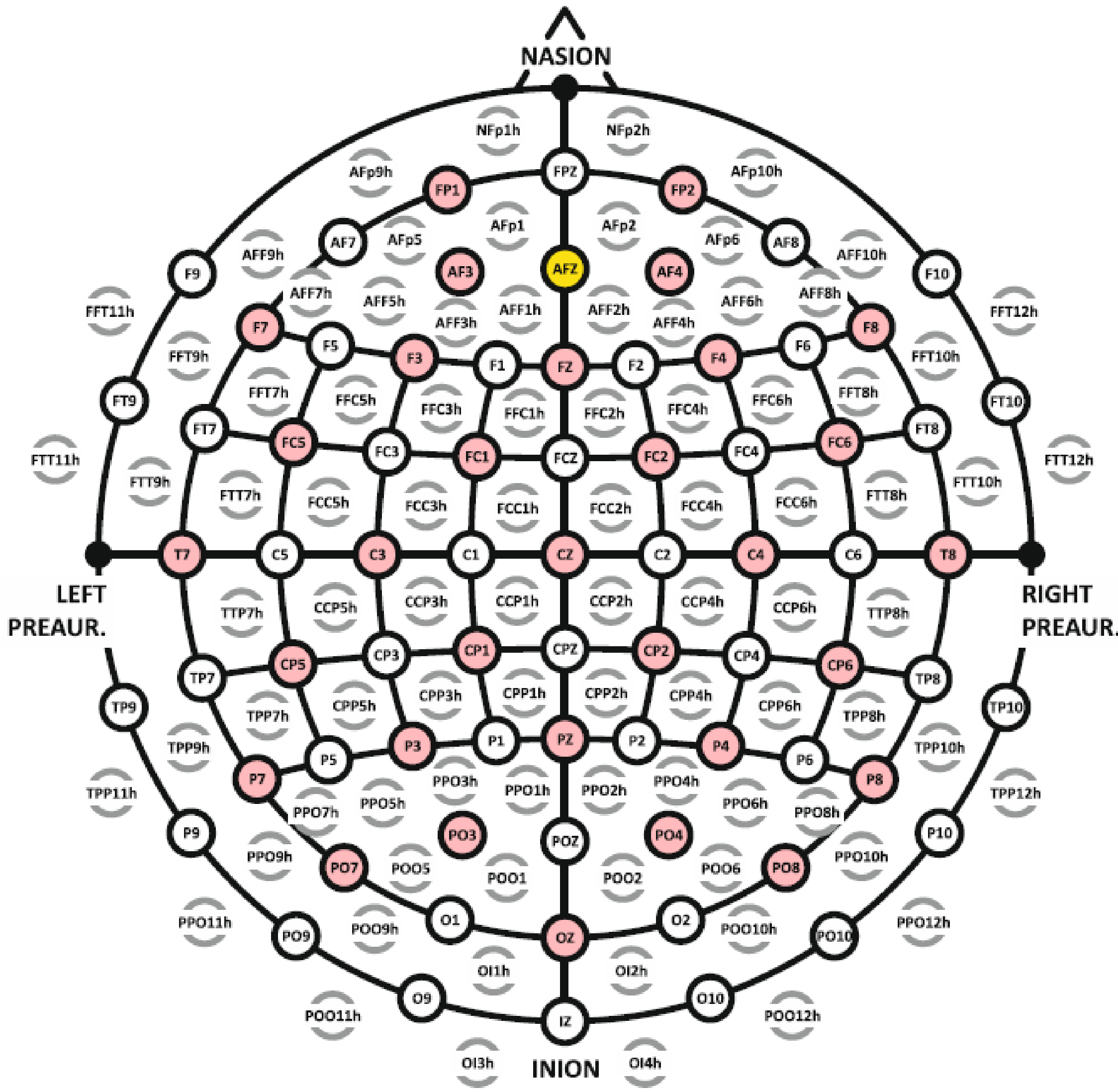
0-Back = Low CL (0)

$$\text{Cumul Avg} \left[\frac{\text{mean of 2-Back}}{\text{mean of N-Back}} \right] 1.25$$

2-Back = High CL (2)

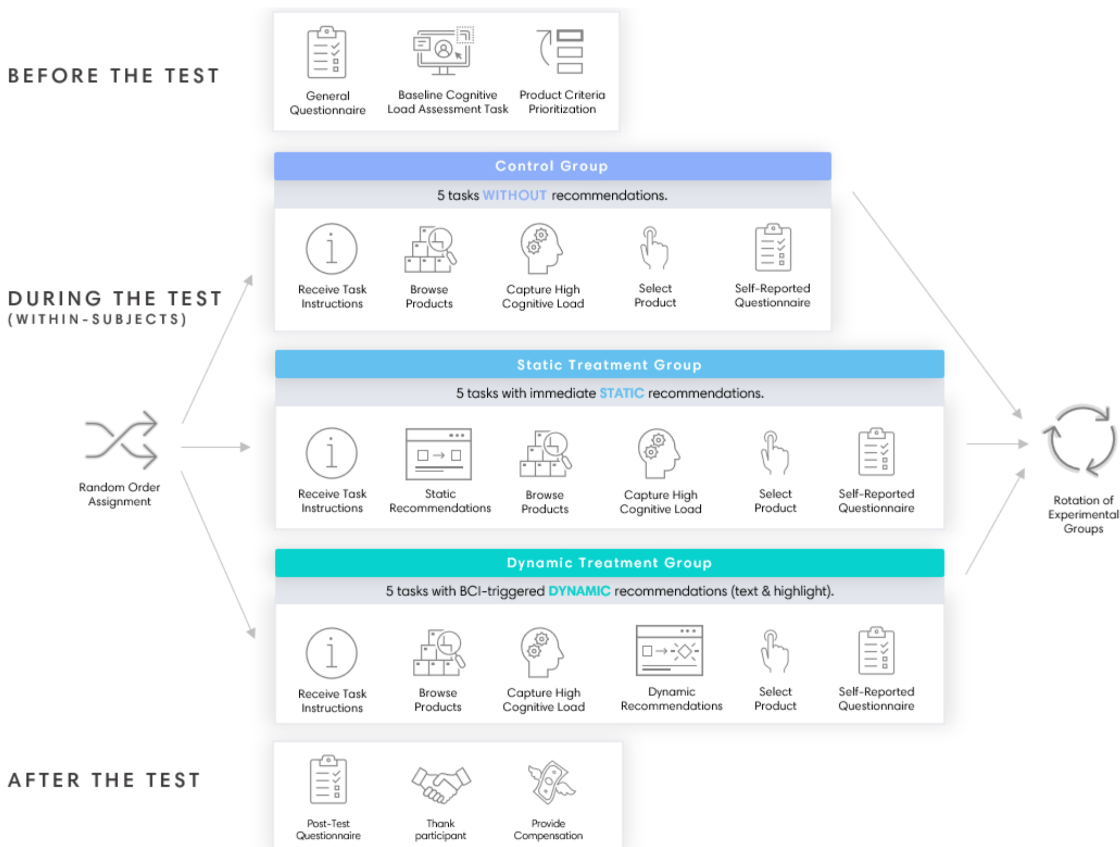
Appendix B

Standard EEG montage by g.tec



Appendix C

Overview of the experimental procedure.



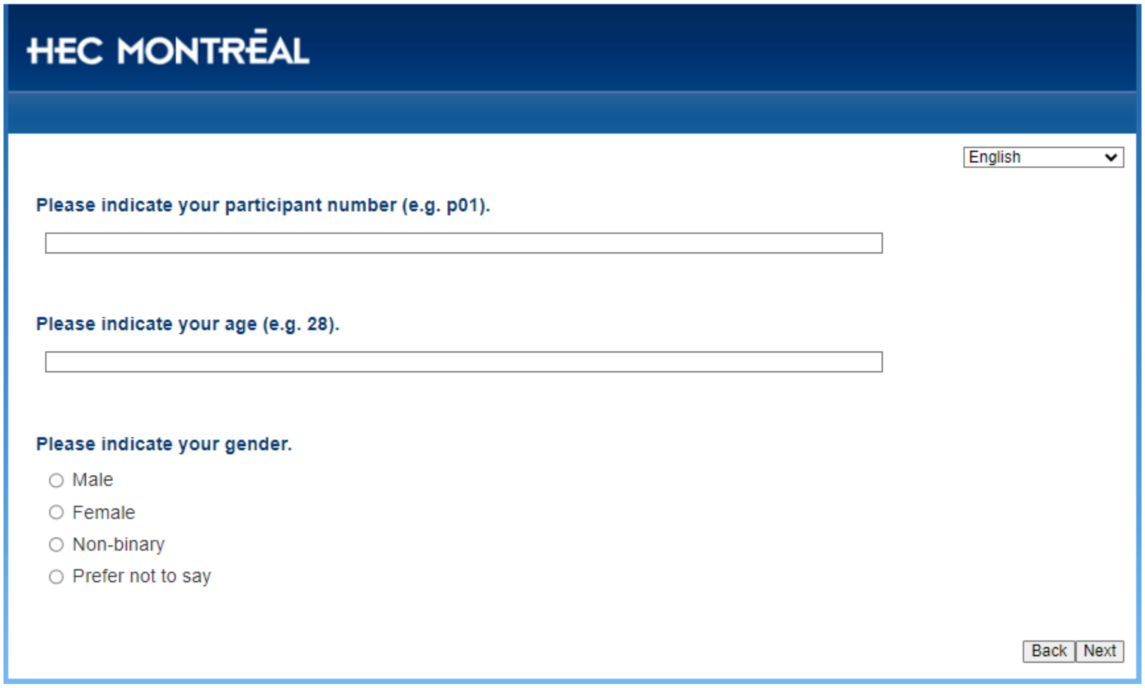
Appendix D

Additional information on the reliability of scale items.

We computed the reliability of all assessed variables using Cronbach's alpha, as discussed in the article. All values exceeded $\alpha = 0.7$, spanning 0.7143 to 0.8942, suggesting acceptable to excellent internal consistency. We further evaluated construct validity through convergent and discriminatory validity tests. High values of factor loadings and average variances above 0.5 indicate strong associations between scale items within each construct, as well as affirm that the items effectively measure a cohesive construct. Lastly, average variances extracted per construct were greater than the squared correlations between that and all other constructs, which suggests adequate discriminant validity.

Appendix E

Pre-experimental questionnaire, basic demographic information


HEC MONTRĒAL

English

Please indicate your participant number (e.g. p01).

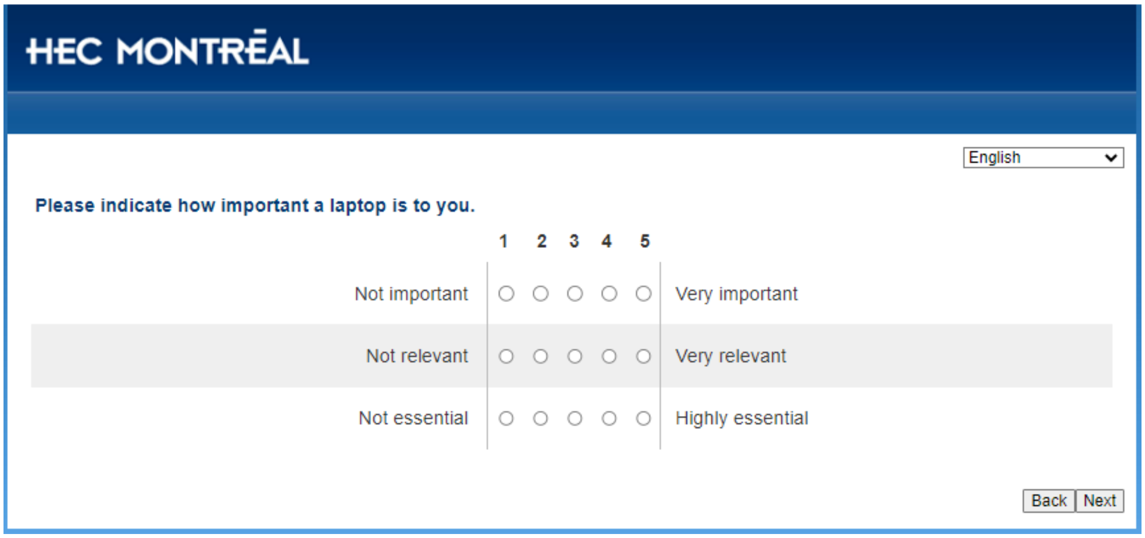
Please indicate your age (e.g. 28).

Please indicate your gender.

- Male
- Female
- Non-binary
- Prefer not to say

Back Next

Pre-experiment questionnaire, consumer product involvement


HEC MONTRĒAL

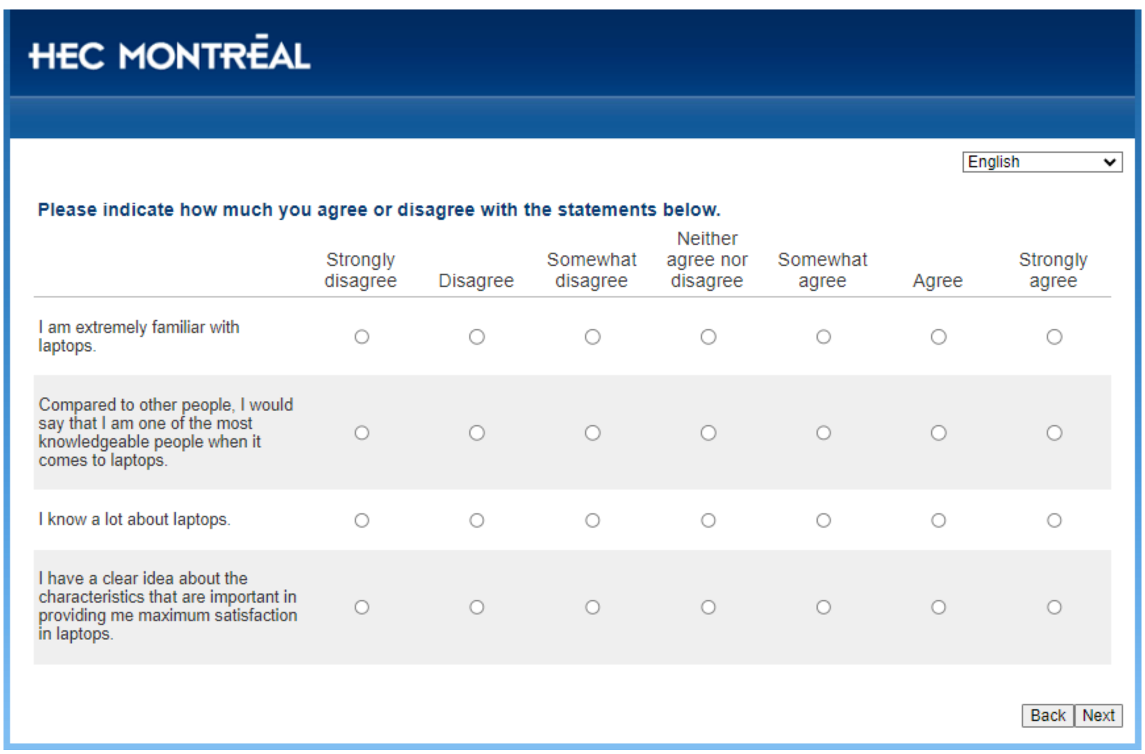
English

Please indicate how important a laptop is to you.

	1	2	3	4	5	
Not important	○	○	○	○	○	Very important
Not relevant	○	○	○	○	○	Very relevant
Not essential	○	○	○	○	○	Highly essential

Back Next

Pre-experiment questionnaire, product expertise


HEC MONTRĒAL

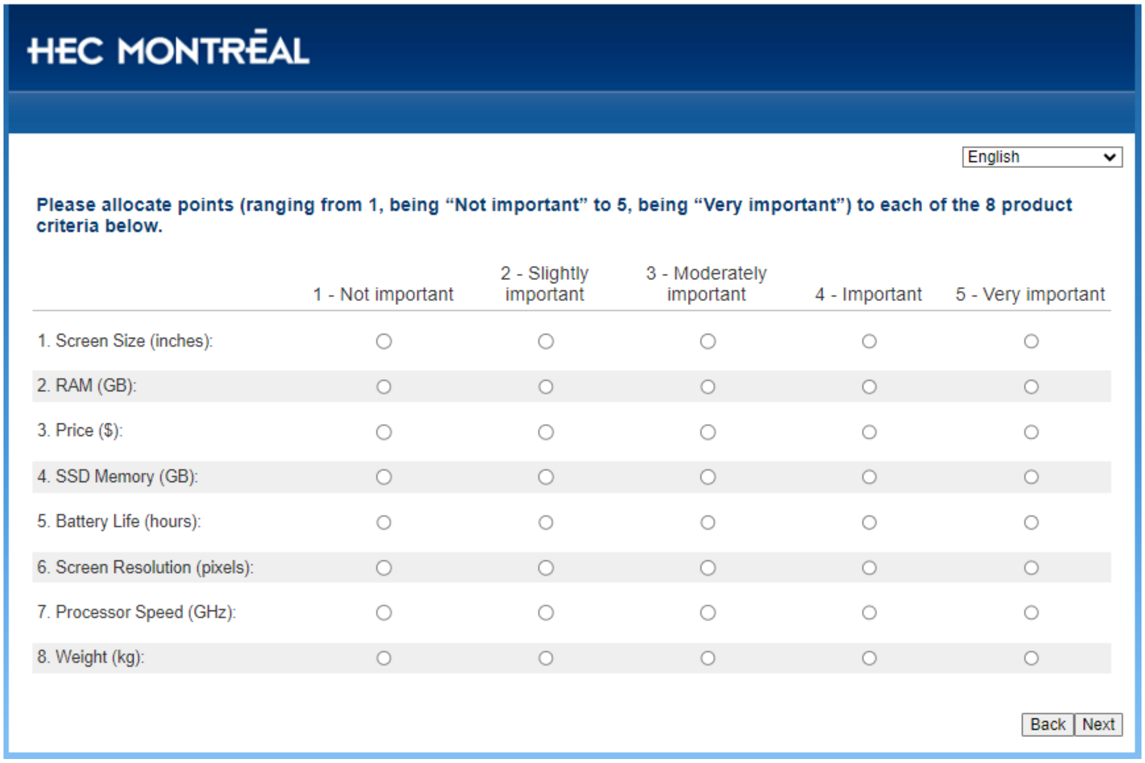
English

Please indicate how much you agree or disagree with the statements below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am extremely familiar with laptops.	○	○	○	○	○	○	○
Compared to other people, I would say that I am one of the most knowledgeable people when it comes to laptops.	○	○	○	○	○	○	○
I know a lot about laptops.	○	○	○	○	○	○	○
I have a clear idea about the characteristics that are important in providing me maximum satisfaction in laptops.	○	○	○	○	○	○	○

Back Next

Pre-experiment questionnaire, MADM-SAW preferences



HEC MONTRÉAL

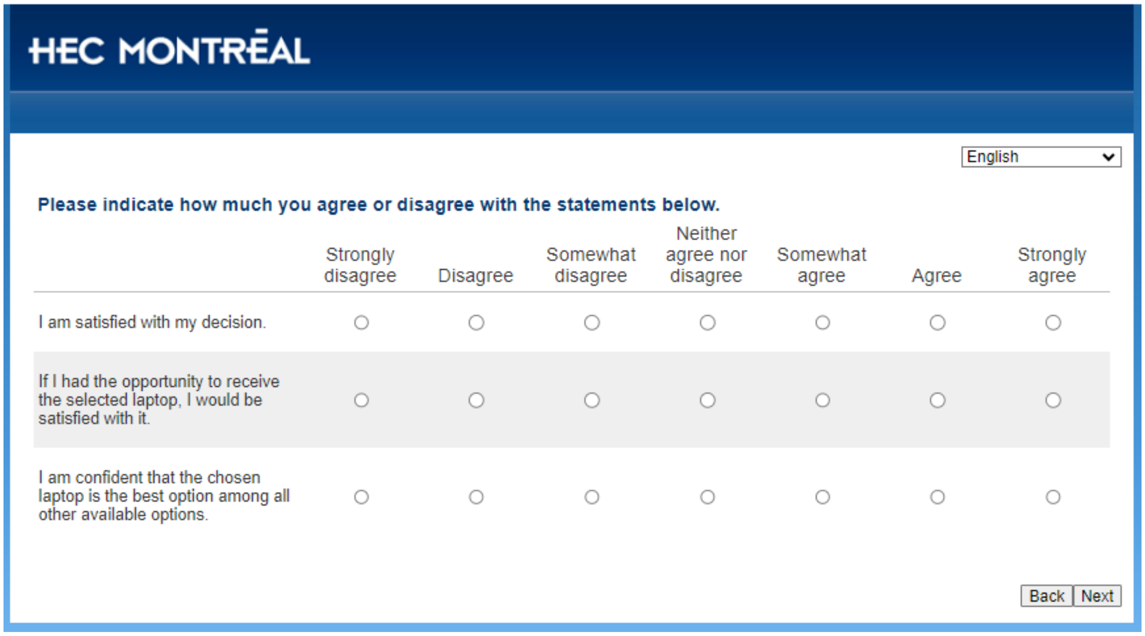
English

Please allocate points (ranging from 1, being "Not important" to 5, being "Very important") to each of the 8 product criteria below.

	1 - Not important	2 - Slightly important	3 - Moderately important	4 - Important	5 - Very important
1. Screen Size (inches):	○	○	○	○	○
2. RAM (GB):	○	○	○	○	○
3. Price ($):	○	○	○	○	○
4. SSD Memory (GB):	○	○	○	○	○
5. Battery Life (hours):	○	○	○	○	○
6. Screen Resolution (pixels):	○	○	○	○	○
7. Processor Speed (GHz):	○	○	○	○	○
8. Weight (kg):	○	○	○	○	○

Back Next

Post-trial questionnaire, randomized choice satisfaction and confidence (page 1 of 2)


HEC MONTRĒAL

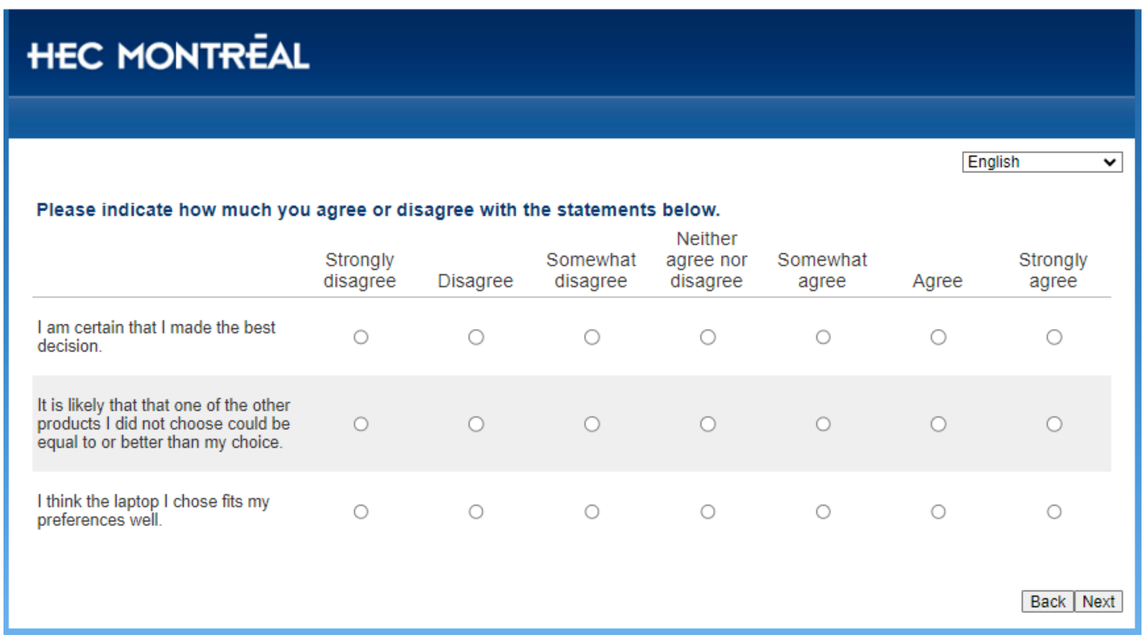
English

Please indicate how much you agree or disagree with the statements below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am satisfied with my decision.	○	○	○	○	○	○	○
If I had the opportunity to receive the selected laptop, I would be satisfied with it.	○	○	○	○	○	○	○
I am confident that the chosen laptop is the best option among all other available options.	○	○	○	○	○	○	○

Back Next

Post-trial questionnaire, randomized choice satisfaction and confidence (page 2 of 2)


HEC MONTRĒAL

English

Please indicate how much you agree or disagree with the statements below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am certain that I made the best decision.	○	○	○	○	○	○	○
It is likely that that one of the other products I did not choose could be equal to or better than my choice.	○	○	○	○	○	○	○
I think the laptop I chose fits my preferences well.	○	○	○	○	○	○	○

Back Next

Post-trial questionnaire, choice overload

HEC MONTRĒAL

English

Please indicate how much you agree or disagree with the statements below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I felt overwhelmed in the decision process making.	○	○	○	○	○	○	○
I was frustrated while deciding which laptop to select.	○	○	○	○	○	○	○
I was confused when deciding which laptop to select.	○	○	○	○	○	○	○
It was difficult for me to choose the most suitable laptop.	○	○	○	○	○	○	○

Back Next

Post-experiment questionnaire, need for cognition (page 1 of 3)

HEC MONTRÉAL

English

For each of the statements below, please indicate whether or not the statement is characteristic of you or of what you believe.

	Extremely uncharacteristic of me	Uncharacteristic of me	Somewhat uncharacteristic of me	Uncertain	Somewhat characteristic of me	Characteristic of me	Extremely characteristic of me
I prefer complex to simple problems.	○	○	○	○	○	○	○
I like to have the responsibility of handling a situation that requires a lot of thinking.	○	○	○	○	○	○	○
Thinking is not my idea of fun.	○	○	○	○	○	○	○
I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.	○	○	○	○	○	○	○
I try to anticipate and avoid situations where there is a likely chance I will have to think in depth about something.	○	○	○	○	○	○	○
I find satisfaction in deliberating hard and for long hours.	○	○	○	○	○	○	○

Next

Post-experiment questionnaire, need for cognition (page 2 of 3)

HEC MONTREAL

English

For each of the statements below, please indicate whether or not the statement is characteristic of you or of what you believe.

	Extremely uncharacteristic of me	Uncharacteristic of me	Somewhat uncharacteristic of me	Uncertain	Somewhat characteristic of me	Characteristic of me	Extremely characteristic of me
I only think as hard as I have to.	○	○	○	○	○	○	○
I prefer to think about small daily projects to long term ones.	○	○	○	○	○	○	○
I like tasks that require little thought once I've learned them.	○	○	○	○	○	○	○
The idea of relying on thought to make my way to the top appeals to me.	○	○	○	○	○	○	○
I really enjoy a task that involves coming up with new solutions to problems.	○	○	○	○	○	○	○
Learning new ways to think doesn't excite me very much.	○	○	○	○	○	○	○
I prefer my life to be filled with puzzles I must solve.	○	○	○	○	○	○	○

Back Next

Post-experiment questionnaire, need for cognition (page 3 of 3)

HEC MONTRĒAL

English

For each of the statements below, please indicate whether or not the statement is characteristic of you or of what you believe.

	Extremely uncharacteristic of me	Uncharacteristic of me	Somewhat uncharacteristic of me	Uncertain	Somewhat characteristic of me	Characteristic of me	Extremely characteristic of me
The notion of thinking abstractly is appealing to me.	○	○	○	○	○	○	○
I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.	○	○	○	○	○	○	○
I feel relief rather than satisfaction after completing a task that requires a lot of mental effort.	○	○	○	○	○	○	○
It's enough for me that something gets the job done; I don't care how or why it works.	○	○	○	○	○	○	○
I usually end up deliberating about issues even when they do not affect me personally.	○	○	○	○	○	○	○

Back Next

Post-experiment questionnaire, psychological reactance (page 1 of 2)

HEC MONTRĒAL

English

Please indicate how much you agree or disagree with the statements below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The thought of being dependent on others aggravates me.	○	○	○	○	○	○	○
I become frustrated when I am unable to make free and independent decisions.	○	○	○	○	○	○	○
It irritates me when someone points out things which are obvious to me.	○	○	○	○	○	○	○
I become angry when my freedom of choice is restricted.	○	○	○	○	○	○	○
Regulations trigger a sense of resistance in me.	○	○	○	○	○	○	○
I find contradicting others stimulating.	○	○	○	○	○	○	○
When something is prohibited, I usually think, "That's exactly what I am going to do."	○	○	○	○	○	○	○

Back Next

Post-experiment questionnaire, psychological reactance (page 2 of 2)

HEC MONTRĒAL

English

Please indicate how much you agree or disagree with the statements below.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
It disappoints me to see others submitting to society's standards and rules.	○	○	○	○	○	○	○
I am contented only when I am acting of my own free will.	○	○	○	○	○	○	○
I resist the attempts of others to influence me.	○	○	○	○	○	○	○
It makes me angry when another person is held up as a role model for me to follow.	○	○	○	○	○	○	○
When someone forces me to do something, I feel like doing the opposite.	○	○	○	○	○	○	○
I consider advice from others to be an intrusion.	○	○	○	○	○	○	○
Advice and recommendations usually induce me to do just the opposite.	○	○	○	○	○	○	○

Back Next

Appendix F

Summary of Advantages of Neuro-Adaptive Recommendations

Observed Advantage	Specific Finding	Possible Consideration (if applicable)
Neuro-adaptive recommendations occasionally outperformed standard recommendations.	Choice confidence and decision quality were higher for one of the three experimental trials in the neuro-adaptive condition.	-
Neuro-adaptive recommendations mitigated some of the drawbacks of standard recommendations.	Conversely to when recommendations were static, users with low product expertise and psychological reactance scores did not perceive significantly higher choice overload with neuro-adaptive recommendations.	Neuro-adaptivity aligns with the user experience principle of progressive disclosure (Ding et al., 2020), suggesting a gradual increase in the density of information displayed to users.
	Neuro-adaptive recommendations did not significantly increase decision times among users with high psychological reactance scores, unlike what was observed with static recommendations.	Standard recommendations were shown to trigger a sense of threat of personal freedom (Brehm & Brehm, 1981; Fitzsimons & Lehmann, 2004), resulting in more time spent to re-establish the sense of freedom by individuals (L. Shen & J. P. Dillard, 2005). As neuro-adaptive recommendations appear only when the system deems necessary, their appearance might have been perceived as more justified.

Neuro-adaptive recommendations are better catered to certain individuals.	Users with lower product expertise experienced higher choice satisfaction and confidence with neuro-adaptive recommendations, but not with static ones.	Lower product expertise is linked to lower levels of certainty about a decision (Kamal & Burkell, 2011; Urbany et al., 1989). Providing recommendations at the optimal moment, rather than persistently, promotes a feeling of being heard in one's struggles and perceiving the experience as more personalized.
	Choice confidence scores were higher among low product involvement users in the presence of neuro-adaptive recommendations, compared to any other condition.	Being exposed to a certain product category may increase product involvement (Maheswarappa et al., 2017; Petty & Cacioppo, 2012). By first exposing participants to the products without any recommendations, they were able to build better rapport and relatedness to the product (Slama & Tashchian, 1985), which eventually brought them more confidence about their selection.
	High need for cognition individuals reported higher choice satisfaction with neuro-adaptive recommendations only.	Allowing users to autonomously select a product before providing them with recommendations provides them with the pleasure they experience from cognitively demanding tasks (Cacioppo & Petty, 1982). When recommendations were static, the system assumed that these users require assistance, which may have reduced their engagement with the task (Petty et al., 2007; Wheeler et al., 2005).

Appendix G

HEC MONTRÉAL

Comité d'éthique de la recherche

Le 13 juin 2022

À l'attention de :
Pierre-Majorique Léger
HEC Montréal

Objet : Approbation éthique de votre projet de recherche

 # Projet : 2023-5071

Titre du projet de recherche : Interfaces neuro-adaptatives en fonction de la charge cognitive dans différents contextes

Source de financement : IVADO - CCS: 38-153-310-64-R2884

Titre de la subvention : L'IA centrée sur l'humain : du développement des algorithmes responsables à l'adoption de l'IA.

Votre projet de recherche a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains par le CER de HEC Montréal.

Un certificat d'approbation éthique qui atteste de la conformité de votre projet de recherche à la *Politique relative à l'éthique de la recherche avec des êtres humains* de HEC Montréal est émis en date du 13 juin 2022. Prenez note que ce certificat est **valide jusqu'au 01 juin 2023.**

Dans le contexte actuel de la pandémie de COVID-19, vous devez vous assurer de respecter les directives émises par le gouvernement du Québec, le gouvernement du Canada et celles de HEC Montréal en vigueur durant l'état d'urgence sanitaire.

Vous devrez obtenir le renouvellement de votre approbation éthique avant l'expiration de ce certificat à l'aide du formulaire *F7 - Renouvellement annuel*. Un rappel automatique vous sera envoyé par courriel quelques semaines avant l'échéance de votre certificat.

Lorsque votre projet est terminé, vous devrez remplir le formulaire *F9 - Fin de projet (ou F9a - Fin de projet étudiant sous l'égide d'un autre chercheur)*, selon le cas. **Les étudiants doivent remplir un formulaire F9 afin de recevoir l'attestion d'approbation éthique nécessaire au dépôt de leur thèse/mémoire/projet supervisé.**

Si des modifications sont apportées à votre projet, vous devrez remplir le formulaire *F8 - Modification de projet* et obtenir l'approbation du CER avant de mettre en oeuvre ces modifications.

Notez qu'en vertu de la *Politique relative à l'éthique de la recherche avec des êtres humains de HEC Montréal*, il est de la responsabilité des chercheurs d'assurer que leurs projets de recherche conservent une approbation éthique pour toute la durée des travaux de recherche et d'informer le CER de la fin de ceux-ci. De plus, toutes modifications significatives du projet doivent être transmises au CER avant leurs applications.

Vous pouvez dès maintenant procéder à la collecte de données pour laquelle vous avez obtenu ce certificat.

Nous vous souhaitons bon succès dans la réalisation de votre recherche.

Le CER de HEC Montréal

HEC MONTRĒAL

Comité d'éthique de la recherche

CERTIFICAT D'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

Projet # : 2023-5071

Titre du projet de recherche : Interfaces neuro-adaptatives en fonction de la charge cognitive dans différents contextes

Chercheur principal :
Pierre-Majorique Léger,
Professeur titulaire, Technologies de l'information, HEC Montréal

Cochercheurs :
Sylvain Sénécal; Patrick Charland; Bella Tadson; Noémie Beauchemin; François Courtemanche; David Brieugne; Amine Abdessemed; Salima Tazi; Alexander John Karran; Jared Boasen

Date d'approbation du projet : 13 juin 2022

Date d'entrée en vigueur du certificat : 13 juin 2022

Date d'échéance du certificat : 01 juin 2023

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2022-06-16 à 11:50

HEC MONTRĒAL

Comité d'éthique de la recherche

ATTESTATION D'APPROBATION ÉTHIQUE COMPLÉTÉE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet des approbations en matière d'éthique de la recherche avec des êtres humains nécessaires selon les exigences de HEC Montréal.

La période de validité du certificat d'approbation éthique émis pour ce projet est maintenant terminée. Si vous devez reprendre contact avec les participants ou reprendre une collecte de données pour ce projet, la certification éthique doit être réactivée préalablement. Vous devez alors prendre contact avec le secrétariat du CER de HEC Montréal.

Nom de l'étudiant(e) : Bella Tadson

Titre du projet supervisé/mémoire/thèse : Evaluating the Impact of Product Recommendations in the Context of E-Commerce Choice Overload: A Neuro-Adaptive Development and Approach

Titre du projet sur le certificat :
Interfaces neuro-adaptatives en fonction de la charge cognitive dans un contexte d'apprentissage en ligne et de magasinage en ligne.

Projet # : 2023-5071

Chercheur principal / directeur de recherche : Pierre-Majorique Léger

Cochercheurs : Sylvain Sénécal; Patrick Charland; Bella Tadson; Noémie Beauchemin; François Courtemanche; David Brieugne; Amine Abdessemed; Salima Tazi; Alexander John Karran; Jared Boasen

Date d'approbation initiale du projet : 13 juin 2022

Date de fermeture de l'approbation éthique pour l'étudiant(e) : 06 décembre 2023

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2023-12-06 à 16:00