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**HEC MONTRÉAL**
École affiliée à l'Université de Montréal

# Two Essays on the Consumer's Decision-Making Assisted by Recommendation Agents in the Era of Privacy Legislation

par
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**Two Essays on the Consumer's Decision-Making Assisted by Recommendation Agents in the Era of Privacy Legislation**

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# Résumé

Avec l'entrée en vigueur de réglementations en matière de protection de la vie privée en ligne instaurées dans plusieurs pays dans le monde, les agents de recommandations (ARs) en ligne sont désormais limités dans le type de données qu'ils peuvent collecter et exploiter sur les consommateurs. Ces restrictions influencent directement la qualité de la recommandation finale qui leur est proposée. En effet, les consommateurs doivent dorénavant fournir un consentement clair et éclairé concernant la collecte, l'utilisation et l'entreposage de leurs données personnelles. La prémisse de cette thèse est que pour accepter l'utilisation de leurs données personnelles, et surtout, d'en valoriser leur utilisation, les consommateurs doivent d'abord et avant tout comprendre les bénéfices de leur utilisation par les ARs. Ainsi, le premier essai de cette thèse est une méta-analyse agrégeant 472 tailles d'effet de 125 études (78 articles) qui ont été publiées entre 1999 et 2025. Cette analyse porte sur l'impact d'être assisté par un AR (comparé à l'absence d'assistance ou à l'assistance par un expert ou un non-expert humain) sur l'effort nécessaire à la décision et la qualité de la décision d'un consommateur. En faisant la distinction entre effort de décision et qualité de la décision sur la base des perceptions des consommateurs et de leurs comportements observés, les résultats cumulés de la méta-analyse démontrent que les consommateurs tendent à sous-estimer l'effort réellement investi dans leur processus de décision lorsqu'ils sont assistés par un AR. Cela signifie que l'assistance par un AR réduit davantage l'effort perçu que ne le reflètent leurs comportements observés, notamment en termes de temps investi et d'information traitée. De plus, les consommateurs ont également tendance à sous-estimer la qualité de leur décision lorsqu'ils sont assistés par un AR. Autrement dit, l'assistance par un AR réduit davantage la qualité de la décision perçue par rapport aux comportements observés, lesquels indiquent en réalité de bien meilleurs choix. Sur la base de ces résultats, l'essai 2 se concentre sur la manière d'améliorer la perception de qualité de l'assistance des ARs par le consommateur, et ce, dans un contexte marqué par l'application des nouvelles règlementations de protection de la vie privée. À travers quatre expérimentations en ligne (total $n = 1\ 366$), l'essai 2 se penche sur l'effet de la transparence de l'utilisation (ou de la non-utilisation) des données personnelles avant la génération de la recommandation, sur l'intention du consommateur à adopter l'AR et sur la volonté de payer annuellement pour ce type de service. Le contrôle accordé aux consommateurs (ou non) sur les données transmises à l'AR pour la génération de la recommandation est utilisé comme variable modératrice. Les résultats indiquent que, dans un contexte où il y a présence de paramètres de contrôle permettant aux consommateurs d'agir sur les données fournies à l'AR, les intentions de ceux-ci à l'égard de celui-ci sont plus positives lorsqu'ils acceptent l'utilisation de leurs données personnelles que lorsqu'ils la refusent. Cet effet s'explique par le niveau de confiance envers le système. À l'inverse, lorsque les consommateurs ne disposent d'aucun paramètre de contrôle sur leurs données, les intentions sont plus favorables lorsque l'AR signale aux consommateurs que leurs données personnelles ne sont pas utilisées comparativement à lorsqu'elles le sont. Ce phénomène s'explique par une réduction des préoccupations en matière de vie privée. Cette thèse vise à approfondir la compréhension du rôle des ARs dans l'accompagnement des consommateurs lors de leurs décisions. Elle cherche aussi à proposer des pistes pour concevoir des systèmes d'AR plus transparents et contrôlables. Ces systèmes seraient alignés sur les nouvelles réglementations en matière de protection de la vie privée. L'objectif est de favoriser des effets positifs, tels qu'une meilleure perception de la qualité des décisions prises avec l'aide des AR et une intention accrue de recourir à ces systèmes même lorsqu'ils signalent l'utilisation de données personnelles.

**Mots clés :** Agent de recommandation, protection de la vie privée, confiance, données personnelles, qualité de la décision, effort de décision, personnalisation de service, contrôle, transparence

**Méthodes de recherche :** Méta-analyse, expérimentations en ligne

# Abstract

With the new online privacy regulations implemented in several countries around the world, recommendation agents (RAs) are increasingly affected by the types of consumer data they are allowed to collect and use, which in turn influences the quality of the final recommendation provided to consumers. Consumers are now required to give clear and informed consent regarding the collection, use, and storage of their personal data. This dissertation's premise is that, for consumers to accept the use of their personal data, and especially to perceive value in such use, they must first understand the benefits of RAs leveraging this information. The first essay of this dissertation presents a meta-analysis aggregating 472 effect sizes from 125 studies (78 papers) published between 1999 and 2025. These studies examine the impact of being assisted by an RA (compared to no assistance or assistance from a human expert or non-expert) on consumers' decision effort and decision quality. By distinguishing between decision effort and decision quality based on consumer perceptions versus actual behaviors, the results show that consumers tend to underestimate the effort they invest in their decision-making process when assisted by an RA. This means that being assisted by an RA lowers perceived effort more than it reduces actual effort, as measured by time spent and information processed. Furthermore, consumers also tend to underestimate the quality of their decision when assisted by an RA. In other words, RA assistance lowers perceived decision quality more than it affects actual decision quality, which is improved, as shown by the quality of the final choice in a given set of products and services. Based on these findings, the second essay focuses on how to improve consumers' perception of the quality of RA assistance within a context shaped by new privacy protection regulations. Through four online experiments (total $n = 1,366$), the second essay examines the impact of increased transparency regarding the use (vs. non-use) of personal data before the recommendation is generated, on consumers' intention to adopt the RA and their willingness to pay annually for such a service. Consumer control (vs. no control) over the data provided to the RA is used as a moderating variable. In contexts where consumers are given control over their data, their intentions toward the RA are more favorable when they consent to the use of their personal data compared to when they do not, an effect mediated by their level of trust in the system.

Conversely, when no data control options are available, consumer intentions are more favorable when the RA signals that no personal data is being used, compared to when it is, a phenomenon explained by reduced privacy concerns. This dissertation aims to deepen our understanding of the role of RAs in assisting consumers during their decision-making. Additionally, this research seeks to offer insights into how more transparent and controllable RA systems can be implemented, aligned with emerging privacy regulations. The goal is to foster positive outcomes, such as enhanced consumer perceptions of decision quality in RA-assisted choices and intentions toward these systems.

**Keywords:** Recommendation agent, privacy concern, trust, personal data, decision quality, decision effort, service personalization, control, transparency

**Research methods:** Meta-analysis, online experiments

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# List of abbreviations

AI = Artificial Intelligence

CCPA = California Consumer Privacy Act

CCT = Constructive Choice Theory

CPRA = California Privacy Rights Act

DSA = Digital Service Act

EU= European Union

GenAI = Generative AI

GDPR = General Data Protection Regulation

IS = Information System

LMM = Large multimodal model

RA = Recommendation Agent

WTP = Willingness to Pay

*À tous ceux qui ont le sens des affaires, sans avoir perdu de vue leur sens de l'humour.*

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# Preface

This PhD dissertation, authored by Sara-Maude Poirier, is an original unpublished work conducted under the guidance of Dr. Sylvain Sénécal and Dr. Pierre-Majorique Léger.

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The topic of this PhD dissertation was motivated by an interdisciplinary research project funded by IVADO, which aimed to advance knowledge in the field of human-centred algorithmic tools, from their more responsible development to their adoption.

# Introduction

Recommendation agents (RAs) are omnipresent artificial intelligence (AI) decision-making tools on retailers' websites. RAs can be conceptualized as "an ecosystem comprising three fundamental elements: data collection and storage, statistical and computational techniques, and output systems” (Puntoni et al., 2021, p. 32) that enable the generation and presentation of personalized recommendations that meet consumers’ preferences (Xiao & Benbasat, 2007). The development of RAs is closely tied to technological advances, evolving from the emergence of simple filtering algorithms to today’s generative AI (GenAI) technologies (Li et al., 2024).

The first RAs, implemented in the 90s, relied heavily on consumers’ direct input, where users directly stated to the RA their preferences, such as ranking the importance of specific products or services. Over time, RAs have evolved beyond explicit feedback to also track consumers’ online behavior and past purchases to predict their preferences. For instance, Netflix’s RA recommends content based not only on a user’s viewing history, ratings, and stated preferences but also on the watching habits of others with similar interests (Li et al., 2024).

With the rise of GenAI, the nature of RAs has continued to evolve, placing greater emphasis than ever on the value of consumer-RA interactions both to better understand consumer needs and to enhance the processing of collecting data (Perkins, 2025). For instance, Victoria's Secret & Co. and Google Cloud have announced a partnership in 2024 to provide a GenAI tool on the lingerie website, optimising consumers’ online search. Thus, consumers can provide photos of a bra they have from an earlier product lineup and get product recommendations for current bras with a similar fit and style (Wilson, 2024).

For its part, Home Depot has integrated a chatbot, Magic Apron, which allows consumers to ask questions about their home project and guide them toward products and services able to answer their specific needs (Home Depot, 2025).

From a consumer's perspective, the adequate performance of RAs should reduce the effort required during decision-making while enhancing the quality of the final purchase (Xiao & Benbasat, 2007). Specifically, RAs usually generate personalized recommendations corresponding to the optimal offering based on the level of accuracy, matching consumers' preferences and needs to the attributes of the product or service (Aksoy et al., 2011). These recommendations serve as decision heuristics for consumers, reducing the effort needed to make superior purchase decisions (Broniarczyk & Griffin, 2014). It can also help consumers discover interesting offerings on the retailer's website (Nilashi et al., 2016).

From a managerial standpoint, the advantageous impact of implementing an RA includes higher revenue generation (Quach et al., 2022), and an enhancement in consumer experience, leading to heightened satisfaction and loyalty (Blut et al., 2023). Consequently, it suggests that allocating resources toward the development of efficient RAs and effective website design may improve how recommendations are presented to consumers.

However, a 2025 report published by eMarketer revealed a significant gap between consumers' expectations of retailers' and brands' RAs and their satisfaction with how well retailers and brands anticipate needs, deliver relevant content, and personalize recommendations (Perkins, 2025). This gap highlights the importance of improving RA performance to better align with consumer preferences and enhance overall user experience. However, the challenge does not lie solely in developing efficient systems, but also in accessing consumer data, which is increasingly restricted due to privacy protection laws, such as the option to opt out of cookies that collect personal data like previous purchases and viewed products. These restrictions create methodological and technological challenges for maintaining personalization while respecting consumer privacy.

Consumer data refers to task-specific preferences and their personal data, commonly referred to as profile data (Ebrahimi et al., 2022; Li & Karahanna, 2015). Task-specific preferences are data related to consumer-specific value functions and attribute importance weights estimated at the time of purchase (Scholz et al., 2013). RA using task-specific data focuses on consumers' interaction in providing their preferences for a specific context, allowing the RAs to identify a product that best meets their expectations for a given situation (Ebrahimi et al., 2022). Task-specific preferences can support RAs in generating initial recommendations or refining existing ones, while giving consumers greater control over the RA's output (Adomavicius et al., 2011). Conversely, profiling through personal data involves consumers' demographic information (e.g., age, location, gender), psychographic attributes (e.g., lifestyle, interests, values), and behavioral patterns (e.g., past purchases, browsing history, and past interactions) (Li & Karahanna, 2015). By constructing such consumer profiles, RAs can predict preferences with greater accuracy. Consumer profiling is also employed to enhance the level of personalization in recommendations, particularly by accounting for each consumer's unique characteristics, interests, and preferences (Blut et al., 2023).

In recent years, the European Union (EU) has proposed several legislations to regulate online privacy and personal data collection. These initiatives have had a significant global impact, inspiring similar data protection laws in many countries and states, including the US (e.g., California), Canada (e.g., Quebec), Brazil, and India, among others (United Nations, 2025). Among these UE legislations, the General Data Protection Regulation (GDPR), in effect since 2018, sets the rules for personal data protection regarding how organizations collect, use, and store consumers' personal data, referring to any information relating to an identified or identifiable individual, whether directly or indirectly, and how they informed consumers about their practices (European Union, 2016). Therefore, those legislations require organizations to obtain explicit and informed consent from consumers before collecting, using, or sharing their personal data. Additionally, organizations must collect only relevant personal data about consumers concerning the purposes for which they are processed, meaning that there is a limit on the amount and nature of information they can collect. The organizations must have the legitimacy to ask for it if it translates into beneficial outcomes for consumers (European Union, 2016).

A strong example of the GDPR's global influence is Quebec's Law 25. Introduced in response to the growing risks posed by new technologies and the increasing speed at which personal data is collected and shared, Law 25 strengthens consumer privacy rights. It imposes stricter obligations on organizations (Gouvernement du Québec, 2025). Organizations are now required to appoint a privacy officer, develop a plan to handle data breaches, and obtain clear, informed, and explicit consent before collecting, using, or sharing personal information (Gouvernement du Québec, 2025). Law 25 also addresses the issue of transparency in algorithmic decision-making for public organizations (article 65.2). When automated systems, such as RAs, make decisions, public organizations must clearly inform individuals and provide insight into the data used and the reasoning behind those decisions. This aims to reduce algorithmic bias, especially in sectors like health, education and finance (Commission d'accès à l'information du Québec, 2025; Fong, 2025).

One high-profile case that illustrates the importance of such protections is Tim Hortons. In 2022, it was revealed that the company's app tracked users' location data even when it was not open, using that information for marketing purposes and sharing it with third-party service providers (Crépeau, 2022). Law 25 is designed to prevent these kinds of practices and ensure that data is only used for the purposes explicitly stated. While Law 25 is a step in the right direction, it has faced criticism similar to the GDPR. Critics point out the lack of clear guidance on what qualifies as simple and transparent language when requesting consent. They also highlight the absence of clear instructions on how to communicate the consequences of accepting or refusing data collection (Fong, 2025).

Recent research about the impact of GDPR implementation on RA assistance has emerged. Through a randomized field experiment on the Alibaba e-commerce platform, Sun et al. (2024) have shown that, from a consumer's point of view, restricting the use of personal data worsens the matching score between product recommendations and user preferences, thereby reducing the quality of the recommendations. In turn, from a retailer's point of view, a lower matching score led to less engagement with the recommendations in terms of browsing, clicks, and purchases (Sun et al., 2024). Moreover, the absence of personal data results in more generic recommendations, favoring popular products from major brands and reducing the visibility of smaller retailers. In addition, much research has shown that in the data collection phase, consumers tend to accept or reject cookie notices for marketing purposes based on how easy it is to escape and return to the main website, reflecting fatigue and a disengagement from consumers in reading these notices (Choi et al., 2018; Kulyk et al., 2020). Consequently, they remain poorly informed about their choices, especially regarding how the use or non-use of their personal data impacts their navigation. Overall, these findings underscore the importance for brands and retailers to more effectively communicate the value of leveraging consumers' personal data through RAs to enhance decision-making and better align with consumer expectations for personalized services.

Thus, this dissertation proposed two essays aiming to understand how consumers value the impact of RA assistance during their decision-making, and to provide managerial and theoretical guidance for implementing responsible RAs able to rely on consumers' personal data for specific product and service searches. The goal is to encourage RA's adoption while ensuring alignment of interests among firms, consumers, and policymakers (Martin & Palmatier, 2020).

**Essay 1** is a meta-analysis including 472 effect sizes from 125 studies (78 papers) published from 1999 to 2025 regarding the impact of RA assistance (vs. no assistance, vs. human expert/non-expert assistance) on consumers' decision effort and quality during the decision-making process, while comparing this effect from consumers' perceptions (i.e., subjective assessment) and their actual behaviors (i.e., how they actually behave when assisted by an RA in terms of effort reduction and high-quality choices). Decision effort refers to the total use of physical, cognitive, or time-related resources to make a decision

(Xiao & Benbasat, 2007, p. 144). For its part, decision quality refers to the fit between consumers' preferences and the weights of the attributes of the final product choice (Aksoy et al., 2011).

Through **Essay 1**, we found that consumers undervalue their effort invested in the decision-making when assisted by an RA, while they tend to undervalue the quality of their final choice. In other words, being assisted by an RA (vs. no assistance, vs. human assistance expert/non-expert assistance) decreases the perceived effort required compared to the actual decision effort and increases the actual decision quality compared to the perceived decision quality. As a significant contribution, our findings highlight a gap between consumers' actual behaviors and perceptions, thereby resolving the mixed findings in the RA literature regarding the impact of this system assistance on consumer decision-making. It also highlights the need for researchers to situate their constructs within the context of their measurement methods. This distinction matters, as the insights derived are not the same. Actual behaviors help assess the impact of RAs on overall consumer well-being in consumption contexts (e.g., Banker & Khetani, 2019) and retailers' actual benefits, whereas consumer perceptions are more indicative of satisfaction and future intentions (Blut et al., 2023; Davis, 1989). All in all, it also means that retailers should focus on communicating RAs' beneficial impact on consumers' decision quality.

Based on the results of Essay 1, **Essay 2** delves into the construct of decision quality when assisted by RA in a privacy legislation context. Specifically, when consumers rely on RA, they often undervalue the quality of their own decisions, even if the outcome is improved. So, **Essay 2** explores what happens when the RA is more transparent about the types of data it uses and more controllable, requiring consumers to actively shape the recommendations. Could this increase consumers' perceived value of the decision made with the help of the RA?

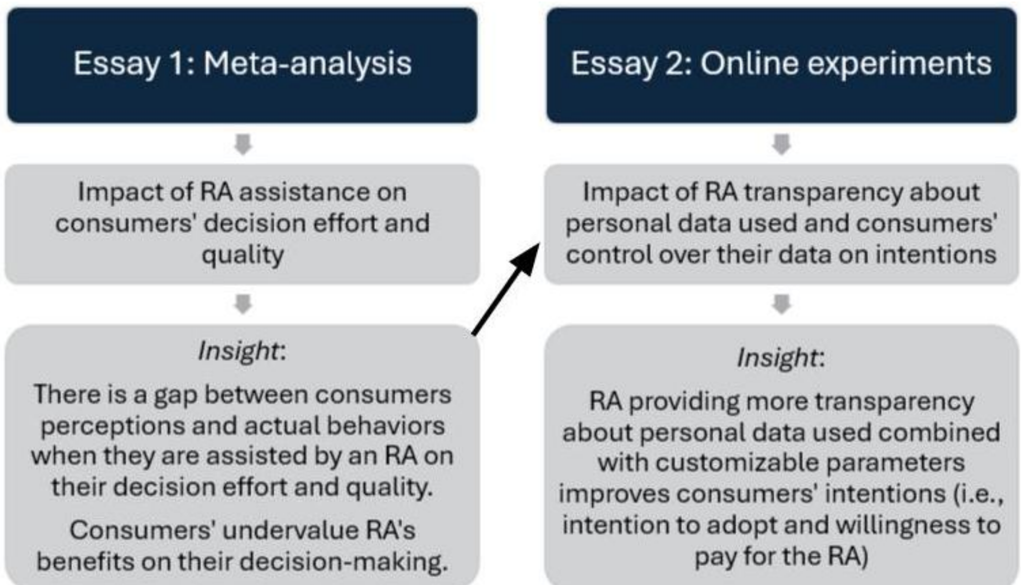
Building on Signaling Theory (Spence, 1973, 2002), **Essay 2** proposes a new settings system for RA that is available during navigation that communicate consumers which data will be used to generate the personalized recommendations, whether it relies on personal data or not, for specific product or service search. Specifically, through four online experiments (n=1366), Essay 2 investigates the impact of personal data used (yes vs. no) on consumers' intention to adopt the RA and willingness to pay (WTP) for this service annually, which is a proxy for measuring perceived decision quality (e.g., Longoni et al., 2019). In addition, Essay 2 looks at the moderating effect of consumer control over data use by the RA, operationalized through the presence or absence of customizability parameters (Zhang & Sundar, 2019).

The concept of control over one's personal data is in line with the Digital Service Act (DSA), another EU legislation that aimed at regulating online platforms and digital services by creating a safer and more accountable environment for users (European Commission, 2022). One of the DSA's objectives is to compel online platform providers to communicate the primary parameters of their RAs and enable users to modify them. Thus, the DSA exemplifies a broader trend calling for increased transparency and consumer control, empowering individuals to opt out of online profiling. All in all, consumers should have more control over both their personal data collection and use, as well as over the personalized content generated by RAs. Thus, Essay 2 explores how consumers' control over their data, whether personal or not, for recommendation generation influences the perceived quality of the RA system and consumers' intention to adopt it. We found that when consumers are informed that their personal data will be used but have no control over that use, their intentions toward the RA become less favorable than if the system does not use their personal data because of higher privacy concerns. However, when the RA includes customizable parameters that allow consumers to manage how their data is used, their intentions toward the RA significantly improve when personal data is involved, compared to when it is not, due to higher trust in the RA.

Therefore, Essay 2 significantly contributes to the literature on RA input design (e.g., Xu et al., 2014) and personal data privacy in marketing (Bornschein et al., 2020; Martin et al., 2017). First, we advance Signaling Theory from a static cue model to a dynamic, conditional signaling framework for digital service design. Our findings showed that a positive effect, such as heightened intention to adopt the RA and pay for its service, emerges when the RA is transparent about the personal data it uses. However, this effect is contingent on consumer control. Second, we contribute to the transparency versus choice debate (e.g., Acquisti et al., 2015; Bornschein et al., 2020) in the personal data usage phase by explaining consumers' responses to transparency in the absence or presence of customizable controls. Finally, our third contribution speaks to the literature about personal data management beyond the cookie notices. Our research provides a deeper understanding of consumer intentions regarding the use of their personal data during navigation, specifically when the RA indicates which data will be used for a particular product or service search.

In conclusion, this dissertation aims to deepen our understanding of the role of RAs in assisting consumer during their decision-making. Figure 1 presents the integration of the two essays within this PhD dissertation. Specifically, this dissertation aims to provide insights into implementing more transparent and controllable RA systems, aligning them with emerging privacy regulations to foster positive outcomes, such as enhanced consumer perceptions of decision quality in RA-assisted choices and intentions toward these systems.

*Figure 1. Narrative regarding the integration of the two essays*




The rest of the document is composed of Essay 1 and Essay 2. The document ends with a general conclusion. Essay 1 is actually under review at the *Journal of Retailing* for its second round of revision. Essay 2 has been submitted to the *Journal of the Academy of Marketing Science*.

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# Chapter 1
# The Influence of Recommendation Agents on Consumers' Decision Effort and Quality: Between Perceptions and Actual Behaviors

## Abstract

Recommendation agents (RAs) assisting consumers during their online decision-making have been extensively studied in marketing and information systems (IS) literature. Many studies suggest a positive impact of RA assistance on reducing consumers' decision effort and increasing decision quality. However, there appears to be a difference in evaluating decision effort and quality, whether through consumer perceptions or actual behaviors. This meta-analysis, including 472 effect sizes from 125 studies (78 papers), suggests that being assisted by an RA decreases to a greater extent perceived effort compared to actual decision effort, and increases to a greater extent actual decision quality compared to perceived decision quality. The impact of RA assistance on decision quality depends on the comparison group, whether it is compared against human assistance or no assistance. In addition, the impact of RA assistance on decision effort is also related to the consumers' preferences elicitation method used by the RA. Overall, results suggest that perceived decision effort and quality are subject to systematic cognitive biases when consumers are assisted by RAs.

**Highlights**:

- Consumers underestimate the actual effort they exert when assisted by an RA.
- Consumers undervalue the actual quality of their decision when assisted by an RA.
- RA's impact on quality depends on what it is compared to: human or no assistance.

**Keywords**: recommendation agent, decision effort, decision quality, online decision-making, meta-analysis, constructive choice theory

## 1.1 Introduction

In the early 2000s, recommendation agents (RAs) were seen as revolutionary tools by marketers, capable of executing complex decision-making strategies during the product consideration phase on behalf of consumers. Over the years, RAs have been rapidly adopted, and research in marketing and information systems (IS) has been abundant. Nowadays, with advancements in AI-driven recommendations, more than a third of e-commerce platforms use RAs to suggest alternatives on their websites or apps, particularly due to their ability to make accurate predictions about consumer needs by segment (EMarketer, 2024). For instance, Netflix's recommendation system suggests content based on a customer's viewing history, ratings, and preferences, as well as the watching habits of others with similar interests, and 75% of what customers watch on this platform comes from RAs (Mackenzie et al., 2013). RAs are a key driver of consumer satisfaction and future use intentions (Blut et al., 2023). It has been suggested that 71% of consumers expect personalization on online service provider platforms and 76 % get frustrated if they do not find it (Breard, 2024).

Consequently, researchers in marketing and IS have sought to understand the impact of RA assistance on consumers' decision effort during the decision-making process, as well as on the quality of their final decision (Kim, 2020; Xiao & Benbasat, 2007). From a normative choice perspective, it is assumed that RAs should suggest high-quality alternatives while minimizing consumers' effort, ensuring that using them does not come at the expense of decision quality (Bettman et al., 1990). Under this rational perspective, effort is seen as a cognitive cost, while quality is predictable through algorithmic precision. Thus, if consumers accept RA assistance, they should be more likely to embrace the recommendation, streamlining their decision-making process and reducing cognitive effort.

However, a growing body of research suggests this idealistic perspective is not always encountered. Despite the promise of reduced effort and optimal quality, consumers often engage with RAs in unexpected ways. Instead of simply selecting the recommended alternative(s), they may invest additional effort in evaluating recommended or other alternatives, reconsidering choices, or even rejecting RA recommendations altogether (e.g., Dietvorst et al., 2015). This misalignment challenges the assumption that effort is always a burden, and that quality is fixed and predictable. These latter findings suggest that consumers-RAs interactions need to be better understood to avoid resource misallocation by retailers and a negative experience for consumers during decision-making.

The mixed findings on the impact of RA assistance on consumers' decision-making process align with Constructive Choice Theory (CCT) (Bettman et al., 1998). CCT posits that consumer preferences are not stable or pre-determined but constructed in the moment, shaped by context, cognitive effort, and evolving preferences. Consumers may willingly spend more effort analyzing recommendations rather than relying on them as effortless decision aids (Bechwati & Xia, 2003; Tsekouras et al., 2022). Likewise, the recommended alternative may no longer remain the best as consumers reinterpret their needs and construct new preferences throughout the decision-making process and RA interactions (Dzyabura & Hauser, 2019). CCT also suggests that consumers are subject to perceptual and cognitive biases during the shopping task, affecting how they perceive, interpret, and respond to RAs. These biases can be either conscious or unconscious

(Dijksterhuis et al., 2005), meaning there may be a gap between consumers' subjective assessment of their effort, the quality of their final choice, and their actual behaviors. Indeed, effort and quality indicators during the decision-making process, such as cues regarding the level of reliability of the system (Yin et al., 2019) or the level of effort RA is investing in processing their preferences (Tsekouras et al., 2022) can bias consumers' evaluation of their decision effort and quality.

We suggest that this heterogeneity in results across studies examining the impact of being assisted by an RA on decision effort and decision quality is explained by how effort and quality are measured. Specifically, some research has assessed decision effort and quality using both perceptual measures and behavioral indicators, occasionally yielding divergent results. For instance, research found that assistance from an RA, compared to shopping alone, increased the accuracy of the purchase decision and improved the actual quality of the alternatives examined in the consideration set, yet, on a perceptual level, it did not affect consumers' satisfaction or confidence in their choice (Heijden & Sangstad Sørensen, 2003; Hostler et al., 2005; Liang et al., 2006). These differences in measurement, whether of perceived or actual decision effort and quality, are crucial for retailers to consider. Understanding both aspects is key to developing systems that perform well and are also perceived as effective, with perceptions being critical drivers of technology adoption (Davis, 1989).

From a sample of 472 effect sizes retrieved from 125 studies (78 papers) published between 1999 to 2025, the goal of this meta-analysis is to compare consumers performance whether they are assisted or not by an RA to see if these systems fulfill their expected promise when assisting consumers, i.e., decreasing consumers' effort and increasing quality of the final choice, by distinguishing between consumers' perceptions of the effort they invested in the decision process and their actual behaviors (e.g., decision time) and by distinguishing between the quality of their shopping process and their final decision (e.g., selecting the best alternative based on their preferences). In other words, we answer the following two questions: Do consumers adopt behaviors that reduce decision-making effort when assisted by an RA, and do they perceive it as such? Do consumers truly make better choices when assisted by an RA, and do they perceive it as such?

This meta-analysis makes several theoretical and methodological contributions and also has managerial implications. First, our findings reveal a gap between consumers' actual behaviors in exerting effort during their shopping process and how they perceive their effort, which helps understand the actual and perceptual impact of RA assistance on consumers' decision-making and resolve the mixed findings in the literature. Thus, compared to no assistance or human assistance, being assisted by an RA does not reduce consumers' effort, yet they perceived it as if it does. Conversely, compared to no assistance or human assistance, being assisted by an RA does enhance decision quality, but consumers generally do not perceive this added value. This highlights the importance of examining both actual behaviors and perceived experiences during decision-making. Our results highlight the need for researchers to situate their constructs within the context of their measurement methods. This distinction matters, as the insights derived are not the same. Actual behaviors help assess the impact of RAs on overall consumer well-being in consumption contexts (e.g., Banker & Khetani, 2019) and retailers' actual benefits, whereas consumer perceptions are more indicative of satisfaction and future intentions

(Blut et al., 2023; Davis, 1989). This contribution has practical implications. It is essential to ensure that consumers not only experience improved outcomes but also perceive those outcomes as meeting or exceeding their expectations. Thus, retailers need to invest in the perceived quality of RAs, rather than solely focusing on the technical performance of RAs.

Second, our meta-analysis confirms that consumers' cognitive and perceptual biases are significantly influenced by the various cues available during the shopping process. Results suggest that the impact of RA assistance on decision quality, combining both perceived and actual measures, is relative to what it is compared to (Jussupow et al., 2024). The effect of RA assistance appears weaker when compared to human experts or non-experts. Therefore, when retailers aim to minimize decision effort during the shopping experience, an RA should be available. However, when the goal shifts to prioritizing decision quality, it may be more beneficial to complement RA assistance with human presence, such as expert advice or consumer reviews.

## 1.2 Theoretical background

### *1.2.1 Perceived and actual decision effort and quality in decision-making assisted by RAs*

RAs, commonly known as recommender or decision systems, are "software agents that elicit the interest and preferences of individual consumers for products, either explicitly or implicitly, and make recommendations accordingly" (Xiao & Benbasat, 2007, p. 137). There are three main components of RA design: the input, where consumers' preferences are obtained explicitly or implicitly, meaning with or without consumers direct input in reporting their preferences; the preferences and information processing, where recommendations are generated; and the output, where the recommendations are presented to consumers (Xiao & Benbasat, 2007).

During online decision-making, RAs can help consumers in two distinct stages. First, RAs can help consumers search through a large set of available alternatives, acquire detailed information on selected alternatives, and build their consideration set comprising the most promising alternatives (Häubl & Trifts, 2000; Xiao & Benbasat, 2007). In a second stage, consumers can use RAs to compare and evaluate alternatives in more detail and perform comparisons based on important attributes before making their optimal and final choice.

RAs are mainly adopted based on the principle that they are easy to use and useful in performing a task (Davis, 1989; Wang & Benbasat, 2005). For instance, Aljukhadar et al. (2012) showed that increasing information overload (i.e., higher number of attributes and alternatives to process) leads consumers to use and comply with the RA recommendation to a greater extent, which in turn increases their decision quality. RAs have been designed to seek a compromise between reducing consumers' effort and increasing the quality of their final purchase. Past research has used various measures to assess decision effort and quality, either perceptions, actual behaviors, or both, to understand consumers' cognitive processes and perceptual bias, and to assess consumers' performance when assisted by RAs (see Appendix A).

On one hand, *decision effort* refers to the total use of physical, cognitive, or time-related resources to make a decision (Xiao & Benbasat, 2007, p. 144). Consumer decision effort reflects the real or perceived effort made by consumers in processing and evaluating product information, and the decision on the product that best fits their preferences. Effort has been mainly operationalized in terms of actual or perceived *decision time*, referring to the time to search and assessed for product information (e.g., Huseynov et al., 2016; Olson & Widing, 2002), by the perceived or actual *amount of information search*, which can refer to the size of the consideration set, the number of alternatives to examine, and the number of stages to narrow down the consideration set (e.g., Dellaert & HÄubl, 2012; Pedersen, 2000), and also by the perceived and actual *choice overload* reflecting how difficult in terms of cognitive load a choice was (e.g., Huang & Zhou, 2019; Xie et al., 2022).

On the other hand, *decision quality* refers to the fit between consumers' preferences and the attributes' weights of the final product choice (Aksoy et al., 2011). This level of accuracy can be measured perceptually (i.e., perceived accuracy) (e.g., Lepkowska-White, 2013) or through objective measurement such as the utility score, and non-dominated choices, i.e., alternatives that are superior to other alternatives in the choice set on at least one attribute (e.g., Yeomans et al., 2019). In addition, several perceived and real proxy measurements have been used by researchers to assess decision quality. For instance, subjective evaluation of the quality of the final choice, such as the likelihood to purchase it or willingness to pay for it (e.g., Longoni et al., 2019) or actual behaviours, such as the compliance with the recommendation or the paid amount for the alternative (Aljukhadar et al., 2012). Decision quality can also be assessed perceptually or with actual behaviors following the decision (e.g., intention to switch or switching behavior for another alternative, feeling of regret, choice confidence, choice satisfaction, choice liking, happiness with choice) (e.g., Maheswarappa et al., 2017).

The use of consumers' perceptions and actual behaviors to assess decision effort and quality are important in this meta-analysis. Indeed, these measurement differences have two implications. First, we included all empirical papers, regardless of construct measurement, whether perceived or actual behaviors. Second, we used the measurement type, whether perceived or actual, of decision effort and quality as a moderator to test if there are any differences in the constructs of interest. In addition, we assume that RAs work in the interest of consumers to provide accurate or satisfying recommendations. Thus, this meta-analysis does not include articles using deliberately biased (i.e., suboptimal) or dominated (i.e., inferior) recommendations (e.g., Xiao & Benbasat, 2018).

### *1.2.2 The impact of RA assistance on decision effort and quality through the CCT*

Past research assessing both effort and quality has shown that these two constructs may or may not be correlated, showing that assistance from an RA does not always minimize effort while enhancing quality (see Appendix B). To explain these discrepancies in the relationship between effort and quality, we draw on the Constructive Choice Theory (CCT) (Bettman et al., 1998). This theoretical lens highlights how contextual factors during the decision-making process can shape the dynamic between effort and quality. This suggests that the optimal trade-off between effort reduction and quality improvement is not always achieved or desired.

CCT is rooted in the Effort-Accuracy Framework (Payne et al., 1988) and Prospect Theory (Kahneman & Tversky, 1979). This behavioral decision theory posits that consumers construct their preferences during the shopping process. Consequently, a so-called rational choice cannot be easily predicted (Dzyabura & Hauser, 2019), i.e., how consumers *should* behave and what they *should* like. What makes a behavior or a choice reasonable is when it is analyzed in its context, i.e., how consumers behave and what they want during the shopping process. In general, it makes sense to think that consumers are seeking a compromise between effort and quality. However, some contexts can justify that consumers perceive increased effort positively, or only pursue effort reduction or quality increase goals (Su et al., 2008). For instance, when consumers are presented with a medical advice from an RA versus one from a human expert, it is reasonable to think the RA will also predict the best treatment since evidence has proven that they outperform human capabilities in statistical forecasts (Logg et al., 2019). However, other factors, such as uniqueness neglect or consumers' understanding of how RA works compared to humans, can shift their priorities (Longoni et al., 2019). As a result, consumers may purposely accept higher decision effort and choose an option that does not necessarily reflect the most accurate and logical decision, but which aligns better with their broader beliefs and preferences.

The Effort-Accuracy Framework proposes that the amount of physical, cognitive, or time-related resources invested in a decision-making task should predict the level of accuracy achieved, reflecting this duality in goals during decision-making (Payne et al., 1988). This framework suggests that consumers adapt their decision strategy based on this trade-off between effort and quality. Thus, higher accuracy would necessitate a strategy requiring a high level of effort (e.g., compensatory strategies), while lower accuracy would mean using heuristics (e.g., product familiarity), suggesting, in both cases, a positive relationship between effort and quality. In this framework, effort is perceived as a cost that consumers must assume to reach a higher level of accuracy, namely decision quality.

Algorithmic systems such as RAs came as a revolution in decision-making, having the potential of executing information-intensive strategies to find a "more than good enough" offering while requiring a low level of effort from the consumers, suggesting, in this situation, a weaker correlation between effort and quality. When consumers use an RA, a low level of search is supposed to result in the highest decision quality compared to a higher level of search (Maheswarappa et al., 2017). In this sense, Huseynov et al. (2016) have shown that the actual mean shopping time and page view decreased when assisted by an RA compared to being not assisted by such an agent, and increased the level of accuracy (i.e., utility score) of the preferred alternative. Tam and Ho (2006) also show that being assisted by an RA, compared to not being assisted, results in a decrease of actual decision effort (time spent, number of pages consulted) and perceived effort, and in an increase of actual decision quality (compliance with the superior option) and perceived quality (satisfaction with the final choice).

Although empirical evidence tends to support this negative effect of RAs on effort and positive effect on quality, some research has reported a negative relationship between these two constructs, where more effort leads to a decrease in quality. For instance, Sinha and Medhurst (2001) showed that a recommendation from an RA was perceived as less useful and of lower quality than a recommendation from a friend. Xu et al. (2017) also suggested that, compared to consumers' and experts' recommendations, those from an RA result in higher perceived decision effort and lower perceived decision quality. These conflicting results underscore two critical dynamics in consumer decision-making: Cognitive limitations, which can constrain the ability to process and integrate information efficiently, and perceptual biases, which shape how consumers evaluate the usefulness and credibility of recommendations, particularly concerning the reference group to which the RA is compared, such as friends, experts, or fellow consumers (Jussupow et al., 2024).

In other cases, researchers have found a positive linear relationship between effort and quality, as suggested by the Effort-Accuracy Framework (Payne et al. 1988). In some cases, compared to not being assisted by an RA, being assisted leads to more effort and more quality (Hostler et al., 2011; Lee & Benbasat, 2010), while in other cases, it led to less effort and less quality (He et al., 2023).

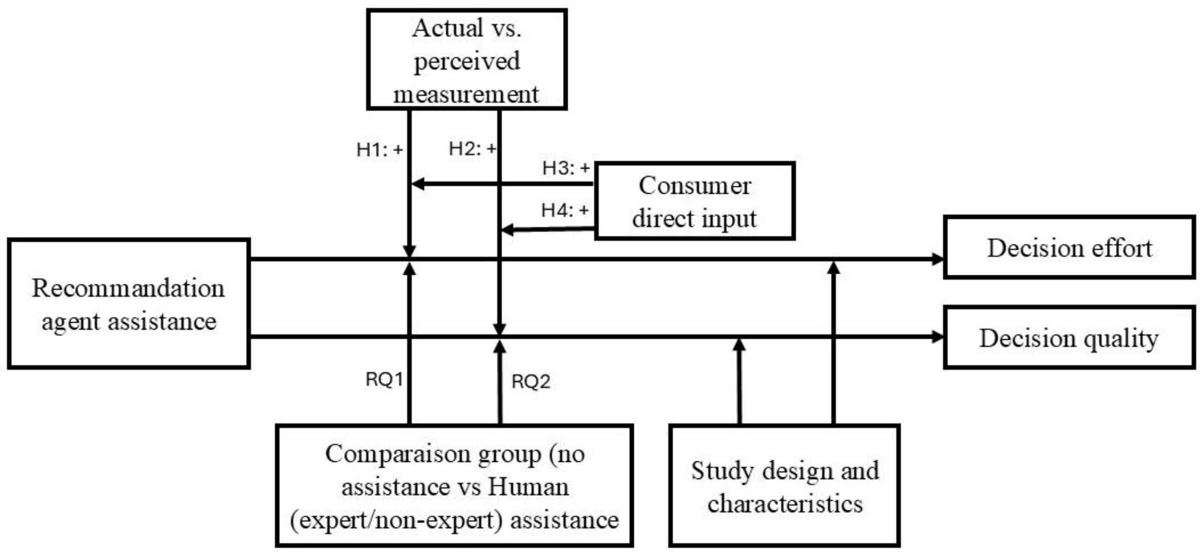
These different types of relationships between effort and quality highlight two elements: First, these relationships might be affected by the measurement type. For instance, Lee & Benbasat (2010) has measured effort and quality both perceptually and with actual behaviors. They showed that more actual effort led to more actual quality, but less perceived effort also led to less perceived quality (Lee & Benbasat, 2010). Second, consumer effort can be sometimes valuable and treated as a benefit rather than a cost (Maheswarappa et al., 2017; Su et al., 2008; Tsekouras et al., 2022). Third, some results reinforced the fact that we should not always expect a relationship between decision effort and quality (e.g., Huang et al., 2024; Markovitch et al., 2024; Sivaramakrishnan et al., 2007; Yang et al., 2024). For instance, Dellaert et al. (2024) showed that there is no difference between being assisted or not by an RA on decision effort (number of alternatives examined) when shopping for health insurance, but that consumers assisted by an RA have made dramatically better choices. This could be explained by the fact that consumers are sometimes focused on only one goal, which can be either reducing effort or increasing quality (Bettman et al., 1998). In this case, the context of choosing health insurance likely triggered a stronger focus on decision quality rather than on reducing effort. The same can occur with decision effort. In some cases, being assisted by an RA did not have any effect on decision quality, whether real or perceived, but had a positive effect in decreasing the perceived and real decision effort (e.g., Chu & Spires, 2000; Turri, 2011). Buying a low-involvement product (e.g., shopping for a book or music CD ) can activate an effort goal, which can explain why some authors have only looked at this construct (e.g., Benlian et al., 2012; Huang & Zhou, 2019). Hence, even if decision effort and quality are related, they are not necessarily correlated.

All in all, these mixed results are important in this meta-analysis for the following two reasons. First, we included all empirical papers that studied decision effort and quality, either jointly or independently, when assisted or not by an RA. Thus, we treated effort and quality as two unrelated dependent variables, and not effort as an antecedent of quality. Second, these mixed findings underline the interesting avenue of looking at the impact of RAs on decision effort and quality but differentiating between perceived effort and quality and actual effort and quality to take account of consumers' cognitive and perceptual biases.

## 1.3 Meta-analytic framework

Figure 2.1 displays our meta-analytical framework. We investigate the difference between perception and actual measurement of decision effort and quality when consumers are assisted by RAs, compared to no assistance or human expert and non-expert assistance. Consumer direct input also serves as an interesting moderator, as study characteristics and publication bias controls.

*Figure 2 Meta-analytic framework*




### *1.3.1 RA assistance on actual and perceived decision effort*

The marketing and IS literature mainly agree that using an RA decreases the decision effort during the decision-making process compared to not being assisted by these tools (Aljukhadar et al., 2012; He et al., 2023; Lee & Benbasat, 2010; Senecal & Nantel, 2004). Still, some research has shown that being assisted by an RA, compared to not being assisted by such a system, increases actual and perceived decision effort (Nguyen et al., 2022; Pereira, 2001; Xie et al., 2022). Especially for consumers with a low need for cognition, RAs can unintentionally increase decision effort if they complicate the process more than what consumers would have experienced when shopping alone (Chattaraman et al., 2024). Thus, RAs appear particularly effective in reducing decision effort when consumers are confronted with many alternatives and attributes to evaluate. However, their impact tends to diminish when the choice set is more limited (Mejia & Guesmi, 2024; Turri, 2011), potentially because interacting with these tools can unnecessarily increase effort in otherwise simple decision-making processes. Therefore, in complex decision-making processes, RAs help guide consumers through the best alternatives within a product category, thereby reducing perceived effort, while simultaneously prompting them to spend more time evaluating alternatives within that category, reflecting a more efficient and focused information search (Olson & Widing, 2002; Wan et al., 2024).

Additionally, some studies assessing consumers' actual and perceived effort at the same time have reported conflicting results. Hostler et al. (2005) have shown that being assisted by an RA increases actual decision effort but does not affect consumers' perception of their effort compared to shopping alone. Other studies suggest that RA assistance increases actual decision effort while simultaneously decreasing perceived effort (Lee & Benbasat, 2010). Thus, two explanations can be proposed: First, consumers may be more willing to invest cognitive resources when assisted by an RA, as the presence of this technology makes the decision process feel less burdensome. In this case, the effort is perceived as lower—or at least not higher—than when shopping alone (Tam & Ho, 2005), possibly because consumers account for the "shared" effort with the RA (Bechwati & Xia, 2003). Indeed, Tsekouras et al. (2022) showed that making the RA's effort explicit, such as through a rotating loader accompanied by the message calculating results, led consumers to perceive that the RA was investing more effort in the decision process compared to when no such effort cue was presented. Based on the reciprocity theory, this perceptual bias triggered a cognitive bias, as consumers subsequently evaluated their own decision effort more favorably when they believed the RA had exerted greater effort on their behalf.

Second, consumers may remain unaware of the increased cognitive effort they invest during decision-making. Based on the Process fluency theory, perception of the shopping processes with the RA can impact cognitive retrospective evaluation of the decision-making (Reber et al., 2004). Retailers may deliberately design RAs and associated interfaces to prolong user engagement while minimizing the perceived mental load (Notebaert, 2019). Using intuitive design, seamless navigation, and engaging user experiences, consumers are encouraged to process a greater number of alternatives and spend more time on the platform. However, due to the fluency of the interaction, the experience is not perceived as cognitively taxing. In retrospect, the decision process is evaluated as effortless, despite the underlying investment of cognitive resources. Thus, we propose that receiving assistance from an RA, as opposed to no RA assistance or human assistance, reduces perceived decision effort to a higher extent than the actual effort observed through consumers' behaviors. In other words, consumers under evaluate their actual effort when using an RA.

**H1**: RA assistance (vs. no RA assistance or human assistance) reduces consumers' perceived effort during the decision-making task to a greater extent than actual effort.

### *1.3.2 RA assistance on actual and perceived decision quality*

Making accurate recommendations is important for satisfaction with a firm’s experience and for consumers’ well-being (Banker & Khetani, 2019). The marketing literature has shown that consumers are highly influenced by RAs (Senecal & Nantel, 2004), and it is therefore important that these systems provide the most accurate recommendations. Indeed, recommendations provided by RAs are used as an anchor (Köcher et al., 2019). Thus, consumers tend to evaluate alternatives similar to the recommended alternatives more carefully, so they ought to be of high quality if firms want their consumers to be satisfied.

Mostly, the IS and marketing literatures have reported an increase in the perceived and actual quality of the final consideration set when using RAs compared to not using them (Aljukhadar et al., 2012; Heijden & Sangstad Sørensen, 2003; Olson & Widing, 2002). However, some studies have shown that consumers may find it difficult to judge the quality of a recommendation, whether it is of high or low quality. Indeed, when faced with high-quality recommendations, consumers often find themselves with little or no means to properly assess the quality of the proposed alternatives. This can result in an experience of uncertainty and a lack of confidence in their final choice (Banker & Khetani, 2019). Conversely, when the system fails to recommend the optimal or superior alternative, research has shown that consumers can be vulnerable to the RA's recommendation by complying with it. Hence, some research contradicts Fitzsimons and Lehmann (2004), who reported that consumers expressed reactance when they received inferior recommendations from RAs. For instance, Xiao and Benbasat (2018) revealed that consumers were more inclined to make a suboptimal purchase decision when they were recommended falsely personalized recommendations because they believed they were high-quality products being recommended.

Therefore, some researchers have reported conflicting results between their perceived and actual measurement of decision quality (e.g., Ghiassaleh et al., 2020; Maheswarappa et al., 2017; Westerman et al., 2007). In fact, some authors have shown that being assisted by an RA, compared to shopping alone, really increase the level of accuracy of the purchase option and the quality of the consideration set, but there was no difference on consumers' satisfaction or confidence in choice (Heijden & Sangstad Sørensen, 2003; Liang et al., 2006). This gap can be explained because consumers' subjective evaluation of the quality of the outcome depends also on the pleasure of interacting with the technology and the satisfaction during the decision-making process—not necessarily whether the decision quality is actually the highest at the end of the process (Chattaraman et al., 2024; Maheswarappa et al., 2017). It can also be explained by the fact that many website quality cues can contribute to build trust toward the agent during the decision-making process, which can favor or not the perception of RA (Wang & Benbasat, 2005).

Thus, consumers' perceived quality in their final choice when assisted by an RA tends to vary whether they received or did not receive quality indicators during the process (e.g., level of product personalization), which can bias their perceptions of their final choice. Indeed, consumers often struggle to accurately assess the recommendations provided by RAs, especially when faced with the challenge of understanding how these systems operate (Felzmann et al., 2020; Yeomans et al., 2019). Even if RAs have been shown to outperform human capabilities in many contexts, the lack of transparency about the quality of the information used to generate the recommendation, the type of RA algorithm (e.g., collaborative, content-based hybrid), and its reliability make it difficult for consumers to assess the recommended alternatives and decrease trust in RAs (Felzmann et al., 2020). Thus, we posit that being assisted by a recommendation agent, compared to no assistance or human assistance, contributes to enhancing the actual quality of the final purchase. However, this improvement remains undervalued by consumers.

**H2**: RA assistance (vs. no RA assistance or human assistance) increases the actual quality of the final purchase to a greater extent than perceived quality.

### *1.3.3 RA assistance on decision effort and quality: the impact of the comparison group*

The literature in communication and persuasion has shown that the source's credibility, attractiveness, and similarity lead to attitude and behavioral changes (Wilson & Sherrell, 1993). In the RA literature, Jussupow et al. (2024) have recently conceptualized the concept of algorithm aversion and appreciation by distinguishing among different configurations putting algorithms' recommendations against either consumers' own decisions or against other human recommendations. Thus, to understand consumers' subjective evaluations and behaviors toward RA recommendations compared to another source, researchers must consider the cognitive processes of consumers evaluating their own decisions, but also consumers' responses to different types of human agents as a basis of comparison. The fact that research into the evaluation of effort and decision quality when assisted by RAs has used several reference groups (see Appendix C) may have influenced the strength of the effect of these systems in helping consumers.

Source credibility is based on three dimensions: expertise, reliability and trustworthiness (Kelman, 1961). In their meta-analysis, Wilson and Sherrell (1993) have shown that expertise is the most important dimension on persuasion during a decision task. Applied to the RA literature, it seems that consumers' perception of expertise does not always predict the influential impact of the agent. For instance, Senecal and Nantel (2004) have shown that consumers perceived human experts as having more expertise in assisting consumers than RAs and other consumers. Conversely, other consumers were perceived as more trustworthy than RA and human experts. Still, RA was the most influential source because consumers complied in a higher proportion with them compared to human experts and other consumers, while there was no difference between human experts and non-experts.

Human non-expert refers to consumers' friends, family, and other consumers. Human non-experts can foster a sense of similarity and enhance identification, which can explain their persuasive influence on consumers (Kwon et al., 2016). However, RAs are usually more accurate and perceived as more accurate than non-expert humans (Logg et al., 2019). Indeed, non-expert humans base their recommendations mainly on their past experience with the alternatives or on a general assessment of the consumer tastes and preferences. Thus, compared to an RA, a human non-expert generally provides lower personalized recommendations. They are also perceived as more useful in finding products quickly and suitable products (Benlian et al., 2012).

Still, consumers might prefer being assisted by humans similar to them if they have the choice because they can assess their cognitive process more easily to reach a conclusion (Sinha & Medhurst, 2001; Yeomans et al., 2019). Moreover, their real influential impact can increase if they are perceived as more competent for the nature of the task. For instance, consumers perceived RAs as more competent to assess utilitarian attributes value while other consumers are perceived as more competent in evaluating hedonic attributes (Longoni & Cian, 2022), notably because hedonism reflects a subjective experience and RAs cannot experience emotion such as pleasure.

Human experts on their part refers to individuals who possess specialized knowledge, skills, and experience in a particular domain or field. Thus, they should be able to assist consumers in finding highly personalized alternatives based on their tastes, but also to help consumers clarify their preferences so that the final recommendations reflect consumers’ construction of their preferences during the shopping process. Through a consumer neuroscience study using event-related potential, Xie et al. (2022) have shown that an experiential product search led consumers to experience higher cognitive load when RA assisted them versus a human expert, which led them to be more likely to follow the human expert's recommendation. However, there was no difference in cognitive load and likelihood to follow the recommendation for a search product, meaning that in some circumstances, RAs and human experts are perceived as having the same level of competency, which does not create either algorithmic appreciation or reactance. Yang et al. (2024) replicated these findings with vice and virtue product categories. Thus, RA are as competent and perceived as human experts when the level of accuracy can be mainly predicted. However, even in a high-uncertainty context, where accuracy can be predicted, consumers could prefer relying on human experts if they perceived that a standardized treatment can impact the outcome (Longoni et al., 2019).

Finally, in some situations, decision quality was compared between consumers shopping without assistance who were relying on their own judgment, and consumers assisted by RAs. Logg et al. (2019) have compared whether consumers want to rely on RA vs. their own judgment, or RA vs. another human agent. In both contexts, consumers were more likely to follow the RA, but they chose the RA less frequently when they could choose based on their own judgment. Thus, consumers are sometimes overconfident in their capabilities and treat their judgment as superior to that of other agents (Harvey, 1997). However, another stream of literature has shown that when consumers need to make risky or high involvement decisions, they tend to be less confident in their own skills relative to the expected proficiency of the agent. Moreover, some consumers can be motivated to delegate when they do not want to be accountable if the decision turns out not as expected (Chang et al., 2016; Holzmeister et al., 2023). For instance, Holzmeister et al. (2023) have shown that consumers are more likely to delegate a financial decision to an algorithm, followed by a financial expert. Consumers also request the agent to take more risk than they perceived to have taken in their own decisions, especially if they are risk averse. Those willing to take risks were more likely to invest on their own. All in all, it is not clear how perceived and actual effort and quality of a decision taken by a consumer assisted by an RA relative to no assistance or human expert or non-expert assistance is impacted. We consequently ask these following two research questions:

**RQ1:** Does RA assistance differ in its effectiveness in reducing consumers' effort, whether perceived or actual, during the decision-making process, depending on the control group applied?

**RQ2:** Does RA assistance differ in its effectiveness in increasing consumers' decision quality, whether perceived or actual, during the decision-making process, depending on the control group applied?

#### *1.3.4 Consumer direct input on the relationship between RA assistance on perceived vs. actual and decision effort and quality*

Consumer direct input refers to the amount of preference information regarding alternative features and importance weighting provided by the consumer before receiving recommendations (Xiao & Benbasat, 2007, p. 149). Therefore, consumers explicitly provide their preferences to the RA to receive highly personalized recommendations (e.g., myautoadvisor). Thus, direct consumer input aligns with CCT, which suggests that preferences are formed during the decision-making process, making consumers willing to invest effort, up to a certain extent. Other RAs can also be less interactive and collect consumers' preferences implicitly, gathered without direct input or conscious effort from consumers. This may include prior purchases and behavioral history or contextual information such as geographic locations, social contexts, states, moods, and demographics of consumers to provide recommendations that align with their preferences at the given moment (Champiri et al., 2015) (e.g., Amazon or Netflix RAs).

Interactive RAs requires more cognitive resources from consumers in order to explicitly report their preferences (i.e., giving the relative importance of each alternative attributes), which can sometimes be a tricky task when they have difficulty articulating them or lack knowledge about the purchase they are about to make (Huffman & Kahn, 1998). However, some researchers have shown that consumers believe an RA's effort directly contributes to reducing their effort (Bechwati & Xia, 2003; Tsekouras et al., 2022). Therefore, consumers evaluate their effort not in terms of the cognitive resources they have had to spend, but rather in terms of the resources they perceive they have saved. Thus, interactive RAs asking consumers to self-report their preferences can be diagnostic in showing RAs' effort to generate the recommendation, leading consumers to evaluate their effort as lower than it is. It can also explain why interactive RAs, compared to non-interactive ones, are perceived as more useful (Ebrahimi et al., 2022). Based on the above, we posit that consumers' direct input should increase the gap between perceived and actual effort, since involving consumers more during the decision-making is more demanding for consumers in terms of cognitive resources, but also contributes to expose RAs' effort in the decision-making task:

**H3**: The effect of consumers' direct input will strengthen the relationship between RA assistance (vs. no assistance or human assistance) and actual and perceived decision effort.

Consumer direct input might be more effort-consuming, but it increases consumers' confidence in the recommendation, and also its level of actual precision (Liang et al., 2006). Conversely, a recent meta-analysis by Ebrahimi et al. (2022) revealed that consumers' interactions with RA are richer when they are asked to explicitly report their preference, which positively impacts affective and cognitive assessment of the recommendation. Direct input can also help consumers with new preference development through the decision-making process (Liang, 2019). Thus, consumers' direct input leads to higher trust in the RA and should lead to higher perceived quality of the recommendation since it can be used as diagnostic information to confirm that preferences were considered. Therefore, we posit that consumers' direct input should reduce the gap between perceived and real quality, since involving consumers more during the decision-making could be a way to increase perceived quality.

**H4**: The effect of consumers' direct input will weaken the relationship between RA assistance (vs. no assistance or human assistance) and actual and perceived decision quality.

## 1.4 Methods

### *1.4.1 Study search and inclusion criteria*

Studies were collected from five major databases, namely ABI/INFORM collection (Proquest), Academic Search Complete (EBSCO), PsychINFO, Scopus, and Web of Science. The search included all published and unpublished peer-reviewed papers written in English and French. The databases were examined using terms like "recommendation agent", "recommender system", "online recommendation", "product recommendation agent", "online shopping assistant", "decision effort", "decision quality" and other synonyms and more precise terms (e.g., collaborative system, accuracy, time spent, amount of information search). Additional forward searches were performed by doing citation search, notably through Google Scholar. For unpublished papers and working papers, we posted requests on academic platforms, namely ELMAR (marketing), AISWorld (IS), SJDM (Judgment and Decision Making), and SSRN. We also conducted a manual search in leading conferences in IS (e.g., AIS eLibrary) and marketing (e.g., ACR) to find relevant proceedings. In some cases, when only the abstract was available, we contacted authors directly. Finally, to ensure literature saturation, we scanned the reference lists of the included papers through the search until we reached saturation, ending the screening process.

Studies were eligible for inclusion if they met the following four criteria. First, they must be quantitative empirical studies (i.e., lab or online experiment, survey, or field experiment). Second, the population of the studies must be individual consumers or users (B2C context). Third, studies had to compare an experimental group to a control group. While the experimental group had to feature an RA, the control group had to include no recommendation agent or another recommendation source (e.g., other consumers, human expert). Studies comparing different types of recommendation agents were excluded (e.g., Punj & Moore, 2007), as well as studies investigating comparison tools that allow consumers to sort alternatives on a single attribute at a time, such as a simple decision aid (e.g., Lurie & Wen, 2014). Fourth, studies must have, as dependent variables, a direct measure or proxy of effort and decision quality (see Appendix D for the list of information extracted from the 78 papers). Application of these criteria yielded 78 papers. These included 65 journal publications and 13 conference proceedings, working papers, and dissertations published between 1999 and 2025 (see Appendix E).

### *1.4.2 Effect size calculation*

The standardized mean difference (*d*) was used as the effect size estimate according to the formulas provided by Borenstein et al. (2021). All available statistical information was incorporated (e.g., means, standard deviations, *F*- or *t*-values, *p*-values, and frequencies). Since this effect size estimate has been shown to be upwardly biased when calculated from small sample sizes (Lipsey & Wilson, 2001), all estimates were corrected for sample size bias (Hedges, 1981). For decision effort, negative d-values indicated a stronger effect of RA aid compared to no aid or other recommendation source in reducing consumers' effort, while positive d-values indicated a stronger effect of no aid or other recommendation source compared to RA aid in reducing consumers' effort during the shopping task. For decision quality, positive d-values indicated a stronger effect of RA aid compared to no aid or other recommendation source in increasing the quality of the final purchase, while negative d-values indicated a stronger effect of no aid or other recommendation source compared to RA aid in increasing consumers' quality of their decision. In total, we obtained 472 effect sizes from 125 studies and 78 papers.

### *1.4.3 Coding moderators*

The first author and an independent coder coded moderators using the coding scheme and definitions in Table 1. Agreement reached 98 %, and discrepancies were resolved by discussion. There are six categories of moderators: measurement type, comparison groups, consumer direct input, study characteristics, and publication bias control for robustness checks.

*Measurement type.* Whether the dependent variable of effort and quality was measured with actual behavior or perceived, using self-reported measurement items (0= Perceived, 1=Actual).

*Comparison of aid types.* Investigating the effectiveness of RA aid through experiments, researchers have chosen various control groups. Frequently, RA aids are compared with no aid (e.g., Dellaert & HÄubl, 2012; Huseynov et al., 2016), human experts (e.g., Song et al., 2022; Xu et al., 2017), or other consumers (e.g., Benlian et al., 2012; Song et al., 2022). Less frequently, RA aids are compared with family or friends' recommendations (e.g., Kim, Kim, Baek, and Kim, 2025; Sinha & Medhurst, 2001) or other decision tools such as filters, search bars, and random recommendations. Thus, we combined other consumers' recommendations with those of family or friends to create the "human non-expert" condition, and combined the decision tools to create the "other type of assistance" condition. In the later situation, consumers were unassisted, but had the possibility to use some tools that were not RAs. Thus, we take into account these to make the distinction between no assistance at all and little assistance with other decision tools. We used dummy-coding to explore which type of aid the treatment group was being compared. Therefore, there was four type of comparisons possible: 1) RA vs. no assistance (0= No, 1= Yes), 2) RA vs. human expert assistance (0= No, 1= Yes), 3) RA vs human non-expert assistance (0= No, 1= Yes), and 4) RA vs other type of assistance (0= No, 1= Yes).

*Consumer direct input.* For the treatment group with the RA aid, we coded whether consumers were involved or not in providing their preferences to the system. Thus, we analyzed whether the consumer provided explicit and direct information to the RA in order to generate the recommendation (0= No, 1= Yes).

*Study characteristics and publication bias control.* We coded for the *Study type* (0 = Field study, 1= Online experiment, 2 = Lab experiment), the type of *Offering* (0 = Product, 1 = Service), the *Year of publication* (mean-centered), and for the *Field* the paper was published in (0 = Marketing, 1= Information system, 2 = Other (i.e., psychology, decision-making)). In addition, we accounted for publication biases by coding specific moderators. Publication bias occurs partly when studies with significant or favorable results are more likely to be published than those with nonsignificant or unfavorable results. This selection process can lead to an overestimation of the true effect size. Fanelli et al. (2017), in an assessment of biases in research, note that "small-study effects, gray literature bias, and citation bias might be the most common and influential issues (p. 3717)." First, studies with smaller sample sizes (or lower precision) may have to report larger effect sizes for the effect to be statistically significant and published. Thus, we included a precision effect (e.g., the inverse of the variance) to control for these small-study effects. We used *Effect size precision*, which refers to the inverse of the effect size variance. Second, we classified papers based on their *Publication status* (0 = Unpublished, 1 = Published). We considered unpublished papers because they usually have weaker effect sizes (Polanin & Snilstveit, 2016). Moreover, a grey literature bias can occur when studies are less likely to be published if the effect is not statistically significant. A citation bias exists in medical research whereby statistically significant studies are more likely to be cited than studies showing no effect (Jannot et al., 2013). This can skew the perceived weight of evidence on a particular topic. The mean-centered total citation per paper controls for this type of bias and it can be found on Google scholar. Third, we also coded for *Journal quality*, whether a journal was published in the 50 journals used in the Financial Times Research Ranking (0 = No, 1= Yes). It accounted for the systematic differences in reported effects that might arise due to the prestige and perceived or actual quality of publication in top-tier journals.

#### *1.4.4 Descriptive analysis for effort and quality*

We used a hierarchical meta-analysis, implemented with the *metafo*r package in R, to appropriately model the nested structure of our data, where we extracted multiple effect sizes from individual papers, thus addressing potential dependence issues. Individual effect sizes (Level 1) were nested within different studies (Level 2), nested in different papers (Level 3). Two influential cases in the quality outcomes dataset and one in the effort outcomes dataset, identified using Viechtbauer and Cheung (2010)'s diagnostics, were removed from further analysis. The final datasets comprised 183 effect sizes from 51 papers for effort and 286 effect sizes from 65 papers for quality. The distribution of effect sizes appeared unimodal but scattered, suggesting substantial heterogeneity (see Appendix F)

*Table 1 Coding scheme of moderators*

| | Definition | Coding |
|---|---|---|
| **Outcome dimensions** | | |
| Measurement type | Categorical variable. Dependent variables that are perceived or actual. Perceived quality or effort means that these measurements are self-reported by participants (Questionnaire). Actual quality or effort means that the variables are measured with objective metrics (e.g., time, number of pages viewed, % of product fit). | 0=Perceived<br>1=Actual |
| **Comparison of aid types** | | |
| RA vs no aid | Categorical variable. Whether the consumer was aided by an RA or received no recommendation. | 0 = No, 1 = Yes |
| RA vs human expert | Categorical variable. Whether the consumer received aid from an RA or a recommendation from another human expert. | 0 = No, 1 = Yes |
| RA vs human non-expert | Categorical variable. Whether the consumer received aid from an RA or a recommendation from another consumer, family, or friends who have experienced the product/service (e.g., online consumer review). | 0 = No<br>1 = Yes |
| RA vs another type of aid | Categorical variable. Whether the consumers were able to receive another type of aid, such as information from a random non-personalized recommendation, filter, search bar, or comparison tool. | 0 = No<br>1 = Yes |
| **Consumer input** | | |
| Direct input from consumers (explicit feedback) | Categorical variable. Whether consumers report the criteria and their preferences to generate the recommendation. | 0 = No<br>1 = Yes |
| **Study characteristics** | | |
| Study type | Categorical variable representing whether the results of the study were acquired in a controlled environment (online or lab experiment), or through a field study. | 0= Field study<br>1= Online Experiment<br>2= Lab experiment |
| Offering | Categorical variable. Whether consumers are receiving recommendations for a product or a service. | 0=Product<br>1= Service |
| Year of publication | Continuous variable indicating the year of publication of the paper. For unpublished studies, the year of availability or data collection of the paper was reported. Mean-centered. | |
| Field | Categorical variable. Whether the paper is from a marketing, information systems, or a journal of another field). When the published or unpublished paper is from another field (e.g., decision-making, management, or psychology), it is included in the "other" condition. | 0= Marketing<br>1= IS<br>2= Other |
| **Publication bias control** | | |
| Effect size precision | Continuous variable calculated as the inverse of the standard error of effect size *g*. Mean-centered. | |
| Publication status | Categorical variable of whether the papers from which the effect size was retrieved was published in a peer-reviewed journal (published) or not (unpublished). Unpublished papers include theses, faculty publications, conference papers, and working papers. | 0 = Unpublished<br>1 = Published |
| Number of citations | Continuous variable indicating the number of citations a paper received on Google Scholar. Mean-centered. | |
| Journal quality | Categorical variable representing whether the paper was published in the 50 journals used in the Financial Times Research Rank. | 0 = No, 1 = Yes |

### *1.4.5 Moderator analysis*

We tested the moderators with four meta-regressions for each dependent variable, namely effort and quality. The first model explored the moderated impact of measurement type, whether effort (see Model 1, Table 2) and quality (see Model 5, Table 3) were perceived or actual. The second model integrated the comparison group (whether RA assistance was compared to no assistance, human non-expert assistance, or human expert assistance) and the moderated impact of consumer direct input (see Model 2 for effort in Table 2, and Model 6 for quality in Table 3). The third model integrated study characteristics and publication bias controls for robustness checks (see Model 3 for effort in Table 2, and Model 7 for quality in Table 3). Finally, the fourth model allowed post-hoc analysis by testing interactions between the comparison group and measurement type, and between direct input and measurement type. By doing meta-regressions, we can test for interaction effects between moderators while controlling for confounding variables.

The three-level model showed a significantly better fit for the effort outcome, and the three-level specification was also the best fit ($\chi^2 = 4.28$, $p = .038$) with $I^2_{Level2}$ = 80.33% and $I^2_{Level3}$ = 19.62%. For the quality outcome, the three-level specification was also a better fit than a two-level one ($\chi^2 = 123.57$, $p < .0001$) with $I^2_{Level2}$= 32.86% and $I^2_{Level3}$ = 67.02%. The high heterogeneity observed through the Higgins' $I^2$ statistics warranted an examination of the moderators. Multicollinearity was not a problem, as evidenced by moderator correlations below .5, and VIFs below 5 (Hair et al., 2010) in all the meta-regressions (see Appendix G for effort, and Appendix H for quality).

## 1.5 Results

### *1.5.1 Effort outcomes*

The grand mean effect size of RA assistance on decision effort, regardless of the measurement type, is negative and not significant, with g = -.053 and a 95 % confidence interval ($CI_{95\%}$) ranging from – .164 to – .059. However, Model 1 in Table 2 indicates that the effect size for perceived effort is negative and significant (β = -0.262, *p* = 0.002).

Moreover, the effect actual effort, compared to perceived effort, is positive and significant in Model 1 (β = .304, *p* = .002) (Table 2). Thus, results suggest that RA assistance reduces consumers' perceived effort to a greater extent than their actual effort, supporting H1. Interestingly, the effect for actual compared to perceived effort remains comparable when adding the comparison group as moderators in the meta-regression (Model 2: β = .290, *p* =.005), as study characteristics and publication bias controls (Model 3: β = .313, *p* = .004). Moreover, as shown in Model 2, we found no significant difference between RA assistance compared to no assistance, compared to human non-expert assistance, and compared to human expert, on decision effort. Post-hoc analyses in Model 4 also showed no interaction between the comparison group and measurement type, whether perceived or actual. Results suggest that the effect of RA assistance on consumers' effort (perceived or actual) does not vary compared to other types of decision aid (or no decision aid), answering RQ1.

Finally, direct input from consumers was significant in Model 3 when the publication bias controls and methodological moderators were added (β = -.448, *p* =.004). Post-hoc analyses of the interaction terms between consumer direct input and measurement type on the relationship between RA assistance and decision effort in Model 4 revealed that the direct input moderator reduces perceived effort (β = -.835, *p* < .001), but that this effect disappears with an actual measure of effort (β = .690, *p* =.007). Thus, results suggest that the relationship between RA assistance and effort is stronger when the RA requires consumers' direct input and is assessed using perceived measures, supporting H3.

*Table 2. Results of the meta-regression for decision effort*

| | **Model 1** | | | **Model 2** | | | **Model 3** | | | **Model 4** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Estimate | SE | p | Estimate | SE | p | Estimate | SE | p | Estimate | SE | p |
| Intercpt | -.262 | .084 | .002 | -.107 | .124 | .392 | .196 | .203 | .337 | .296 | .226 | .191 |
| Actual | .304 | .100 | .003 | .290 | .103 | .005 | .313 | .108 | .004 | -.006 | .200 | .974 |
| RA vs Human non-expert | | | | -.209 | .208 | .316 | -.314 | .224 | .163 | -.386 | .272 | .158 |
| RA vs Expert | | | | .209 | .201 | .300 | .252 | .218 | .249 | .676 | .320 | .036 |
| RA vs other aids | | | | -.145 | .124 | .245 | -.187 | .158 | .236 | .037 | .277 | .894 |
| Direct input | | | | -.182 | .112 | .105 | -.448 | .151 | .004 | -.835 | .218 | .001 |
| Lab study | | | | | | | -.116 | .140 | .411 | .101 | .161 | .533 |
| Field study | | | | | | | .097 | .195 | .618 | .234 | .208 | .262 |
| IS | | | | | | | .062 | .157 | .694 | -.040 | .172 | .816 |
| Other discipline | | | | | | | .126 | .198 | .525 | -.008 | .214 | .969 |
| Service | | | | | | | .114 | .160 | .478 | .155 | .177 | .381 |
| Year of publication | | | | | | | -.011 | .011 | .297 | -.002 | .012 | .888 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Unpublished | -.274 | .187 | .145 | -.180 | .202 | .373 |
| FT50 | -.240 | .174 | .169 | -.336 | .192 | .083 |
| Number citations | .001 | .001 | .101 | .001 | .001 | .157 |
| Precision | -.001 | .001 | .356 | .001 | .001 | .884 |
| Actual : Human non-expert | | | | .343 | .491 | .485 |
| Actual :RA expert | | | | -.506 | .409 | .217 |
| Actual : Other aids | | | | -.309 | .297 | .300 |
| Actual : Direct input | | | | .690 | .252 | .007 |

### *1.5.2 Quality outcomes*

The grand mean effect size of RA assistance on decision quality, regardless of the measurement type, is positive and significant, with g = .1596 and a 95 % confidence interval ($CI_{95\%}$) ranging from .0156 to .3036, indicating that being assisted by an RA, versus no assistance or human assistance, increase decision quality. According to the Hedge's g threshold, this effect size can be qualified as small.

Model 5 showed that the effect size for actual quality was more important than perceived quality (β = .208, *p* = .008) (Table 3), supporting H2. However, this effect was attenuated but remained significant when adding the comparison groups in Model 6 (β = .158, *p* = .045). The effect became marginally significant when adding all the moderators in Model 7 (β = .150, *p* = .063).

Moreover, as shown in Model 6, the effectiveness of RA assistance varies depending on the comparison group. The effect of the RA assistance on decision quality, combining actual and perceived measures, was consistently weaker when the comparison group was a human expert (Model 6: β = -.645, p < .001 and Model 7: β = -.793, p < .001). The effect was smaller when the comparison was a non-expert human (Model 6: β = -.297, *p* =.081 and Model 7: β = -.458, *p* = .019). The effect of RA assistance was not different when consumers were unassisted or had the opportunity to use other tools than RAs (Model 6: β = 0.002986, *p* =.982). None of the moderators in Model 7 reached significance. Post-hoc analyses in Model 8 also showed no interaction between the comparison group and measurement type. Results suggest that the effect of RA assistance on consumers' decision quality (perceived or actual) does vary compared to other types of decision aid (or no decision aid) answering RQ2. Finally, direct input from consumers was not significant in Models 6 and 7, nor the interaction between consumer direct input and measurement type in post-hoc analyses presented in Model 8. Thus, results suggest that the moderation of measurement type on the relationship between RA assistance and quality (H2) is not moderated by consumers' direct input. Thus, H4 is not supported.

*Table 3. Results of the meta-regression for decision quality*

| | Model 5 | | | Model 6 | | | Model 7 | | | Model 8 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Estimate | SE | p | Estimate | SE | p | Estimate | SE | p | Estimate | SE | p |
| Intercpt | .062 | .079 | .435 | .176 | .127 | .167 | .157 | .165 | .340 | .236 | .180 | .191 |
| Actual | .208 | .078 | .008 | .158 | .079 | .045 | .150 | .080 | .064 | -.028 | .183 | .880 |
| RA vs Human non-expert | | | | -.297 | .170 | .081 | -.458 | .194 | .019 | -.543 | .247 | .029 |
| RA vs Expert | | | | -.645 | .166 | .001 | -.793 | .192 | .001 | -.754 | .206 | .000 |
| RA vs other aids | | | | .003 | .139 | .983 | -.095 | .151 | .531 | .044 | .202 | .828 |
| Direct input | | | | .107 | .121 | .377 | .019 | .132 | .885 | -.138 | .160 | .388 |
| Lab study | | | | | | | -.088 | .136 | .520 | -.061 | .139 | .662 |
| Field study | | | | | | | -.085 | .182 | .640 | -.051 | .184 | .781 |
| IS | | | | | | | .193 | .166 | .246 | .190 | .165 | .250 |
| Other discipline | | | | | | | .200 | .190 | .295 | .232 | .190 | .223 |
| Service | | | | | | | .251 | .134 | .061 | .238 | .133 | .076 |
| Year of publication | | | | | | | .002 | .012 | .852 | .002 | .012 | .884 |
| Unpublished | | | | | | | -.194 | .194 | .319 | -.181 | .192 | .346 |
| FT50 | | | | | | | .168 | .180 | .352 | .179 | .180 | .321 |
| Number citations | | | | | | | .001 | .001 | .210 | .001 | .000 | .176 |
| Precision | | | | | | | -.002 | .001 | .140 | -.002 | .001 | .212 |
| Actual : Human non-expert | | | | | | | | | | .145 | .327 | .657 |
| Actual :RA expert | | | | | | | | | | -.081 | .286 | .776 |
| Actual : Other aids | | | | | | | | | | -.189 | .186 | .310 |
| Actual : Direct input | | | | | | | | | | .300 | .190 | .116 |

### *1.5.3 Robustness checks*

The integration of study characteristics and publication bias controls in Model 3 (Table 2) for effort and Model 7 (Table 3) for quality showed that the results were robust. Moreover, the visual interpretation of the funnel plots did not show clear evidence of asymmetry (see Appendix I for effort, and Appendix J for quality). Specifically, there was no noticeable absence of smaller studies showing nonsignificant or negative effects. Because it can be challenging to discern asymmetry with a dense plot, we ran Egger's regression test (Egger et al., 1997), which suggested no asymmetry for the quality outcome, ($t$ (284) = 1.848, p = 0.066). Results of the Begg and Mazumdar (1994) rank correlation test, a method that is less affected by outliers for assessing funnel plot asymmetry, did not indicate significant bias for quality (Kendall's tau = 0.0323, p = 0.414). Thus, publication bias from non-published research and small-study effects did not appear to be an issue for quality outcomes. For the effort outcome, the rank correlation test was significant (Kendall's tau = 0.1267, p = 0.011), but the Egger's regression test was not, ($t$(181) = -.740, p = .460). Given that the precision moderator in the meta-regression (Model 3) was also nonsignificant, there was no major concern for small-study effects on the effort outcome.

Additionally, we conducted a *p*-curve analysis to assess if there was evidence of p-hacking: the manipulation of data analysis within a study until it produces statistically significant results. The analysis included 138 significant effect sizes for quality and 105 for effort. The absence of a visual pile-up of effect sizes below the .05 threshold suggested the absence of p-hacking for both outcomes. Right-skewness tests supported this observation for both outcomes; half p-curve, (Z = -34.197 and -21.774, $p < .001$) and full p-curve, (Z = -32.255 and -22.41, $p$ < .001), for effort and quality respectively. Consequently, there was no indication of selective reporting.

Finally, we identified outliers in Models 3 and 7 by calculating the z-scores of their residuals. This analysis excluded 17 observations for effort and 16 for quality, respectively, with absolute z-scores greater than 1.96 from the quality and effort outcome datasets. Models 9 (decision effort) and 10 (decision quality) (see Appendix K) showed similar results for effort and quality outcomes. This consistency suggests that the presence of outliers did not skew our initial findings.

## 1.6 General discussion

Results showed that RA assistance decreases perceived effort but not the actual effort, suggesting that consumers generally underestimate the cognitive resources they invest during their decision-making when interacting with RAs. Indeed, compared to no assistance or human assistance, being assisted by an RA does not show a decrease in time spent, cognitive load experienced, or number of information examined. However, consumers tend to perceive a significantly lower use of their cognitive resources than when they are unassisted or assisted by a human. Thus, the efficiency of RA assistance might probably be looked at in terms of how it helps consumers spend cognitive resources on better alternatives, rather than on how it decreases time spent or the amount of information examined.

Conversely, RA assistance increases actual decision quality, but not perceived decision quality. Thus, results suggest that consumers generally undervalue RAs. Indeed, compared to no assistance or human assistance, being assisted by an RA clearly shows that consumers examine and choose more quality alternatives. However, whether an RA assists them or not, they do not perceive this increase in quality. Moreover, when aggregating actual and perceived measurements, results suggest that, compared to human expert assistance and human non-expert assistance, RA assistance leads to a weaker effect on decision quality. This means that human assistance in recommending alternatives has a more positive impact on the quality of the decision than RAs. This effect is not solely driven by consumers' subjective evaluations of RAs, but also by how they interact with and respond to the recommendations provided. Our findings suggest that consumers are not inherently averse to algorithmic systems since they adopt behaviors that follow mostly RAs' recommendations, but they show more appreciation for human assistance over algorithms in general (Jussupow et al., 2024; Logg et al., 2019).

Finally, our results suggest that asking consumers to provide their preferences to the RA explicitly strengthens the perception of reducing cognitive resources when assisted by this system to a greater extent than the actual resources they expend during the decision-making process. This corroborates past research, showing that consumers evaluate their effort in terms of the cognitive effort they perceive they saved (Bechwati & Xia, 2003). Thus, interactive RAs asking consumers to self-report their preferences can be diagnostic in showing RAs' effort to generate the recommendation, leading consumers to evaluate their effort as lower than it is.

Contrary to our expectations, consumers direct input does not have any effect on perceived or actual decision quality when assisted by an RA. This suggests that interacting with the RA system during the decision-making process does not reduce the gap between perceived and actual decision quality. Thus, asking consumers' preferences might not be a diagnostic cue that helps consumers assess the quality of their final choice, and other cues, such as the level of reliability of the system, might be made clearer at the time of purchase (e.g., Yin et al., 2019). This is in line with Nilashi et al. (2016) who suggest that recommendation quality is not enough; more transparency about how the RA system is working is important for its evaluation.

### *1.6.1 Theoretical contributions*

Our first theoretical contribution builds on CCT (Bettman et al., 1998), suggesting that the shopping context strongly shapes consumers' behaviors and perceptions when interacting with RAs. In this regard, our meta-analysis reveals a gap between how consumers perceived their effort invested in the decision-making process and how they really behaved in terms of time spent and number of alternatives examined. We also found a discrepancy between how consumers perceived and evaluate the quality of their final choice, and the actual level of quality of this final decision depending on whether they complied or not with the optimal alternative for them. Therefore, our meta-analysis resolves the mixed findings in the literature regarding the impact of RA assistance on decision effort and decision quality. Examining the consumer decision-making process necessitates addressing both behaviours and perceived experiences. One cannot be fully understood without the other, as both are essential to grasp the cognitive processes and perceptual biases that shape consumer adaptations and evaluations. Indeed, studying consumer behavior while assisted by RAs thus provides valuable insights into their impact on consumer well-being in a consumption context (e.g., Banker & Khetani, 2019), while analyzing consumers' perceptions sheds light on their future interactions with the system and the retailer (Blut et al., 2023).

Second, our meta-analysis helps resolve the mixed findings regarding effort minimization and quality maximization when assisted by an RA. Results show that the strength and significance of the effect for both constructs are influenced by the nature of their measurement, which may help explain the heterogeneity in prior findings. While many past studies exploring effort and quality have used mixed measurement approaches—sometimes comparing perceived effort with actual quality or actual effort with perceived quality—these choices often appear somewhat *ad hoc* (e.g., Hostler et al., 2011; Lajos et al., 2009; Lee & Benbasat, 2010). As a result, it becomes difficult to draw meaningful conclusions about the impact of RA on these two constructs without grounding the findings in how each was measured (Aksoy et al., 2011). The trade-off may be based on actual behavior, perceived experience, or a combination of both. However, its nature must be specified to properly interpret the impact of RAs on the decision-making process. Indeed, perceived effort leads to a stronger effect than actual effort, while the reverse occurs for quality, where actual quality leads to a stronger effect than perceived quality. Therefore, our results highlight the need for researchers to situate their constructs within the context of their measurement methods.

Finally, our third contribution addresses the literature on cognitive and perceptual biases. By examining two key moderators: (1) the comparison group used to assess effort and decision quality when assisted by an RA, and (2) the extent of consumer direct input when interacting with an RA. Our results suggest that both moderators are evaluated based on diagnostic cues available to consumers throughout the purchasing process. While much of the literature has focused on how the characteristics of the alternatives (number of attributes per alternative or the number of alternatives (Aljukhadar et al., 2012) and the type of alternatives (Wien & Peluso, 2021)) or how the type of RA system (Xu et al., 2017) affect decision effort and quality, our findings emphasize that how consumers interact with the RA, i.e., direct input from consumers in rating alternatives attributes, and the benchmark against which the RA is evaluated influence respectively perceived and actual decision effort, and perceived and actual decision quality.

Indeed, even as research and development efforts aim to improve RA systems through technical enhancements, our results suggest that consumer performance, when assisted by RAs, is not fixed or inherently determined by system design alone. Instead, it is context-dependent, shaped by the informational environment available to the consumer and their ability to interpret it during the decision-making process (Bettman et al., 1998). Moreover, our results suggest that consumers generally express appreciation rather than aversion toward recommendation agents (Logg et al., 2019). Specifically, consumers tend to view RAs as effective decision heuristics that help reduce cognitive effort, and they often behave in ways that reflect a recognition of the quality of the recommendations provided. However, when it comes to decision quality, consumers still tend to privilege human judgment, indicating a persistent bias in favor of human over algorithmic input in final evaluations.

### *1.6.2 Managerial implications*

From a managerial perspective, our results show managers that there is work to be done to enhance the performance of RAs regarding the quality perceived by consumers.

Indeed, our results show that RA assistance, compared to no assistance or human assistance, has an impact on consumers' actual behaviors in choosing quality alternatives. Thus, RAs show a concrete positive impact, but more effort should also be made on user experience and quality nudges to communicate the performance of RAs (Nilashi et al., 2016). Thus, we believe that RA do a great job in quality enhancement, but if quality is the main attribute consumers look at when shopping for a certain offering category, RA assistance should be complemented by the presence of consumers' reviews or by the possibility to be assisted by a human expert.

Moreover, as a second implication, our results suggest that RA assistance, compared to human assistance or no assistance at all, does not lead to a reduction of consumers' actual effort, meaning RA assistance does not decrease time spent or the number of alternatives evaluated. Still, consumers appreciate the presence of an RA in assisting them, perceiving it helps them save more cognitive effort. This effect is strong enough to be observed by retailers, so they have everything to gain from the presence of an RA on their website when analyzing decision effort: not only the presence of RA does not lead consumers to spend less time and process less information on the retailer website, but it also improves the overall usefulness perception of the website. Consumer-RA interaction can also reinforce the positive perception of RA assistance. This suggests that incorporating perceptible indicators during the consumer's decision-making process such as showing that the RA is working with and for them, could be beneficial. For instance, regardless of whether the system actually uses the information provided, prompting consumers to explicitly state their needs or preferences can help them recognize and evaluate the RA's usefulness.

### *1.6.3 Limitations and research avenues*

Drawing from our results, we propose a research agenda for studying the impact of RA assistance on consumers’ decision quality and effort. These recommendations take into account our empirical findings, along with limitations regarding the meta-analytic method.

*Toward a more rigorous examination of the effort construct and adaptive RAs*. Over the years, research has placed considerable emphasis on enhancing the actual and perceived decision quality of purchases made with the support of RAs, while comparatively less attention has been given to reducing consumers’ decision effort (Tsekouras et al., 2022). This is somewhat surprising, given that numerous studies have highlighted consumers’ preference for RAs precisely because of their ability to reduce cognitive effort (Benlian et al., 2012; Häubl & Trifts, 2000). Our meta-analysis results reinforce this notion, showing that consumers tend to perceive RAs as more effective at reducing effort than they may be in practice. This positive perception aligns with the broader concept of perceived usefulness (Davis, 1989), which drives adoption of RA system. Yet very little research has explored how RAs might dynamically adjust their level of assistance based on the consumer's decision-making process. For example, by monitoring indicators such as mouse clicks or browsing behavior, RAs could detect rising cognitive effort and adapt their support accordingly (Fernández-Fontelo et al., 2023). We therefore call for more research on adaptive RAs and effort regulation within consumer decision-making contexts, to better align system design with consumers' evolving cognitive needs (Beauchemin et al., 2024; Mirhoseini et al., 2024). Moreover, our meta-analysis did not help to understand how effort is allocated whether consumers are assisted by RAs or by humans, or when they do not receive assistance at all. More research should focus on how consumers search depending on the assistance they receive, rather than how they perform in terms of effort reduction. Thus, more research should be done regarding how effort should be allocated to reduce the difficulty of choices rather than reducing effort in general.

*Toward a systematic redefinition of the quality construct*. This meta-analysis focuses on quality in terms of optimal choice for consumers, meaning with high accuracy and precision. This way of approaching quality is in line with much research, but in the mid-2010s, this efficacy-focused approach has been reported has highly restrictive to measure consumers performance with RAs, and some researchers have advocated for more inclusive elements in the calculation, such as alternative diversity and novelty (Blut et al., 2023; Nilashi et al., 2016), but also elements in the new era of eco-responsible consumption, such as sustainability (Satinet et al., 2024). These elements have the effect of enriching the decision-making process and building consumers' preferences through it. Therefore, even if the outcome results in a trade-off between accuracy, novelty, sustainability, serendipity, and diversity, it can increase consumers' trust in the system and perceived value in the recommendation (Dzyabura & Hauser, 2019; Nilashi et al., 2016). It is only recently that Dzyabura and Hauser (2019) propose a recommender system incorporating preference-weight learning, including accuracy, diversity, novelty, and serendipity to measure decision quality. Despite this, the discourse surrounding the advent of AI-driven recommendations by tools such as chatbots relying on natural language processing, or generative AI (i.e., Google's AI Overview, ChatGPT) is still very much connected to their effectiveness in terms of predictive performance in answering consumers' queries. Thus, we urge researchers to start redefining the construct of quality, and to be systematic in applying the concept of diversity, novelty, and serendipity in addition to accuracy when studying consumers' behaviours and perceptions. Indeed, this new definition can help better understand why consumers adapt their strategy during the decision-making process, rather than exploring if the RA is making the best predictable recommendations for them and if consumers comply with them.

*Generative AI: from search aid to answer aid.* Since our results supported the fact that consumers' decision-making should be studied according to its context and the interactions consumers have with the RA, more research should be done regarding generative AI queries helping consumers find the optimal product for them with less effort (e.g., ChatGPT Operator). Traditional RAs on retailer websites are decision aid search, while generative AI recommender systems are perceived as answer aids (Reach, 2024). This changes the dynamics between RAs and consumers, where consumers are less engaged in the search process, but generative AI furnishes fewer diagnostic cues to evaluate the quality of the final recommendations. Further research should explore how generative AI queries from consumers to find a good product on many retailer platforms influence decision effort and quality.

*Bridging two parallel literatures.* This meta-analysis did not make the distinction between the RA types, such as collaborative or content-based RA, or even hybrid ones, and did not add moderators related to the explainability of these RA systems in generating recommendations. Research in marketing and IS has mainly been interested in testing different RA types to improve quality of recommendations (Ariely et al., 2004; Blut et al., 2023; Xiao & Benbasat, 2007; Yoon et al., 2013), and how the presentation of these recommendations by RAs can increase perceived quality (Peng & Liang, 2023). For instance, Ariely et al. (2004) showed that collaborative RAs perform better initially, when the agent has little information about the consumers, but content-based RAs perform better in the long run. Over time, research has shown that collaborative RAs are more persuasive than content-based ones (Matt et al., 2023). Blut et al. (2023) have shown that collaborative-filtering RAs perform best in improving perceived decision quality and RA satisfaction, while content-based RAs were the ones performing the worst. Other research suggests that being accurate should also come with transparency features such as explainability (i.e., explanations of the output), which can be beneficial for consumers satisfaction with the RA (Shin & Park, 2019). Indeed, these two streams of research - how systems work and how they communicate - seem to have met very rarely. This may contribute to widening the gap between actual and perceived quality, insofar as privacy protection, consumer control, and the right to explanations when using algorithmic systems are increasingly framed by legislation that heeds consumers' fears.

**Statement:** During the preparation of this work, the authors used ChatGPT-4 and Grammarly for copy-editing, after which, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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For the complete list of papers included in the meta-analysis, please see Appendix L.


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# Appendix

## *APPENDIX A. Type of variables for perceived and actual effort and quality and the direction of the effect*

*Table 4. Type of variables for perceived and actual effort and quality and the direction of the effect*

| Measurement | Variables | Direction | Sources |
|---|---|---|---|
| Actual effort | Amount of information search (attribute/alternative examined) | Decrease | Dellaert & Häubl (2012), Aljukhadar et al. (2012), Haübl & Trifts (2000), Olson & Widing (2002), Wan & Li (2024), Bodoff & Ho (2015), Tam & Ho (2006) |
| | | Increase | Dellaert & Häubl (2012), Hostler et al. (2011), Chu & Spires (2000), Peng & Liang (2023), Wan & Li (2024), Li et al. (2022), Bodenbenner & Neumann (2012) |
| | | No effect | Dellaert & Häubl (2012), Dellaert et al. (2024), Matt et al. (2013), Jeff (2013), Olson & Widing (2002), Chu & Spires (2000), Rolon-Mérette et al. (2024), Peng & Liang (2023), Wan & Li (2024), Bodoff & Ho (2015), Kumar & Hosanagar (2019), Lee et al. (2020) |
| | Size of the consideration set | Decrease | Haübl & Trifts (2000) |
| | | Increase | Goodman et al. (2013), Pereira (2001), Scholz et al. (2013), Li et al. (2022) |
| | | No effect | Goodman et al. (2013), Scholz et al. (2013) |
| | Number of stages narrowing down the consideration set | Increase | Pereira (2001) |
| | Decision time | Decrease | Huseynov et al. (2016), Hostler et al. (2005), Meija & Guesmi (2024), Yeh & Kuo (2019), Verruck (2017), Tan et al. (2010), Tam & Ho (2006) |
| | | Increase | Dellaert & Häubl (2012), Xu et al. (2017), Notabaert (2019), Lee & Benbasat (2010), Goodman et al. (2013), Jeff (2013), Maheswarappa et al. (2017), Olson & Widing (2002), Bodenbenner & Neumann (2012) |
| | | No effect | Dellaert & Häubl (2012), Lajos et al. (2009), Goodman et al. (2013), Jeff (2013), Maheswarappa et al. (2017), Westerman et al. (2007), Meija & Guesmi (2024), Verruck (2017) |
| | Cognitive overload | Increase | Rolon-Mérette et al. (2024), Xie et al. (2022) |
| | | No effect | Rolon-Mérette et al. (2024), Xie et al. (2022) |
| | Heterogeneity of the consideration set | No effect | Ghiassaleh et al. (2020) |
| Perceived effort | Perceived time spent | Decrease | Olson & Widing (2002), Pedersen (2000) |
| | | No effect | Olson & Widing (2002) |
| | Perceived cost of information search | Decrease | Su et al. (2008) |
| | Perceived amount of information search (attributes/alternatives evaluated) | Increase | Pedersen (2000) |
| | | No effect | Pedersen (2000) |
| | Perceived size of the consideration set | No effect | Pedersen (2000) |

| | | | |
|---|---|---|---|
| | Perceived cognitive overload/decision difficulty | Decrease | Huang & Zhou (2019), Aljukhadar et al. (2012), Pereira (2001) |
| | | Increase | Nguyen et al. (2022), Goodman et al. (2013), Turri (2011) |
| | | No effect | Goodman et al. (2013), Hostler et al. (2005), Turri (2011), Ghiassaleh et al. (2020) |
| | Perceived decision effort | Decrease | Bechwati & Xia (2003), Xu et al. (2017), He et al. (2023), Lee & Benbasat (2010), Liu et al. (2022), Verruk (2017) |
| | | Increase | Goodman et al. (2013), Chattaraman et al. (2024), Xu et al. (2017), Liu et al. (2022) |
| | | No effect | Goodman et al. (2013), Chattaraman et al. (2024), Bechwati & Xia (2003), Verruk (2017) |
| | Perceived usefulness of the recommendation | Decrease | Bentlian et al. (2010, 2012), Kumar & Benbasat (2006), Tam & Ho (2005) |
| | | Increase | Sinha & Swearingen (2001) |
| | | No effect | Liang et al. (2006) |
| Actual quality | Compliance (purchase) with superior/optimal option/ Purchase | Decrease | Senecal & Nantel (2004), Longoni & Cian (2022), Maheswarappa et al. (2017), Xie et al. (2022), Longoni et al. (2019), Tan et al. (2010), Diehl et al. (2003), Ghiassaleh et al. (2020) |
| | | Increase | Dellaert & Häubl (2012), Huseynov et al. (2016), Senecal & Nantel (2004), Longoni & Cian (2022), Aljukhadar et al. (2012), Banker & Khetani (2019), Hostler et al. (2005), Haübl & Trifts (2000), Dellaert et al. (2024), Matt et al. (2013), Maheswarappa et al. (2017), Westerman et al. (2007), Andrews (2010), Olson & Widing (2002), Peng & Liang (2023), Lee et al. (2020), Tan et al. (2010), Diehl et al. (2003), Li et al. (2022), Tam & Ho (2006) |
| | | No effect | Senecal & Nantel (2004), Banker & Khetani (2019), Matt et al. (2013), Westerman et al. (2007), Pedersen (2000), Xie et al. (2022), Peng & Liang (2023), Lee et al. (2020), Verruck (2017), Diehl et al. (2003), Ghiassaleh et al. (2020), Li et al. (2022) |
| | Switching behaviors after purchase | Decrease | Haübl & Trifts (2000), Andrews (2010), Olson & Widing (2002) |
| | | Increase | Yeomans et al. (2018) |
| | | No effect | Olson & Widing (2002) |
| | Consideration set quality/ Evaluation of good options | Decrease | Tan (2003) |
| | | Increase | Heijiden & Sorensen (2003), Haübl & Trifts (2000), Dellaert et al. (2024), Tan (2003), Scholz et al. (2013) |
| | Accuracy of the recommendation | Increase | Yeomans et al. (2018), Lee & Benbasat (2010), Liang et al. (2006), Olson & Widing (2002), Pereira (2001), Wan & Li (2024) |
| | | No effect | Lee & Benbasat (2010), Olson & Widing (2002), Chu & Spires (2000) |
| Perceived quality | Intention to comply/purchase the superior/optimal option | Decrease | Song et al. (2022), Qin et al. (2022), Markovitch et al. (2025), Huang et al. (2024), Xie et al. (2022), Baum & Spann (2014), Longoni et al. (2019) |
| | | Increase | Peng et al. (2023) |
| | | No effect | Peng et al. (2023), Malampallayil & Binghamton (2019), Kim et al. (2025), Rolon-Mérette et al. (2024), Huang et al. (2024), Yang et al. (2024), Xie et al. (2022), Longoni et al. (2019) |

| | | |
|---|---|---|
| Perceived quality of the recommendation | Decrease | Sinha & Swearingen (2001), Xu et al. (2017), He et al. (2023), Heijiden & Sorensen (2003), Wien & Peluso (2021), Meija & Guesmi (2024), Yang et al. (2024), Liu et al. (2022), Tan et al. (2010) |
| | Increase | Xu et al. (2017), Heijiden & Sorensen (2003), Hostler et al. (2011), Yoon et al. (2021), Sivaramakrishnan et al. (2007), Hostler et al. (2012), Liu et al. (2022), Tan et al. (2010) |
| | No effect | Yoon et al. (2021), Sivaramakrishnan et al. (2007), Wien & Peluso, Rolon-Mérette et al. (2024), Meija & Guesmi (2024), Yang et al. (2024) |
| Choice confidence | Decrease | Rohden & Espartel (2024), Maheswarappa et al. (2017) |
| | Increase | Aljukhadar et al. (2012), Haübl & Trifts (2000), Maheswarappa et al. (2017), Olson & Widing (2002) |
| | No effect | Banker & Khetani (2019), Hostler et al. (2005), Rohden & Espartel (2024), Westerman et al. (2007), Olson & Widing (2002), Pereira (2001), Ghiassaleh et al. (2020) |
| Intention to switch alternative after purchase/satisfaction with the final purchase | Decrease | Notabaert (2019), Liang et al. (2006), Hostler et al. (2012), Pedersen (2000), Kmett et al. (1999), Tam & Ho (2006) |
| | Increase | Lajos et al. (2009), Maheswarappa et al. (2017), Markovitch et al. (2025) |
| | No effect | Lajos et al. (2009), Liang et al. (2006), Maheswarappa et al. (2017), Westerman et al. (2007), Turri (2011), Kim et al. (2025), Rolon-Mérette et al. (2024) |
| Intention to pay for the recommendation | Decrease | Yang et al. (2024), Longoni et al. (2019) |
| | No effect | Yang et al. (2024), Adomavicius et al. (2018) |
| Perceived accuracy of the recommendation | Decrease | Song et al. (2022), Lepkowska-White (2024) |
| | Increase | Olson & Widing (2002) |
| | No effect | Lepkowska-White (2024), Olson & Widing (2002), Pedersen (2000) |

***APPENDIX B. Research measuring both effort and quality, and the type of relationship between the two constructs***

*Table 5. Research measuring both effort and quality, and the type of relationship between the two constructs*

| Source | Study | Type of relation | Actual effort | Perceived effort | Actual quality | Perceived quality |
|---|---|---|---|---|---|---|
| Dellaert & Häubl (2012) | 1 | Positive relationship<br>No correlation | Increase, No effect | - | Increase | - |
| | 2 | Negative relationship<br>Positive relation | Decrease, Increase | - | Increase | - |
| Huseynov et al. (2016) | 1 | Negative relationship | Decrease | - | Increase | - |
| Xu et al. (2017) | 1 | Positive relationship | Increase | Decrease, Increase | - | Decrease, Increase |
| Notabert (2019) | 1 | Positive relationship | Increase | - | - | Increase |
| He et al. (2023) | 1 | Positive relationship | - | Decrease | - | Decrease |
| Aljukhadar et al. (2012) | 1 | Negative relationship | Decrease | Decrease | Increase | Increase |
| Hostler et al. (2005) | 1 | Negative relationship<br>No correlation | Decrease | No effect | Increase | No effect |
| Hostler et al. (2011) | | Positive relationship | Increase | - | - | Increase |
| Lajos et al. (2009) | | No correlation | No effect | - | - | Decrease, No effect |
| Lee & Benbasat (2010) | 1 | Positive relationship<br>No correlation | Increase | Decrease | Increase<br>No effect | - |
| Haübl & Trifts (2000) | 1 | Negative relationship | Decrease | - | Increase | Increase |
| Dellaert et al. (2024) | 1 | No correlation | No effect | - | Increase | - |
| Matt et al. (2013) | 1 | No correlation | No effect | - | Increase, No effect | - |
| Jeff (2013) | | No correlation | No effect, Increase | - | No effect | - |
| Liang et al. (2006) | 1 | Negative relationship | - | Decrease, No effect | Increase | Increase, No effect |
| Maheswarappa et al. (2017) | 1 | Negative and positive relationship<br>No correlation | Decrease, No effect | - | Increase, Decrease<br>No effect | Increase, Decrease<br>No effect |
| | 2 | Negative and positive relationship<br>No correlation | Increase, No effect | - | Increase | Increase, Decrease |
| Westerman et al. (2007) | 1 | No correlation | No effect | - | Increase, No effect | No effect |
| Turri (2011) | 1 | No correlation | - | No effect | - | Increase, No effect |

| | | | | | | |
|---|---|---|---|---|---|---|
| Olson & Widing (2002) | 1 | Negative and positive relationship<br>No correlation | Decrease, Increase | Decrease | Increase, No effect | Increase |
| | 2 | No correlation | Increase, No effect | No effect | No effect | No effect |
| Chu & Spires | 1 | No correlation | Decrease, Increase | - | No effect | - |
| Pereira (2001) | 1 | Negative and positive relationship<br>No correlation | Increase | Decrease | Increase | No effect |
| Pedersen (2000) | | Negative and positive relationship<br>No correlation | - | Decrease, Increase<br>No effect | No effect | Increase, No effect |
| Rolon-Mérette et al. (2024) | 1 | No correlation | Increase, No effect | - | - | No effect |
| Xie et al. (2022) | 1 | Negative relationship<br>No correlation | Increase, No effect | - | Decrease, No effect | Decrease, No effect |
| Peng & Liang (2023) | 1 | Positive relationship<br>No correlation | Increase, No effect | - | Increase, No effect | - |
| Lee et al. (2020) | 1 | No correlation | No effect | - | Increase, No effect | - |
| Liu et al. (2022) | 1 | Positive relationship<br>No correlation | - | Decrease<br>Increase | - | Increase, Decrease |
| Wan & Li (2024) | 1 | Negative and positive relationship<br>No correlation | Decrease, Increase<br>No effect | - | Increase | - |
| Verruk (2017) | 1 | No correlation | Decrease, No effect | Decrease<br>No effect | No effect | - |
| Tan et al. (2010) | 1 | Positive and negative relationship | Decrease | - | Increase, Decrease | Increase, Decrease |
| Scholz et al. (2013) | 1 | Positive relationship | Increase, No effect | - | Increase | - |
| Ghiassaleh et al. (2020) | 1 | No correlation | - | No effect | Decrease, No effect | No effect |
| | 3 | No correlation | No effect | - | Decrease, No effect | - |
| Li et al. (2022) | 1 | Positive relationship | Increase | - | Increase | - |
| Tam & Ho (2006) | 1 | Negative relationship | Decrease | Decrease | Increase | - |
| | 2 | Negative relationship | Decrease | - | - | Increase |
| Tam & Ho (2005) | 1 | Positive relationship | - | Increase | Increase | - |
| | 2 | Positive relationship | - | Increase | Increase | - |
| | 3 | Positive relationship | - | Increase | Increase | - |

## *APPENDIX C. Comparison groups used to evaluate RA assistance on decision effort and quality*

*Table 6. Comparison groups used to evaluate RA assistance on decision effort and quality*

| Comparison group | Definition | Outcomes of interest | Source |
|---|---|---|---|
| RA assistance versus no assistance | No assistance refers to a decision process in which the consumer is alone in navigating the retailer website or can use other decision tools, such as a search menu or a filter tool, to screen alternatives based on one attribute at a time. | Effort | Su et al. (2008), Nguyen et al. (2022), Huang & Zhou (2019), Goodman et al. (2013), Chattaraman et al. (2024), Kumar & Benbasat (2006), Yeh & Kuo (2019), Bodoff & Ho (2015), Kumar & Hosanagar (2019), Bodenbenner & Neumann (2012) |
| | | Quality | Van Der Heijiden & Sorensen (2003), Banker & Khetani (2019), Yoon et al. (2013), Sivaramakrishnan et al. (2007), Henning-Thurau et al. (2012), Peng et al. (2023), Rohden & Espartel (2024), Andrews (2010), Hostler et al. (2012), Diehl et al. (2003), Kmett et al. (1999), Adomavicius et al. (2018) |
| | | Effort and quality | Dellaert & Häubl (2012), Huseynov et al. (2016), Notebaert (2019), Aljukhadar et al. (2012), Hostler et al. (2005), Hostler et al. (2011), Lajos et al. (2008), Lee & Benbasat (2010), Haübl & Trifts (2000), Dellaert et al. (2024), Matt et al. (2023), Jeff (2013), Liang et al. (2006), Maheswarappa et al. (2017), Westerman et al. (2007), Turri (2011), Olson & Widing (2002), Chu & Spires (2000), Pereira (2001), Tan (2003), Pedersen (2000), Rolon-Mérette et al. (2024), Peng & Liang (2020), Lee et al. (2020), Wan & Li (2024), Verruck (2017), Tan et al. (2010), Dorner et al. (2013), Ghiassaleh et al. (2020), Li et al. (2022), Tam & Ho (2006), Tam & Ho (2005) |
| RA assistance versus human non-expert assistance | Human non-expert refers to family members or friends who recommend the consumer, or to other consumers who make a review online. | Effort | Benlian et al. (2010), Benlian et al. (2012), Kumar & Benbasat (2006) |
| | | Quality | Senecal & Nantel (2004, Longoni & Cian (2020), Lepkowska-White (2013), Wien & Peluso (2021), Malampallayil & Binghamton (2019), Kim et al. (2025), Baum & Spann (2014) |
| | | Effort and quality | Sinha & Swearingen (2001), Xu et al. (2017), He et al. (2023), Liu et al. (2022), Dorner et al. (2013) |
| RA assistance versus human expert assistance | Human experts refer to individuals who possess specialized knowledge, skill, and experience in a particular domain or field, such as sellers or professionals. | Quality | Senecal & Nantel (2004), Yoon & Lee (2021), Song et al. (2022), Qin et al. (2022), Markovitch et al. (2024), Huang et al. (2024), Yang et al. (2024), Longoni et al. (2019) |
| | | Effort and quality | Xu et al. (2017), Bechwati & Xia (2003), Meija & Guesmi (2024), Xie et al. (2022) |

***APPENDIX D. List of information extracted from the 78 papers included in the meta-analysis***

*Table 7. List of information extracted from the 78 papers included in the meta-analysis*

| Paper ID | Source | Comparison type | Direct input | Relation between effort/quality | Decision effort (operationalisation and measurement) | Main Results | Decision quality (operationalisation and measurement) | Main Results |
|---|---|---|---|---|---|---|---|---|
| #1 | Dellaert & Häubl (2012) | RA vs no aid | Yes | Mixed (Positive, negative relationships, and no correlation) | Number of alternatives inspected (Actual)<br><br>Time spent to evaluate alternatives (Actual) | The number of alternatives inspected is lower when assisted by a RA (vs. not assisted).<br><br>Participants spent more time on a given alternative when assisted by a RA (vs. not assisted). | Utility of the most preferred alternative (Actual)<br><br>Position of the chosen alternative in terms of utility score (Actual) | Utility score is high when assisted by a RA (vs. not assisted).<br><br>Participants chose alternatives that were presented higher up in the list when assisted by a RA (vs. not assisted) |
| #2 | Huseynov et al. (2016) | RA vs no aid | Yes | Negative relationship | Mean shopping time (Actual)<br><br>Mean page view (Actual) | Being assisted by a RA (vs. not assisted) reduced the mean shopping time and the mean page-view during the decision-making. | # of respondent who didn't switch to another item after receiving the recommendation (Actual)<br><br># of respondent who purchased the desired item (i.e., the purchase | Being assisted by a RA (vs. not assisted) increases the # of respondents who didn't switch to another item after the purchase and who purchased the desired item. |

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| | | | | | | | matches consumers' preferences) (Actual). | |
| #3 | Senecal & Nantel (2004) | RA vs human expert<br><br>RA vs human non-expert (other consumers) | No | Only quality | [redacted] | [redacted] | Compliance with recommendation (Actual) | Consumers follow more product recommendation when it came from the RA (vs. human expert and non-expert). |
| #4 | Yeomans et al. (2018) | RA vs Human non-expert | No | Only quality | [redacted] | [redacted] | Accuracy (Actual)<br><br>Likeliness to switch recommenders (Perceived) | RA is more accurate in its prediction than human non-expert (stranger, friends, family).<br><br>Participants were more likely to switch recommender when they started with the RA (vs. human). |
| #5 | Sinha & Swearingen (2001) | RA vs. Human non-expert (Friends) | Yes | Negative relationship | Usefulness of recommender source (Perceived) | Friends were perceived as being more useful during the decision making than a RA. | Quality of the recommendation (Perceived) | Friends performed higher in providing good recommendations compared to a RA. |
| #6 | Xu et al. (2017) | RA vs Human (expert and non-expert | Yes | Positive relationship | Decision effort (Perceived)<br><br>Decision time (Actual) | Attribute-based RA decreases perceived effort compared to humans<br><br>Alternative-based RA increases perceived effort compared to humans | Decision quality (Perceived) | Attribute-based RA decreases perceived quality compared to humans.<br><br>Alternative-based RA increases perceived quality compared to humans. |
| #7 | Su et al. (2008) | RA vs no aid | Yes | Only effort | Perceived cost of information search (Perceived) | Consumers assisted by a RA (vs. not assisted) perceived the cost of information search to be lower than those without RA assistance. | [redacted] | [redacted] |

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| #8 | Notebaert (2019) | RA vs no aid | Yes | Positive relationship | Time spent on the Website (Actual) | Being assisted by a RA (vs. not assisted) increases the time spent on the website. | Satisfaction during purchase (Perceived) | Being assisted by an RA (vs. not assisted) increases satisfaction. |
| #9 | Longoni & Cian (2020) | RA vs human non-expert (consumers) | No | Only quality | | | Compliance with the recommendation (Actual) | When the shopping goal was utilitarian (hedonic), consumers chose more often the recommendation made by the RA (human) compared to the human (RA). |
| #10 | Nguyen et al. (2022) | RA vs other type of aid (i.e., menu-based) | Yes | Only effort | Cognitive effort (Perceived) | Being assisted by a RA (vs. another search tool) increases perceived cognitive effort. | | |
| #11 | Huang & Zhou (2019) | RA vs no aid | Yes | Only effort | Perceived information overload (Perceived)<br><br>Perceived information underload (Perceived) | Being assisted by a RA (vs. not assisted) decreases perceived information overload and increases perceived information underload. | | |
| #12 | He et al. (2023) | RA vs human non-expert (consumers) | Yes | Positive relationship | Decision effort (Perceived) | Consumers perceived lower decision effort when receiving system-generated recommendation compared to consumer-generated recommendation. | Decision quality (Perceived) | Consumers perceived lower decision quality when receiving system-generated recommendation compared to consumer-generated recommendation. |
| #13 | Van Der Heijiden & Sorensen (2003) | RA vs no aid | Yes | Only quality | | | Number of non-dominated alternatives (Actual)<br><br>Share of non-dominated alternatives in consideration set (Actual) | Being assisted by a RA (vs. not assisted) increases the number of non-dominated alternatives purchased, and the share of non-dominated alternatives in the consideration set.<br><br>When the shopping task is of high (low) complexity, consumers are more (less) confident when assisted by RA (vs. not assisted). |

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| | | | | | [redacted] | | Perceived decision quality (Perceived) | |
| #14 | Aljukhadar et al. (2012) | RA vs no aid | Yes | Negative relationship | RA consultation after experiencing information overload (Actual)<br><br>RA consultation after experiencing perceived overload (Perceived) | After experiencing information overload or perceived overload, consumers decided to consult RA in higher proportion. | Choice quality (i.e., utility score) (Actual)<br><br>Choice confidence (Perceived)<br><br>Compliance with recommendation (Actual) | Consumers assisted by an RA (vs. not assisted) made higher choice quality and were more confident about their choice. |
| #15 | Banker & Khetani (2019) | RA vs no aid | Yes | Only quality | [redacted] | | Choose dominated (inferior)/nondominated (superior) product (Actual)<br><br>Choice confidence (Perceived) | Consumers who received a non-dominated recommendation by a RA (vs. no recommendation) chose more superior options and less inferior option.<br><br>There is no effect on choice confidence. |
| #16 | Hostler et al. (2005) | RA vs no aid | Yes | Negative relationship<br><br>No correlation | Time spent (Actual)<br><br>Cognitive effort (Perceived) | Being assisted by a RA (vs. no assistance) decreases the time spent but had no effect on cognitive effort. | Decision quality (Actual)<br><br>Choice confidence (Perceived) | Being assisted by a RA (vs. not assisted) increases decision quality but had no effect on choice confidence. |
| #17 | Hostler et al. (2011) | RA vs no aid | Yes | Positive relationship | Product search, i.e., the ratio between the number of products purchased and the number of products examined (Actual) | Being assisted by a RA (vs. no assistance) increases product search, so consumers purchased more product than they had examined. | Product promotion effectiveness (i.e., the ability to create attractiveness toward the recommendation) (Perceived) | Being assisted by a RA (vs. no aid) increases product promotion effectiveness. |

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| #18 | Lajos et al. (2008) | RA vs no aid | Yes | No correlation | Decision time (Actual) | Being assisted by a RA (vs. not assisted) has no effect on decision time. | Product satisfaction (Perceived)<br><br>Intention to switch brand (Perceived) | Receiving a recommendation by a RA decreases consumers satisfaction compared to not receiving any recommendation.<br><br>Being assisted by a RA (vs. not assisted) had no effect on consumers intention to switch brand. |
| #19 | Lee & Benbasat (2010) | RA vs no aid | Yes | Mixed results (Positive relationship, No relationship, No correlation) | Decision-making time (Actual)<br><br>Perceived effort (Perceived) | Being assisted by a RA (vs. not assisted) increases decision-making time but decreases perceived effort. | Accuracy (Actual) | Being assisted by an alternative-based RA (vs. not assisted) increases accuracy compared. There is no difference in accuracy between attribute-based RA and not being assisted. |
| #20 | Haübl & Trifts (2000) | RA vs no aid | Yes | Negative relationship | Amount of search (Actual)<br><br>Consideration set size (Actual) | Being assisted by a RA (vs. not assisted) decreases the amount of search and the size of the consideration set. | Consideration set quality (Actual)<br><br>Purchase of nondominated alternative (Actual)<br><br>Switching (Actual)<br><br>Confidence in decision (Perceived) | Being assisted by a RA (vs. not assisted) increases the quality of the consideration set, the number of nondominated alternatives purchased, and the confidence in decision. It also decreases the switching behaviors toward another alternative during the post-purchase phase. |
| #21 | Bechwati & Xia (2003) | RA vs no aid or human expert | Yes | Only decision effort | Perceived own effort (Perceived)<br><br>Perceived saved effort (Perceived) | Being assisted by a RA (vs. not assisted) decreases consumers effort and effort saving. There was no difference on perceived consumers effort and effort. | | |

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| #22 | Goodman et al. (2013) | RA vs no aid | No | Only decision effort | Decision difficulty (Perceived)<br><br>Decision time (Actual)<br><br>Size of the consideration set (Actual) | When consumers have more developed preferences, they experience higher decision difficulty, they spend more time deciding, and have a higher consideration set size when receiving a recommendation compared to not receiving it.<br><br>There is no difference in decision difficulty among consumer with less developed preferences. | | |
| #23 | Yoon et al. (2013) | RA vs other type of aid (i.e., random recommendation) | Yes | Only decision quality | | | Recommendation quality (Perceived) | Receiving a recommendation from an RA increase the quality of the recommendation compared to received random recommendation. |
| #24 | Yoon & Lee (2021) | RA vs human expert | Yes | Only decision quality | | | Personalization quality (Perceived) | Being assisted by an RA didn't impact the level of personalization quality compared to being assisted by a human expert. |
| #25 | Sivaramakrishnan et al. (2007) | RA vs no aid | Yes | Only decision quality | | | Product attitude (Perceived) | When the perceived extent of information available was low (high), consumers were more (less) likely to purchase product on the website when they were assisted by an RA compared to no aid. |
| #26 | Henning-Thurau et al. (2012) | RA vs no aid | No | Only decision quality | | | Movie value (Perceived) | There is no difference on movie value whether participants were assisted or not by a RA. |
| #27 | Chattaraman et al. (2024) | RA vs no aid | Yes | Only decision effort | Decision effort (Perceived) | Being assisted by a RA (vs. not assisted) increases perceived decision effort for consumers with low need for | | |

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| | | | | | | cognition. There was no difference for consumers with high need for cognition. | [redacted] | |
| #28 | Dellaert et al. (2024) | RA vs no aid | Yes | Only decision quality | Number of alternatives examined (Actual) | There is no difference on the number of alternatives examined between consumers assisted by a RA or not. | Decision quality (Actual)<br><br>Attention to the best alternatives (Actual) | Being assisted by a RA (vs. not assisted) increases decision quality and the level of attention to the best alternatives. |
| #29 | Matt et al. (2023) | RA vs no aid and other type of aid | Yes | No correlation | Number of played tracks during decision-making (Actual) | There is no difference on the number of played tracks whether consumers were aid by a RA (collaborative, content-based or retailer best-seller), compared to receiving no aid or random recommendation. | Compliance with the recommendation (Actual) | There is no difference on compliance with the recommendation whether consumer was aid by a content-based RA or received a random recommendation.<br><br>Being assisted by a collaborative RA or receiving retailer best seller recommendation increases consumers compliance with the recommendation compared to random recommendation. |
| #30 | Benlian et al. (2010) | RA vs human-non expert (consumers) | No | Only decision effort | Perceived usefulness (Perceived) | Receiving recommendation from a RA increases the effectiveness of search during the decision-making compared to recommendation from other consumers. | [redacted] | |
| #31 | Peng et al. (2023) | RA vs no aid | No | Only quality | [redacted] | | Recommendation acceptance (Perceived) | When the price of the offer is lower than expected, there is no difference in intention to accept the offer whether it comes from a RA or no. However, when the price of the offer is higher than expected, the intention to accept it is |

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| | | | | | [redacted] | | | | higher when it comes from a RA (vs. not a RA). |
| #32 | Song et al. (2022) | RA vs human expert | Yes | Only quality | [redacted] | | | Recommendation acceptance (Perceived)<br><br>Perceived accuracy (Perceived) | Consumers are more willing to accept recommendation from a human expert than a RA.<br><br>Consumers perceived that human experts lead to higher accuracy in recommendation than a RA. |
| #33 | Rohden & Espartel (2024) | RA vs no aid | No | Only quality | [redacted] | | | Perceived uncertainty (Perceived) | Consumers are more uncertain when they are shopping with a RA (vs. without a RA). This effect is stronger for consumers with high levels of risk aversion. |
| #34 | Lepkowska-White (2013) | RA vs human-non expert (consumers) | No | Only quality | [redacted] | | | Attitude toward purchase (e.g., perceived accuracy) (Perceived) | There is no difference on consumers attitude toward a recommendation from a RA by a third-party retailer and a recommendation from a consumer.<br><br>Consumers attitude is more positive toward a recommendation from other consumers compared to a seller's RA. |
| #35 | Jeff (2013) | RA vs no aid | Yes | No correlation | Average number of pages assessed (Actual)<br><br>Average amount of total time spent per pages (sec) (Actual) | There is no effect on decision effort whether consumers were assisted or no by an RA.<br><br>However, when the recommendation comes with numerus information (review, attributes information), being assisted by RA (vs. not assisted) increases decision effort. | | Degree of match with requirements of shopping task (Actual)<br><br>Deviation of purchase price with budget (Actual) | There is no effect on decision quality whether consumers were assisted or no by an RA. However, when the recommendation comes with numerus information (review, attributes information), being assisted by RA (vs. not assisted) decreases decision quality. |

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| #36 | Qin et al. (2022) | RA vs human expert | Yes | Only quality | [redacted] | [redacted] | Intention to buy (Perceived) | Consumers are less likely to buy a product recommended by an RA compared to a human expert. |
| #37 | Wien & Peluso (2021) | RA vs human-non expert (consumers) | No | Only quality | [redacted] | [redacted] | Product attitude (Perceived) | When the product is framed as hedonic, participants have a more favorable attitude toward human expert recommendation compared to a RA. There is no difference when it is a product framed as utilitarian. |
| #38 | Liang et al. (2006) | RA vs other type of aid (i.e., random recommendation) | Yes | Negative relationship | System value (useful, efficient) (Perceived) | RA is perceived as more useful and efficient than random recommendation. | Content satisfaction (Perceived)<br><br>Personalized service satisfaction (Perceived)<br><br>Precision (Actual)<br><br>Recall (Actual) | RA increases decision quality (content satisfaction, service satisfaction, precision and recall) to a higher extent than random recommendation. |
| #39 | Maheswarappa et al. (2017) | RA vs no aid | Yes | Mixed results (Positive and negative relationships, No correlation) | Search time (Actual) | When consumers' subjective knowledge is low or medium, there is no difference on decision time between being assisted or not by a RA. Being assisted by RA (vs. not assisted) increases decision time when subjective knowledge is high.<br><br>When consumers involvement is low, being assisted (vs. not assisted) by a RA increases search time. | Quality of the chosen option (Actual)<br><br>Decision confidence (Perceived)<br><br>Decision satisfaction (Perceived) | When subjective knowledge of consumers is low, being assisted by a RA (vs. not assisted) increases decision quality, and confidence. No effect on satisfaction.<br><br>When subjective knowledge is medium, being assisted (vs. not assisted) by a RA has no effect on decision quality, decreases decision confidence and satisfaction. |

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| | | | | | | No effect when involvement is high. | | When subjective knowledge is high, being assisted by an RA (vs. not assisted) increases decision quality, but decreases decision confidence and satisfaction.<br><br>When consumers involvement is low, being assisted (vs. not assisted) by a RA increases quality, confidence, but decreases satisfaction. When involvement is high, quality, confidence and satisfaction decrease. |
| #40 | Westerman et al. (2007) | RA vs no aid | Yes | No correlation | Time spent (Actual) | Being assisted or no by a RA did not impact the time spent to decide. | Decision confidence (Perceived)<br><br>Happiness with decision (Perceived)<br><br>Quality of the final choice (Actual) | Being assisted by an RA (vs. not assisted) increases decision quality but has no effect on confidence and happiness with the choice. |
| #41 | Turri (2011) | RA vs no aid | Yes | No correlation | Decision difficulty (Perceived) | In large assortment condition (i.e., number of alternatives to evaluate), being assisted by a RA (vs. not assisted) decreases decision difficulty. No difference in small assortment set. | Decision regret (Perceived) | In large assortment set, there is no difference in regret between having been assisted or not by RA. |
| #42 | Andrews (2010) | RA vs no aid | No | Only quality | [redacted] | | Optimal offer accepted (Actual) | Being assisted by a RA (vs. not assisted) leads to higher chance of accepting the optimal offer, reduces switching behaviors and increases the chance to choose the preferred brand. |

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| | | | | | [redacted] | | Switching behaviors (Actual)<br><br>Preferred brand chosen (Actual) | |
| #43 | Olson & Widing (2002) | RA vs. no aid (alphabetical format)<br><br>RA vs. other type of aid (i.e., expert report) | Yes | Mixed results (Positive and negative relationships, No correlation) | Number of brands thoroughly evaluated (Actual)<br><br>Perceived decision time (Perceived)<br><br>Decision time in second (Actual) | Compared to no aid or other type of aid, a RA reduces the number of brands evaluated and the perceived decision time. However, it increases decision time in seconds. | Relative/discrete accuracy (Actual)<br><br>Switching behavior (Actual)<br><br>Perceived decision accuracy (Perceived)<br><br>Confidence in decision (Perceived)<br><br>% who selected their computed best brand (Actual) | RA assistance (vs. no assistance) has no effect on relative and discrete accuracy, decreases switching behaviors, increases perceived decision accuracy and confidence.<br><br>Compared to other type of aid, RA increases relative and discrete accuracy, decreases switching behaviors, increases the % of consumers who selected their best computed brand, perceived accuracy and perceived confidence. |
| #44 | Chu & Spires (2000) | RA vs no aid | Yes | No correlation | Amount of information search (Actual)<br><br>Variability in information search (Actual) | Being assisted by a RA (vs. not assisted) increases the amount of search but decreases the variability in information search. | Decision proximity to WADD (Actual) | Being assisted by a RA (vs. not assisted) has no effect on decision proximity. |
| #45 | Pereira (2001) | RA vs no aid | Yes | Mixed results (Positive and negative relationships, No correlation) | Size of the consideration set (Actual) | Being assisted by a RA (vs. not assisted) increases the size of the consideration and the number of stages | Confidence in decision (Perceived) | Being assisted by a RA (vs. not assisted) has no effect on confidence in decision but increases similarity among |

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| | | | | | Cognitive decision effort (Perceived)<br><br>Number of stages in the phase narrowing down the consideration set (Actual) | narrowing down the consideration set.<br><br>However, it decreases the cognitive decision effort. | Similarity among considered option (Actual)<br><br>Accuracy (Actual) | considered option and accuracy. |
| #46 | Hostler et al. (2012) | RA vs no aid | Yes | Only quality | [redacted] | [redacted] | Product promotion effectiveness (Perceived)<br><br>Satisfaction (Perceived) | Being assisted by a RA (vs. not assisted) increases product promotion effectiveness and satisfaction. |
| #47 | Malampa llayil & Bingham ton (2019) | RA vs Human non-expert (i.e., friends) | No | Only quality | [redacted] | [redacted] | Likeliness to follow the recommendatio n (Perceived) | Receiving recommendation by a RA compared to friends has no effect on consumers likeliness to follow the recommendation. |
| #48 | Tan (2003) | RA vs other type of aid (attribute screening aid (ASA), hyper-linked screening aid (HSA)) | Yes | Mixed results (Positive and negative relationships, No correlation) | Consideration time (Actual)<br><br>Consideration size (Actual) | Being assisted by a RA increases consideration time compared to ASA, but decreases consideration time compared to HSA.<br><br>Being assisted by a RA decreases consideration size compared to HSA, but increases consideration size compared to ASA. | Decision accuracy (Actual)<br><br>Consideration set quality (Actual) | When the information load was low, RA assistance decreases decision accuracy versus HSA and ASA.<br><br>When the information load was high, RA assistance decreases decision accuracy (vs. HSA and ASA) when the sorting function is absent. However, when the sorting function is present, RA assistance increases decision accuracy (vs. HSA and ASA).<br><br>RA assistance increases consideration set quality compared to ASA, but decreases it compared to HSA. |

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| #49 | Pedersen (2000) | RA vs no aid | Yes | Mixed results (Positive and negative relationships, No correlation) | Amount of information (Perceived)<br><br>Consideration set size (Perceived)<br><br>Attributes evaluated (Perceived)<br><br>Attention to quantitative attributes (Perceived)<br><br>Search time task completion time (Perceived)<br><br>Information source (Perceived) | Being assisted by an RA (vs. not assisted) increases the amount of information and the number of sources of information but decreases perceived search time to complete de task.<br><br>There is no effect on perceived consideration set size, number of attributes evaluated and attention to quantitative attributes. | Internet search satisfaction (Perceived)<br><br>Mortgage rate (Perceived)<br><br>Mortgage rate (Actual)<br><br>Saving rate (Perceived)<br><br>Raving rate (Actual)<br><br>Current account rate (Perceived)<br><br>Current account rate (Actual) | Being assisted by RA (vs. not assisted) increases internet search satisfaction but has no effect on the other variable of decision quality measured. |
| #50 | Kim et al. (2025) | RA vs Human non-expert (i.e., friends) | Yes | Only quality | [redacted] | | Intention to adopt the recommendation (visit intention) (Perceived)<br><br>Satisfaction with the recommendation (Perceived) | There is no effect of RA versus human non-expert on intention to adopt or satisfaction with the recommendation.<br><br>The difference was du to interaction between the type of answer (personalized vs humorous). |
| #51 | Markovitch et al. (2024) | RA vs human expert | No | Only quality | [redacted] | | Satisfaction index (Perceived<br><br>Intention to accept the recommendation (Perceived) | Being assisted by a RA decreases satisfaction, intention to accept the recommendation and intention to recommend it compared to being assisted by a human agent. |

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| | | | | | [redacted] | | Intention to recommend the product (Perceived) | |
| #52 | Rolon-Mérette et al. (2024) | RA vs no aid | No | No correlation | Number of click (Actual)<br><br>Cognitive load (Actual)<br><br>Visual attention (Actual) | Being assisted by a RA (vs. not assisted) increases visual attention but has no effect on number of click and cognitive load. | Satisfaction with results (Perceived)<br><br>Perceived relevance of the results (Perceived)<br><br>Purchase intention of the items (Perceived) | Being assisted by a RA (vs. not assisted) has no effect on satisfaction and perceived relevance of the results, and on the purchase intention of the items. |
| #53 | Huang et al. (2024) | RA vs human expert | No | Only quality | [redacted] | | Intention to accept the recommendatio n (Perceived) | When trust into the agent is low, being assisted by an RA (vs. human expert) decreases intention to accept the recommendation.<br><br>However, when trust is high, there is no difference. |
| #54 | Meija & Guesmi (2024) | RA vs human expert | No | Mixed results (Positive relationship and no correlation) | Time spent (Actual) | Consumers spent less time when assisted by an RA (vs. human expert) in a large recommendation list.<br><br>No difference when the recommendation list is small. | Perceived quality (Perceived) | In a small recommendation list, consumers perceived the quality as higher when it comes from a human expert compared to an RA.<br><br>No difference when the recommendation list is large. |
| #55 | Yang et al. (2024) | RA vs human expert | No | Only quality | [redacted] | | Purchase intention of the recommendatio n (Perceived) | When the product is framed as a vice, consumers are more likely to purchase the recommendation, willing to pay for it and have a more |

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| | | | | | [redacted] | | Willingness to pay for the recommendation (Perceived)<br><br>Attitude toward the recommended product (Perceived) | positive attitude when it comes from human (vs. RA).<br><br>No difference when the recommendation is a virtue. |
| #56 | Xie et al. (2022) | RA vs human expert | No | Mixed results (Negative relationship No correlation) | Response time (Actual)<br><br>Cognitive load (Actual) | When the product was experiment, consumer response time was shorter when the recommendation came from a human (vs. RA). Cognitive load was higher when the recommendation comes from an RA (vs. human)<br><br>No difference when it was a search product. | Purchase likelihood for the recommendation (Perceived)<br><br>Acceptance rate (Actual) | Consumers showed greater preferences for the recommendation, and acceptance rate, when it comes from human (vs. RA) when the product was experiential.<br><br>No difference when it was a search product. |
| #57 | Benlian et al. (2012) | RA vs human-non expert (consumers) | No | Only effort | Perceived usefulness (Perceived) | Receiving recommendation from a RA increases the effectiveness of search during the decision-making compared to recommendation from other consumers. | [redacted] | |
| #58 | Baum & Spann (2014) | RA vs human-non expert (consumers) | No | Only quality | [redacted] | | Intention to follow the recommendation (Perceived)<br><br>Probability to purchase the recommendation (Perceived) | Being assisted by an RA (vs. human non-expert) decreases the intention to follow the recommendation and the probability to purchase it. |

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| #59 | Peng & Liang (2020) | RA vs no aid | No | Mixed results (Positive relationship No correlation) | Direct and indirect Product view (Actual) | Being assisted by a Collaborative filtering (CF) RA increases indirect product view more than no RA assistance. No effect on direct sale. | Direct and indirect sale (Actual) | Being assisted by a View-also-view CF RA increases indirect sale more than no assistance. No effect on direct sale.<br><br>No difference on direct and indirect sale when the RA is framed as "people-also-purchase" CF. |
| #60 | Lee et al. (2020) | RA vs. other type of aid (non-personalized recommendation) | No | No correlation | Total view (Actual) | Being assisted by a RA (vs. receiving random recommendation) has a marginal effect in increasing total view of products. | Compliance with the recommendation (Actual) | Being assisted by a RA (vs. receiving random recommendation) increases compliance with the recommendation. |
| #61 | Longoni et al. (2019) | RA vs human expert | Yes | Only quality | | | Accept the appointment (compliance) (Actual)<br><br>Willingness to pay (Perceived)<br><br>Willingness to accept the recommendation (Perceived) | Being assisted by a RA (vs human expert) decreases actual and perceived decision quality. |
| #62 | Kumar & Benbasat (2006) | RA vs human-non expert (consumers)<br><br>RA vs no aid | No | Only effort | Perceived usefulness (Perceived) | Being assisted by a RA (vs. non-expert human) increases perceived usefulness. | | |
| #63 | Liu et al. (2022) | RA vs human-non expert (consumers) | No | Mixed results (Positive relationship No correlation) | Perceived decision effort (Perceived) | When shopping for search product, perceived decision effort is lower when assisted by a RA versus non-human expert. The reverse occurs | Perceived decision quality (Perceived) | When shopping for search product, perceived decision quality is higher when assisted by a RA versus non-human expert. The reverse occurs |

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| | | | | | | when shopping for experiential product. | | when shopping for experiential product |
| #64 | Yeh & Kuo (2019) | RA vs no aid | Yes | Only effort | Time spent (Actual) | Being assisted by a RA (vs. no assistance) reduces time spent during the decision-making. | [redacted] | [redacted] |
| #65 | Wan & Li (2024) | RA vs no aid | No | Mixed results (Negative and positive relationship No correlation) | # of webpage viewed (Actual)<br><br># of focal product pages viewed (Actual)<br><br># of category of page viewed (Actual)<br><br># of search result page viewed (Actual) | Being assisted by a RA (vs. not assisted) increases in focal product viewed, but decreases on the number of product category viewed.<br><br>No difference in # of webpage views and # of search result page views. | Affinity score (Actual)<br><br>Horizontal fit (Actual) | Being assisted by an RA (vs. not assisted) increases affinity score and the horizontal fit (quality based on consumers tastes). |
| #66 | Verruck (2017) | RA vs no aid | No | No correlation | Time to make a decision (Actual)<br><br>Perceived decision effort (Perceived) | Being assisted by a RA (not assisted) decreases time to make a decision and perceived decision effort. | Compliance with superior product (Actual) | No difference on compliance with superior product whether the consumers was assisted or not by a RA. |
| #67 | Tan et al. (2010) | RA vs. other type of aid (screening support) | Yes | Mixed result (Positive and negative relationship) | Decision time (Actual) | Being assisted by a RA decreases decision time to a higher extent than screening tool support. | Decision quality (Actual)<br><br>Perceived decision quality (Perceived) | When product attribute is high, being assisted by a RA increases decision quality compared to screening tool support.<br><br>However, when product attribute is low, RA compared to low screening support decreases decision quality. |
| #68 | Dorner et al. (2013) | RA vs human-non expert (consumers)<br><br>RA vs no aid | No | Mixed results (No correlation, positive relationship) | Consideration set size (Actual) | Being assisted by a RA compared to a human non-expert increases the consideration set size.<br><br>No difference when no aid. | Transition probability to choice set, i.e., the ratio of products in the consideration set | Being assisted by a RA (vs. no aid or non-expert human) increases the transition probability to choice set. |

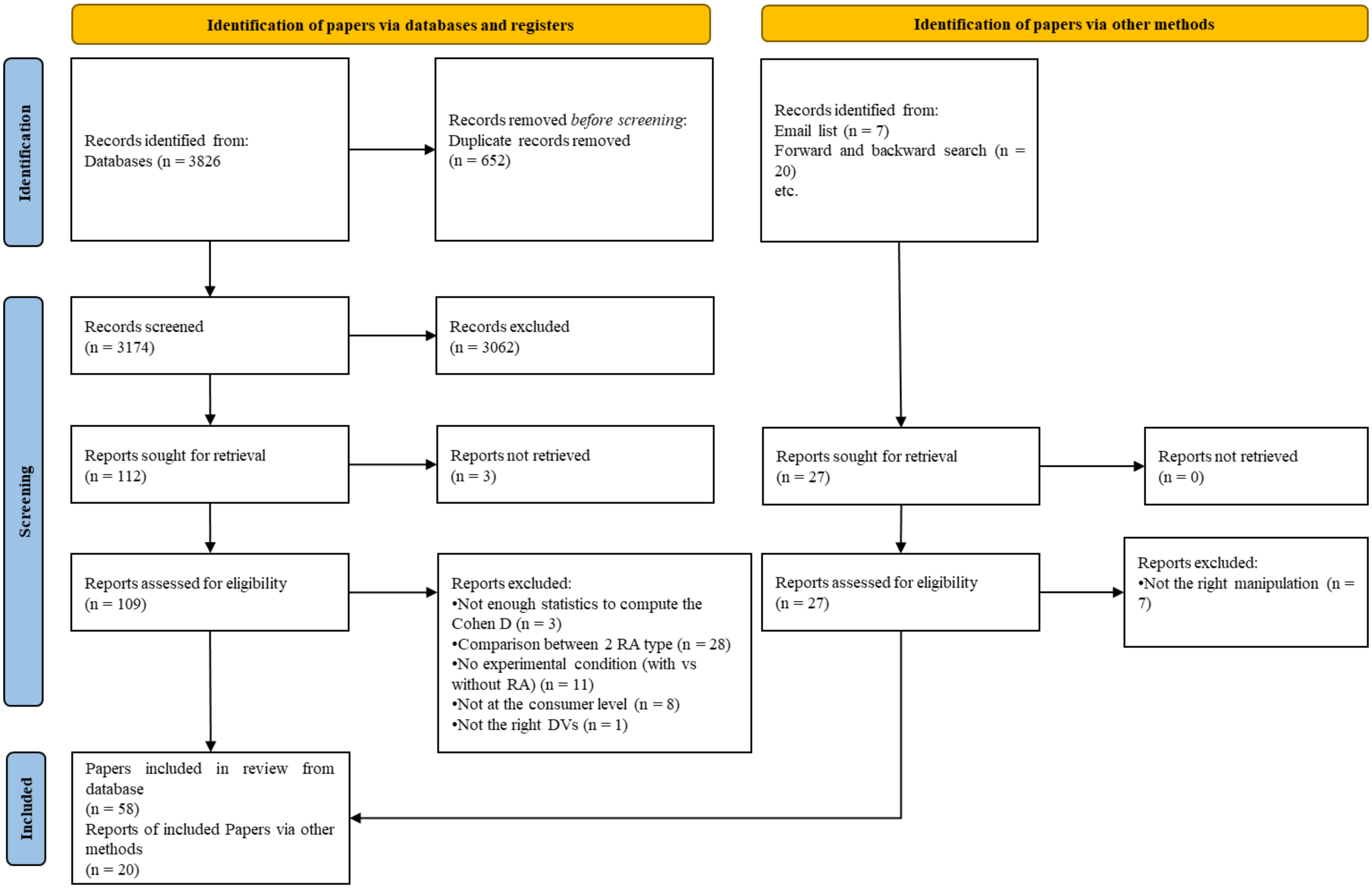
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | transferred to the choice set (Actual) | |
| #69 | Diehl et al. (2003) | RA vs. other type of aid (random ordering) | Yes | Only quality | [redacted] | | Quality of the chosen option (Actual) | When consumers are more quality focus than price focus, quality of the chosen option is higher when the options were ordered (vs. random).<br><br>No difference when quality and price are equally important.<br><br>When consumers are more price focus than quality focus, the quality of the chosen option was lower when the options were ordered (vs. random) |
| #70 | Ghiassaleh et al. (2020) | RA vs no aid | No | No correlation | Decision complexity (Perceived) | There is no difference on perceived decision complexity whether consumers are assisted or not by a RA. | Choice uncertainty (Perceived)<br><br>Commitment to choice (Actual) | There is no difference on perceived decision uncertainty whether consumers are assisted or not by a RA.<br><br>Commitment to choice is decreased when consumers are assisted by a RA (vs. not assisted). |
| #71 | Bodoff & Ho (2015) | RA vs. other type of aid (random recommendation) | Yes | Only effort | Information search (total no. of sampling) (Actual) | During the first two shopping session on the website, there is no difference in information search whether consumers are assisted by a RA or receiving random recommendations.<br><br>During the third and fourth shopping session, RA decreases information search compared to other type of aid | [redacted] | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | (i.e., random recommendation). | | |
| #72 | Kumar & Hosanagar (2019) | RA vs no aid | No | Only effort | # of web pages viewed per session (Actual)<br><br># of product pages viewed per session (Actual) | There is no difference between being or not assisted by a RA. | | |
| #73 | Li et al. (2022) | RA vs no aid<br><br>RA vs. other type of aid (random recommendation) | No | Positive relationship | Consideration set size (Actual)<br><br>Average page viewed per visit (Actual) | Being assisted by a RA (vs. not assisted) increases consideration set size and average page viewed per visit. | Performance (Actual)<br><br>Order value in euro (Actual) | Being assisted by a RA (vs. not assisted) increases the order value in euro.<br><br>Being assisted by a RA (vs. not assisted, or random recommendation) increases the performance. |
| #74 | Kmett et al. (1999) | RA vs no aid | Yes | Only quality | | | Satisfaction with the choice (Perceived) | Being assisted by a RA (vs. not assisted) increases satisfaction with the choice. |
| #75 | Tam & Ho (2006) | RA vs. other type of aid (random recommendation) | No | Negative relationship | Decision effort (time and click) (Actual)<br><br>Perceived usefulness (Perceived)<br><br>Number of pages consulted (Actual)<br><br>Time spent during decision-making (Actual) | Being assisted by a RA (vs. receiving random recommendations) decreases decision effort. | Compliance with the decision (Actual)<br><br>Satisfaction with the final choice (Perceived | Being assisted by a RA (vs. receiving random recommendations) increases decision quality. |
| #76 | Tam & Ho (2005) | RA vs. other type of aid (random recommendation) | No | Positive relationship | Willingness to spend more effort (Perceived) | Being assisted by a RA increases willingness to spend more effort compared to receiving random recommendation. | # of download (Actual) | Being assisted by a RA increases the # of download compared to receiving random recommendation. |
| #77 | Bodenbenner & | RA vs. other type of aid | No | Only effort | Page viewed per visit (Actual) | Being assisted by a RA (vs. random recommendation) | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Neumann (2012) | (random recommendation) | | | Time per visit (Actual) | increases decision time and page viewed per visit. | | |
| #78 | Adomavicius et al. (2018) | RA vs no aid | Yes | Only quality | | | Willingness to pay for the recommendation (Perceived) | There is no difference in consumers WTP for the recommendation whether they were assisted or not by a RA. |

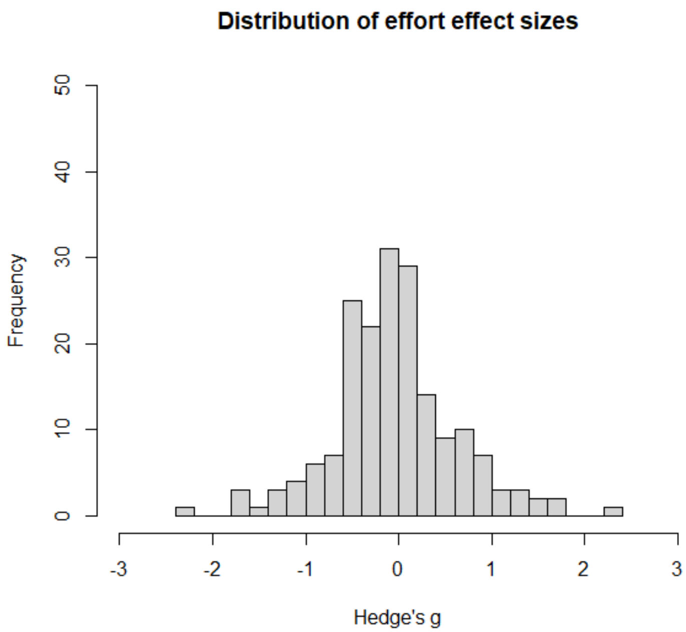
### *APPENDIX E. PRISMA Flow Chart*

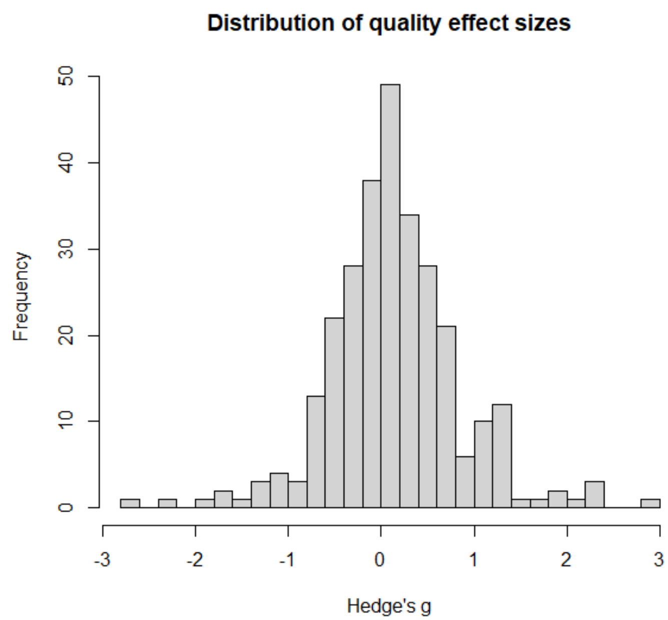
*Figure 3. PRISMA Flow Chart*



***APPENDIX F. Distribution of effort and quality effect sizes***

*Figure 4. Distribution of effort and quality effect sizes*



## *APPENDIX G. Correlations for the moderators of effort*

*Table 8. Correlations for the moderators of effort*

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. REAL | | | | | | | | | | | | | | |
| 2. RA.HUMAN | .04 | | | | | | | | | | | | | |
| 3. RA.EXPERT | -.34** | -.16** | | | | | | | | | | | | |
| 4. RA.OTHERS | .21** | -.19** | -.24** | | | | | | | | | | | |
| 5. DIRECT.INPUT | -.05 | -.34** | -.15* | .24** | | | | | | | | | | |
| 6. LAB | -.05 | -.19** | -.18** | .34** | .32** | | | | | | | | | |
| 7. FIELDSTUDY | .16** | .19** | -.11 | .08 | -.24** | -.18** | | | | | | | | |
| 8. IS | .12* | -.23** | -.22** | .41** | .14* | .43** | .14* | | | | | | | |
| 9. OTHERDISCIPLINE | -.20** | .30** | .20** | -.20** | -.07 | .06 | -.01 | -.29** | | | | | | |
| 10. SERVICE | -.08 | .16** | -.01 | .15* | .08 | -.06 | -.01 | -.20** | .10 | | | | | |
| 11. MYEAR | -.28** | .12* | .35** | -.45** | -.47** | -.43** | .15* | -.14* | .18** | -.16** | | | | |
| 12. NO.PUB | .06 | -.05 | -.13* | -.15* | -.09 | .02 | -.10 | .33** | -.16** | -.14* | .03 | | | |
| 13. FT50 | .09 | -.05 | -.04 | .28** | -.03 | .09 | .37** | .31** | -.22** | .07 | .06 | -.24** | | |
| 14. MCITATION | .17** | .25** | .18** | -.04 | -.15* | -.15* | .03 | -.16** | -.10 | .02 | -.31** | -.17** | .22** | |
| 15. Precision | .13* | -.05 | -.07 | -.08 | -.20** | -.13* | .45** | .20** | -.05 | -.08 | .21** | -.08 | .29** | -.06 |

*Note.* * indicates *p* < .05. ** indicates *p* < .01.

## *APPENDIX H. Correlations for the moderators of quality*

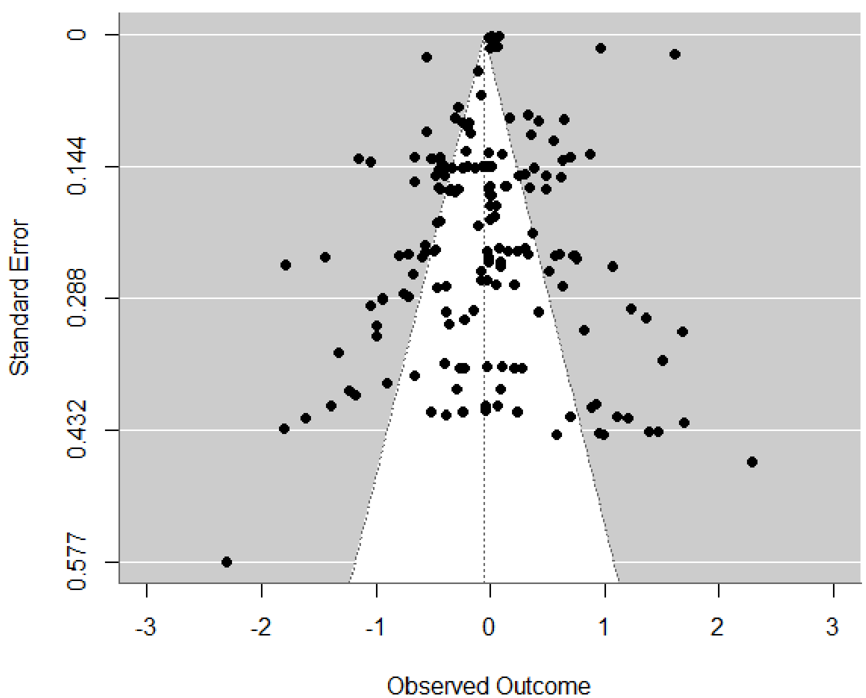
*Table 9. Correlations for the moderators of quality*

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. REAL | | | | | | | | | | | | | | |
| 2. RA.HUMAN | .04 | | | | | | | | | | | | | |
| 3. RA.EXPERT | -.34** | -.16** | | | | | | | | | | | | |
| 4. RA.OTHERS | .21** | -.19** | -.24** | | | | | | | | | | | |
| 5. DIRECT.INPUT | -.05 | -.34** | -.15* | .24** | | | | | | | | | | |
| 6. LAB | -.05 | -.19** | -.18** | .34** | .32** | | | | | | | | | |
| 7. FIELDSTUDY | .16** | .19** | -.11 | .08 | -.24** | -.18** | | | | | | | | |
| 8. IS | .12* | -.23** | -.22** | .41** | .14* | .43** | .14* | | | | | | | |
| 9. OTHERDISCIPLINE | -.20** | .30** | .20** | -.20** | -.07 | .06 | -.01 | -.29** | | | | | | |
| 10. SERVICE | -.08 | .16** | -.01 | .15* | .08 | -.06 | -.01 | -.20** | .10 | | | | | |
| 11. MYEAR | -.28** | .12* | .35** | -.45** | -.47** | -.43** | .15* | -.14* | .18** | -.16** | | | | |
| 12. NO.PUB | .06 | -.05 | -.13* | -.15* | -.09 | .02 | -.10 | .33** | -.16** | -.14* | .03 | | | |
| 13. FT50 | .09 | -.05 | -.04 | .28** | -.03 | .09 | .37** | .31** | -.22** | .07 | .06 | -.24** | | |
| 14. MCITATION | .17** | .25** | .18** | -.04 | -.15* | -.15* | .03 | -.16** | -.10 | .02 | -.31** | -.17** | .22** | |
| 15. Precision | .13* | -.05 | -.07 | -.08 | -.20** | -.13* | .45** | .20** | -.05 | -.08 | .21** | -.08 | .29** | -.06 |

*Note.* * indicates $p < .05$. ** indicates $p < .01$.

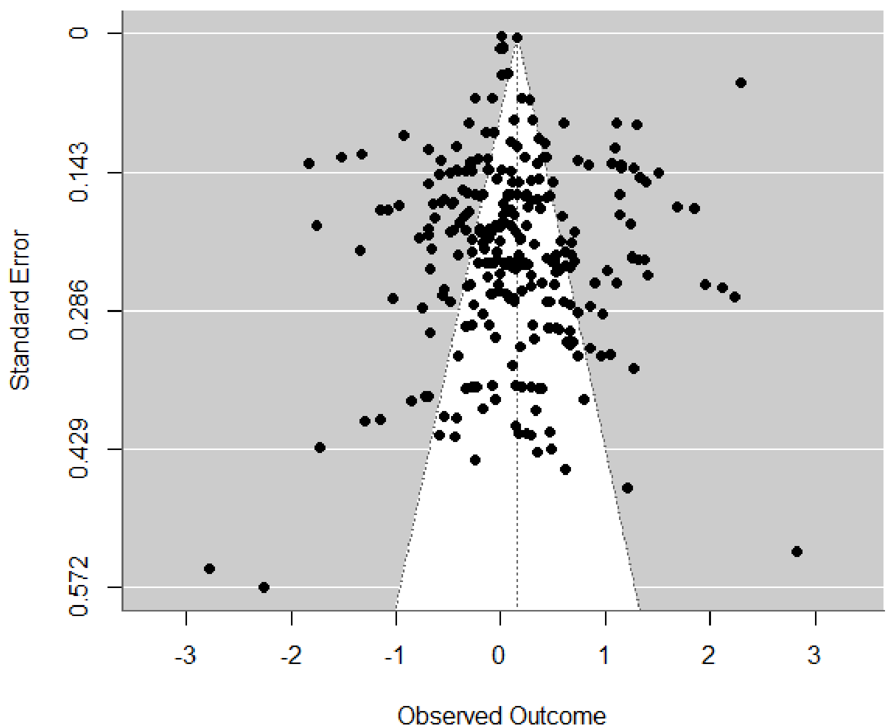
***APPENDIX I. Funnel plot for decision effort***

*Figure 5. Funnel plot for decision effort*



***APPENDIX J. Funnel plot for decision quality***

*Figure 6. Funnel plot for decision quality*



## *APPENDIX K. Effort and quality outcomes without outliers for robustness checks*

*Table 10. Effort and quality outcomes without outliers for robustness checks*

| | **Model 9 (effort outcomes without outliers)** | | | **Model 10 (quality outcomes without outliers)** | | |
|---|---|---|---|---|---|---|
| Variable | Estimate | SE | pval | Estimate | SE | pval |
| Intercpt | .125 | .170 | .462 | .084 | .123 | .496 |
| Actual | .249 | .085 | .004 | .176 | .069 | .011 |
| RA vs Human non-expert | -.342 | .175 | .053 | -.252 | .153 | .101 |
| RA vs Expert | .336 | .179 | .063 | -.515 | .146 | .000 |
| RA vs other aids | -.105 | .131 | .425 | -.083 | .121 | .491 |
| Direct input | -.392 | .128 | .003 | .012 | .103 | .905 |
| Lab study | -.118 | .116 | .313 | -.036 | .112 | .746 |
| Field study | .251 | .161 | .121 | -.002 | .144 | .989 |
| IS | -.007 | .133 | .955 | .295 | .127 | .021 |
| Other discipline | .052 | .167 | .757 | .039 | .143 | .785 |
| Service | .196 | .128 | .128 | .156 | .104 | .134 |
| Year of publication | -.017 | .009 | .060 | -.008 | .009 | .366 |
| Un-published | -.154 | .161 | .340 | -.159 | .144 | .271 |
| FT50 | -.162 | .148 | .277 | -.049 | .136 | .719 |
| Number citations | .001 | .001 | .065 | .001 | .001 | .051 |
| Precision | -.001 | .001 | .425 | -.001 | .001 | .209 |

***APPENDIX L. List of references included in the meta-analysis.***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# Chapter 2
# Recommendation Agents that Consumers Trust when Their Personal Data is Used: The Roles of Transparency and Control


## Abstract

When does transparency about data use increase the adoption of recommendation agents (RAs)? We study prospective transparency (signaling consumers, before any output, which information the RA will use) and the role of customizable parameters governing that use. Across four online experiments (total $n = 1{,}366$) spanning job search, hotels, and cars, we manipulate whether the RA signals the use of consumers' personal data (i.e., profile data) in addition to task-specific preferences, and whether consumers can customize those settings. Results reveal a robust conditional signal: transparency about personal data usage increases adoption and willingness to pay when the RA is customizable, via higher trust; the same signal reduces adoption when the RA is not customizable, via heightened privacy concerns. We contribute a conditional signaling perspective to transparency and RA design by showing that the value of transparency hinges on consumer control. Managerially, "transparency-with-control" should be implemented at the point of configuration to unlock trust and monetization while mitigating privacy concerns.



**Keywords**: recommendation agent, personal data, control, signaling theory, algorithmic transparency, trust

## 2.1 Introduction

Consumers are increasingly exposed to personalized recommendations driven by their personal data, commonly referred to as profile data, when shopping online (Schweidel et al., 2022). However, growing privacy regulations and restrictions on personal data use create challenges for both consumers and retailers (Quach et al., 2022). Recent research shows that limiting personal data reduces the match between recommendations and user preferences, leading to lower-quality recommendations and less engagement in terms of clicks, purchases, and browsing (Sun et al., 2024). Without such data, recommendations become more generic, limiting personalization and reducing the visibility of smaller retailers.

One of the most noticeable changes introduced by these privacy regulations is the cookie notices requesting consent for different types of data collection when users enter a website (Burgess, 2020; Degeling et al., 2019). These notices ask for permission to use cookies on consumers' devices to track their online activities and personalize their experience on the website. However, a growing body of research suggests that these cookie consent notices often fail to obtain informed consent regarding the use of personal data (Bauer et al., 2021; Habib et al., 2022; Kulyk et al., 2020). Users are increasingly experiencing privacy fatigue, leading them to accept or reject cookies reflexively (Borberg et al., 2022; Habib et al., 2022; Kulyk et al., 2020), without fully understanding the implications for their online experience on retailers' websites, notably to receive personalized recommendations (Acquisti et al., 2015; EMarketer, 2024; Kulyk et al., 2020). As a result, consumers may unknowingly diminish recommendation quality, and retailers lose opportunities to provide meaningful personalization. Understanding how to communicate the use of consumers' data during navigation is therefore both practically and theoretically important (Bornschein et al., 2020; Sun et al., 2024).

Thus, we advocate for the implementation of RA system settings accessible during navigation. These settings should allow consumers to view the personal data about themselves that is used to generate recommendations for a specific product or service search, and to act on this data through customizable parameters. This access should remain available even after consent has been given, including during the usage and re-usage phases (Habib et al., 2022; Puntoni et al., 2021; van Ooijen & Vrabec, 2019). Although such systems currently exist for advertising personalization (e.g., Google Ads Center (Google, 2022)), this research investigates a related but novel context where RA's settings are accessible to consumers during navigation. This research also contributes to the literature on RAs, which has mainly focused on how they work (i.e., the engine) (e.g., Ebrahimi et al., 2022) or how to present the recommendation (i.e., the output) (e.g., Wang & Benbasat, 2007), with relatively less attention given to input design (e.g., Xu et al., 2014; Zhang & Sundar, 2019).

This research addresses these gaps by drawing on Signaling Theory (Spence, 1973, 2002). Across four online experiments in diverse contexts (job search, hotels, and cars), we test whether transparency about personal data usage affects consumers' intention to adopt an RA and their willingness to pay (WTP). We also examine the moderating role of control, operationalized as customizable RA settings that allow consumers to choose which data are used. We propose that transparency fosters trust when paired with customizable parameters but triggers privacy concerns when those parameters are absent.

This research makes three contributions to the literature on RA input design (e.g., Xu et al., 2014) and personal-data privacy in marketing (Bornschein et al., 2020; Martin et al., 2017; Martin & Murphy, 2017; Quach et al., 2022; Schweidel et al., 2022). First, we extend Signaling Theory from a static cue view to a conditional, design-level account: a cue of prospective transparency, disclosing the use of personal data by RAs before any output, acts as a positive signal only when paired with customizable parameters. In that case, intentions to adopt the RA and WTP increase more than when the RA signals the non-use of personal data; without customizable parameters, the same cue can backfire. Second, we contribute to the transparency-versus-choice debate (e.g., Acquisti et al., 2015; Bornschein et al., 2020) in the personal data usage phase. We explain the mechanisms by which consumers' responses to transparency are affected in the absence or presence of customizable parameters. Prospective transparency without customizable parameters heightens privacy concerns when personal data is used, whereas prospective transparency with customizable parameters increases trust when personal data is used. Finally, our third contribution speaks to the literature about personal data management beyond the cookie notices. So far, the literature has primarily focused on personal data collection and consumers' willingness to disclose such data at the beginning of the navigation process on a retailer's website (e.g., Miyazaki, 2008). Our research provides a deeper understanding of consumer intentions regarding using their personal data during navigation, specifically when the RA indicates which data will be used for a particular product or service search.

## 2.2 Theoretical background

Signaling theory is about reducing information asymmetry between two parties (Spence, 1973, 2002), in our case, between consumers and retailers. Specifically, throughout their journey, consumers emit, consciously or not, various signals that retailers capture to personalize their online experience (Schweidel et al., 2022). For instance, by analyzing consumers' browsing patterns, RAs can adjust the personalized content depending on the consumers' goals (Ding et al., 2025). Conversely, retailers also send signals to consumers, who observe and interpret them, notably regarding how their own signals will be handled. In turn, consumers' perceptions of these signals shape how they adapt and respond to retailers. This theory has attracted the interest of researchers to understand how website transparency features impact consumers' responses, such as trust toward the retailer (Benlian & Hess, 2011) and privacy concerns (Lambillotte et al., 2022). Aguirre et al. (2015) found that when retailers are transparent about collecting information for highly personalized content, consumers report a higher intention to click through it compared to when brands are not transparent.

Thus, the design of RA systems should offer consumers explanations and visibility regarding the data used and processed to reach conclusions (Felzmann et al., 2020). Retailers should provide consumers with both prospective and retrospective transparency (Felzmann et al., 2019). Prospective transparency implies that consumers have access *ex-ante* to information used by the system and an upfront understanding of the system's operation (e.g., how the RA generates recommendations). Conversely, retrospective transparency ensures that consumers have access to *post hoc* explanations and rationales behind the RA system outcomes (e.g., why certain recommendations were presented to consumers).

So far, much of the research has predominantly focused on retrospective transparency (e.g., Nilashi et al., 2016; Wang & Benbasat, 2007). It has been demonstrated that retrospective transparency is crucial for consumers in establishing trust, with its significance being comparable to the quality of recommendations (Nilashi et al., 2016). Wang and Benbasat (2007) showed that explaining the reasoning behind the RA final recommendations enhances consumers' trust in its competence and benevolence.

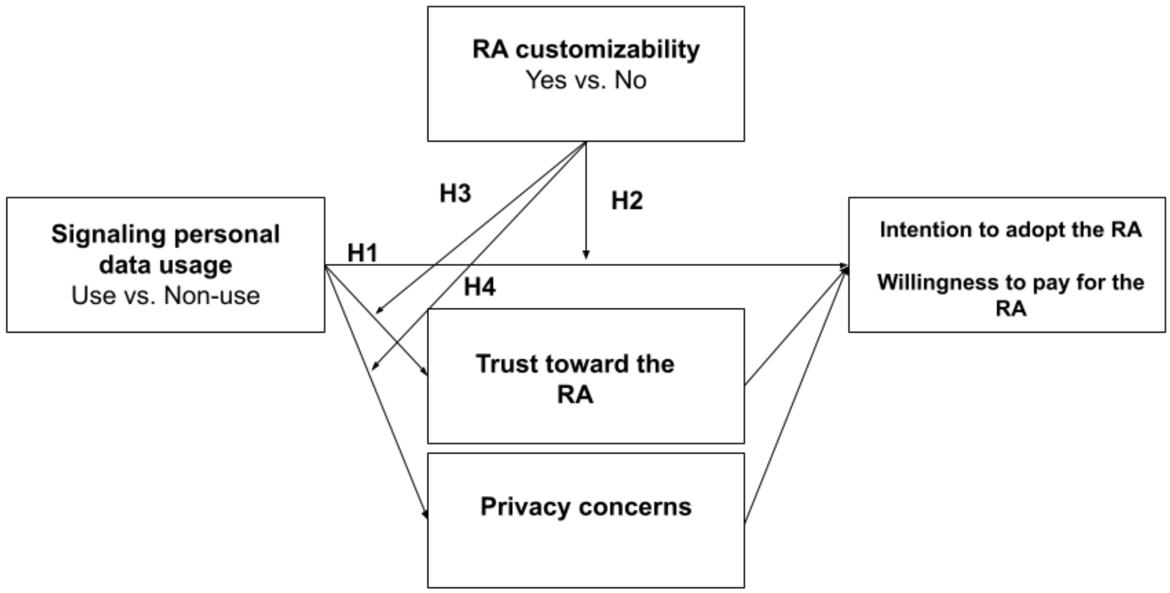
For its part, prospective transparency occurs before the generation of the recommendation. For instance, Xu et al. (2014) have shown that an RA interface showing trade-off among product attribute values, considering it as trade-off transparency features, improves perceived product diagnosticity and perceived enjoyment when using the RA. In practice, consumers often lack access to the settings of these systems employed by retailers, which restricts their understanding of how these systems function (Felzmann et al., 2020; Yeomans et al., 2019). Moreover, many new privacy legislations require that consumers be fully informed about how their personal data is collected and used before providing consent, which emphasizes the need for further research on prospective transparency. This aligns with previous recommendations from AI experts and researchers, who have argued that consumers should have the right to prospective transparency, including the right to know when an RA is making decisions about them and which factors are being considered (Puntoni et al., 2021; Sigal, 2019).

Signaling theory (Spence, 1973, 2002) has important implications in this research. First, retailers should be able to communicate with consumers before generating recommendations and specify which information will be used to generate the recommendations. It should also allow consumers to change their minds during the navigation regarding the use of their personal data to adjust how recommendations are generated through accessible settings at all times (Habib et al., 2022). As past studies have advocated, consumers who agree to the use of their personal data should have the right to continue to decide how it will be handled during navigation and for what purpose specifically. For instance, Krasnova et al. (2010) have reported that, on social media platforms, consumers express a desire to control which friends among their network of friends can see some of their personal data, such as how they feel or what they are doing. The same should apply to RAs since consumers often shop for various products and services on a retailer's website. Some product and service categories warrant greater use of consumers' personal data to tailor recommendations than others. Moreover, consumers should have the option to opt out and opt in at any moment from being profiled, especially if they are shopping for someone else.

## 2.3 Hypotheses development

Figure 1 presents our conceptual framework. We examine the interactive effects of whether the RA system signals the use of consumers' personal data to generate recommendations and whether it is customizable by consumers, on their intention to adopt it and their annual WTP for its service. Consumers' trust in the RA serves as the mechanism underlying their responses to signals regarding personal data use when the RA is customizable. In contrast, privacy concerns explain their reactions when the system is not customizable.

*Figure 7. Conceptual framework*




### *2.3.1 Effect of transparency regarding personal data usage on consumers' intentions*

Recommendations by RAs are generated through consumers' task-specific preferences and their personal data, commonly referred to as profile data (Ebrahimi et al., 2022; Li & Karahanna, 2015). Task-specific preferences are data related to consumer-specific value functions and attribute importance weights estimated at the time of purchase (Scholz et al., 2013). RA using task-specific data focuses on consumers' interaction in providing their preferences for a specific context, allowing the RAs to identify a product that best meets their expectations for a given situation (Ebrahimi et al., 2022; Liang, 2019). Task-specific preferences can support RAs in generating initial recommendations or refining existing ones, while giving consumers greater control over the RA's output (Adomavicius et al., 2011). Conversely, profiling through personal data involves consumers' demographic information (e.g., age, location, gender), psychographic attributes (e.g., lifestyle, interests, values), and behavioral patterns (e.g., past purchases, browsing history, and past interactions) (Li & Karahanna, 2015). By constructing such consumer profiles, RAs can predict preferences with greater accuracy. Consumer profiling is also employed to enhance the level of personalization in recommendations, particularly by accounting for each consumer's unique characteristics, interests, and preferences (Blut et al., 2023). In this research, we distinguish between RAs that generate recommendations solely based on task-specific preferences and those that combine task-specific preferences with consumers' personal data to deliver more highly personalized recommendations.

Past research regarding the impact of task-specific preferences has been mixed. In some cases, it has been shown that consumers' direct input in providing task-specific preferences has been perceived as more useful, which in turn increases the affective and cognitive assessment of the recommendation (Ebrahimi et al., 2022) and is also beneficial for consumers in developing new preferences (Liang, 2019). Thus, interacting with RA helps consumers perceive that the system helps them save effort (Bechwati & Xia, 2003; Tsekouras et al., 2022). However, Blut et al. (2023) have shown that compared to other RAs using personal data to generate recommendations, RAs using only consumers' task-specific preferences reported through direct input to generate the recommendations performed worse, weakening the impact of perceived recommendation quality on satisfaction and future use intentions. Moreover, combining consumers' task-specific preferences with personal data has been shown to improve the level of personalization in recommendations (Xu et al., 2011).

Consumers are generally optimistic about the quality of product and service personalization when based on their personal data (Zhang & Sundar, 2019). Indeed, consumers are more willing to share personal data needed if the service is highly personalized (Karwatzki et al., 2017). In their seminal paper, Awad and Krishnan (2006) demonstrated that consumers tend to overvalue the benefits of being profiled for personalized services (e.g., RA recommendations) compared to ad personalization, positively influencing their willingness to disclose personal information. This positive effect is especially true when retailers reduce information asymmetry and are transparent about which data is collected and used for generating the recommendation, and how this use of personal data concretely translates into beneficial outcomes for consumers (Martin, 2016). Indeed, overt data collection strategies, where consumers are aware that their data are being collected, for highly personalized online content result in increased click-through intentions compared to covert information collection strategies (Aguirre et al., 2015). This is also in line with Tsai et al. (2011), showing that when a website makes salient its privacy policy, consumers are willing to pay a premium price for their products.

Thus, we posit that in a context where retailers signal to consumers which information will be used by the RA system to enhance the quality of recommendations, the use of personal data combined with task-specific preferences should lead to higher intentions to adopt the RA system and greater WTP for its services, compared to when it relies solely on consumers' task-specific preferences without personal data.

**H1a**: Consumers have greater intentions to adopt the RA when it explicitly signals the use of their personal data, compared to when it explicitly signals the non-use of personal data.

**H1b**: Consumers will be more willing to pay for the RA service when it explicitly signals the use of their personal data, compared to when it explicitly signals the non-use of personal data.

*2.3.2 System design customizability, trust toward the RA system, and consumers' privacy concerns*

Recent research into consumer privacy vulnerability in the digital sphere mentions the dual perception that transparency features can trigger (e.g., Karwatzki et al., 2017). This duality means that transparency regarding the use of personal data for personalization purposes can either foster greater trust or trigger risk perceptions and, consequently, privacy concerns (Bornschein et al., 2020). Privacy concern is grounded in the possibility of adverse outcomes associated with the misuse of personal information (Choi et al., 2018). Privacy concerns have been treated as perceived risks by consumers of disclosing their personal data, meaning that they are uncertain about how the firm will handle their data (Dinev & Hart, 2006).

Therefore, transparency alone is not always sufficient to encourage consumers to allow the use of their personal information due to trust issues toward the firm in data management (Bornschein et al., 2020; Martin et al., 2017; Waseem et al., 2024). A key determinant in whether transparency leads to trust or, conversely, to privacy concerns, is consumers' perceived control over their personal data (Martin et al., 2017; Martin & Murphy, 2017). Therefore, how to increase consumers' perceived control in service personalization has been of interest since it directly impacts consumers' intention to disclose their personal information (Aïmeur et al., 2016; Bornschein et al., 2020). Control refers to the extent to which consumers can manage the flow of their information in a specific situation across all stages, from initiation to continuation or termination (Lambillotte et al., 2022; Martin et al., 2017; van Ooijen & Vrabec, 2019).

Control has especially been operationalized through customizable settings on retailer websites, notably to allow consumers to handle their preferences and permissions regarding how the firm manages and uses their data for content personalization (Zhang & Sundar, 2019). Consistent with the "Control paradox" (Brandimarte et al., 2013), consumers who experience more perceived control respond by revealing a lot more information than if they did not experience this control because they overestimate the level of protection and underestimate the risk of personal data disclosure. This paradox clearly shows that consumers' characteristics and sensibility do not explain by themselves consumers' behaviors in handling their personal data, but how RA systems are designed and framed also play a role (i.e., presence or absence of customization parameters).

Martin et al. (2017) have demonstrated that together, transparency and control can mitigate the effect of accessing consumers' personal information by reducing emotional violation and increasing trust toward the firm. It has been shown that when consumers have control over their personal information (i.e., self-disclose the information they want to share), their privacy concerns are lowered (Brandimarte et al., 2013).

Thus, transparency about personal data used and control features shall be, altogether, a way to signal that consumers and retailers are linked through a social contract, based on trust (Martin, 2016). Indeed, trust perceptions mean that consumers believe that the firm is acting in their best interests when handling their personal data (Kruikemeier et al., 2020). Thus, we suggest that both transparency and control signals should make the social contract more reliable. Indeed, Krasnova et al. (2010) have shown that perceived control by consumers through control parameters on the platforms increases trust toward the retailer, which in turn significantly reduces the perception of risk privacy in disclosing personal information.

However, it has been observed that transparency by itself can sometimes create confusion and uncertainty, especially when other factors may play a more crucial role in building trust (Felzmann et al., 2019). As a result, transparency alone can also reinforce a sense of vulnerability and risk perception because consumers become aware of the personal data collected and used about them (Bornschein et al., 2020). In this case, the social contract based on trust between consumers and retailers is perceived as less reliable (Kruikemeier et al., 2020; Okazaki et al., 2009). Consequently, consumers will adopt protective behaviors to safeguard their privacy, such as less intention to use the online service or to disclose personal information (Choi et al., 2018).

This vulnerability is mainly expressed in terms of perceived loss of control over their data (Lambillotte et al., 2022; Zhang & Sundar, 2019). For instance, Lambillotte et al. (2022) have shown that personalized content makes consumers feel less in control, which in turn increases the perceived risk of disclosing their information to retailers for further use. This loss of control is accentuated when the personalization is made using personal data, such as tracking consumers' behaviors, compared to when consumers explicitly provide their task-specific preferences to the system (Zhang & Sundar, 2019). Thus, it seems that consumers are more willing to accept the use of their personal data, but mainly when they are invited to consent to their use before the recommendation is generated explicitly.

Based on the above, we posit that when the RA system is transparent about the personal data it uses, the positive impact of such data use on consumers' intentions to adopt the RA and their WTP for it depends on whether the RA is customizable. When the RA is customizable, signaling the use of consumers' personal data will result in higher adoption intentions and WTP compared to when it signals the non-use of their personal data. This effect is driven by greater trust in the RA's ability to handle their data to deliver enhanced personalization. Conversely, when the RA is not customizable, signaling personal data usage will lead to lower adoption intentions and WTP compared to signaling non-use. This effect is driven by heightened privacy concerns regarding how the RA handles their information.

**H2a**: The effect of signaling personal data usage on RA adoption intention depends on whether the RA system is customizable. Specifically, when the RA system is customizable (not customizable), signaling the use of consumers' personal data leads to higher (lower) adoption intentions compared to when signaling the non-use of personal data.

**H2b**: The effect of signaling personal data usage on consumers' WTP for the service depends on whether the RA system is customizable. Specifically, when the RA system is customizable (not customizable), signaling the use of consumers' personal data increases (decreases) WTP for the RA service compared to when signaling the non-use of personal data.

**H3a**: When the RA is customizable, trust mediates the effect of signaling personal data usage on consumers' intention to adopt the system. Specifically, when the RA system is customizable, signaling the use of consumers' personal data leads to higher trust in the RA compared to when signaling the non-use of personal data, which in turn increases consumers' intention to adopt the system.

**H3b**: When the RA is customizable, trust mediates the effect of signaling personal data usage on consumers' WTP for the service. Specifically, when the RA system is customizable, using consumers' personal data leads to higher trust in the RA compared to signaling the non-use of personal data, which in turn increases consumers' WTP for the RA service.

**H4a**: When the system is not customizable, privacy concern mediates the relationship between signaling personal data usage and consumers' adoption intention. Specifically, when the RA system is not customizable, signaling the use of consumers' personal data leads to higher privacy concerns toward the RA compared to signaling the non-use of personal data, which in turn leads to lower intention to adopt the system.

**H4b**: When the system is not customizable, privacy concern mediates the relationship between signaling personal data usage on WTP for the service. Specifically, when the RA system is not customizable, signaling the use of consumers' personal data leads to higher privacy concerns toward the RA compared to signaling the non-use of personal data, which in turn decreases consumers' WTP for the RA service.

## 2.4 Research overview

We test our hypotheses in four online experiments (Table 11). In the first experiment, Study 1, we test the main effect of signaling the use (vs. non-use) of consumers' personal data on their intention to adopt the RA and WTP for its service annually (H1). Additionally, we test the moderating impact of RA customizability on the relationship between signaling consumers' personal data usage on their intentions toward the RA (H2). In Study 2, we replicate this design and test for the mediating role of trust toward the RA in explaining their intention toward the system when it is customizable, and whether it signals the use of their personal data (H3). In study 3, we add the mediating role of privacy concerns in explaining their intentions toward the RA when it is non-customizable, and whether it signals the use of their personal data (H4). Finally, Study 4 replicates Study 3 in another shopping context. The research was approved by our institution's Research Ethics Board (#2023-5067). Data analysis procedures for each study are presented in Appendix A. In Studies 1–4, we control for participants' privacy values, age, gender, and education. We also account for whether participants reside in California, a state with strong online data protection laws (e.g., the California Consumer Privacy Act (CCPA) and California Privacy Rights Act (CPRA)), and whether they have previously experienced a data breach (Studies 3–4). To enhance the readability of our results, the full models are provided in Appendices F-I.

*Table 11. Overview of the experiments*

| | **Study 1** | **Study 2** | **Study 3** | **Study 4** |
|---|---|---|---|---|
| **Objectives** | • Test the impact of signaling consumers' personal data usage on consumers' intention to adopt the RA and WTP for its service annually (H1a, H1b)<br>• Test the impact of signaling consumers' personal data usage and RA customizability on consumers' intention to adopt the RA and WTP for its service annually (H2a, H2b) | • Retest H1 and H2 as in Study 1<br>• Test the mediating role of trust toward the RA in explaining consumers' intentions in adopting the RA and WTP for its service, whether it signals the use of consumers' personal data, in a customizable context (H3a, H3bb). | • Retest H1, H2 and H3 as in Studies 1 and 2<br>• Test the mediating role of privacy concerns in explaining consumers' intentions to adopt the RA and their WTP for its service, depending on whether it signals the use of personal data, in a non-customizable context (H4a, H4b). | • Retest H1, H2, H3, and H4 as in Studies 1, 2 and 3. |
| **Design** | Between-subjects design | Between-subjects design | Between-subjects design | Between-subjects design |
| **Context** | Job offer | Hotel | Hotel | Car |
| **Independent variables** | Signaling consumers' personal data usage and RA customizability | Signaling consumers' personal data usage and RA customizability | Signaling consumers' personal data usage and RA customizability | Signaling consumers' personal data usage and RA customizability |
| **Dependent variables** | Intention to adopt the RA, WTP for its service annually | Intention to adopt the RA, WTP for its service annually, and trust toward the RA | Intention to adopt the RA, WTP for its service annually, trust toward the RA, and privacy concerns | Intention to adopt the RA, WTP for its service annually, trust toward the RA, and privacy concerns |

## 2.5 Study 1

### *2.5.1 Design and participants*

To test H1 and H2, a 2 (Signaling personal data usage: use vs. non-use) x 2 (RA system customizability: yes vs. no) between-subjects design was used. In total, 240 participants recruited on Prolific (London, United Kingdom) completed an online survey on Qualtrics (Provo, Utah, United States). After participants' removal, 222 remained (see Appendix A for details on the removal procedure). Each participant was randomly assigned to one of the three conditions (see Table 12). Participants ranged from 19 to 79 years old (M = 41.32, SD = 14.20) and 51 % were female.

*Table 12. Presentation of the three conditions for the 2 x 2 experimental design*

<table>
<tr><th></th><th>RA system customizability<br><br>NO</th><th>RA system customizability<br><br>YES</th></tr>
<tr><td>Signaling personal data usage: USE</td><td>Condition 1</td><td rowspan="2">Condition 3<br><br>Participants decided whether they wanted the RA to use their personal data or not.</td></tr>
<tr><td>Signaling personal data usage: NON-USE</td><td>Condition 2</td></tr>
</table>

### *2.5.2 Procedure and measurement*

In each condition, participants were informed that they were beginning their job search. To select the stimulus, we conducted a pre-test presented in Appendix B. Participants were told that to find highly personalized job offers, they used a mobile application featuring an RA, which helped them discover the best job offers across thousands of online platforms. Before the RA presented them with the criteria for identifying their ideal job preferences, all participants were exposed to the system settings to gain visibility on how it identifies the best job offers. The system settings provided information on the two types of data the RA typically uses to generate highly personalized recommendations: (1) consumers' task-specific preferences for criteria relevant to the search (e.g., average salary, type of position, remote or hybrid work) and (2) consumers' profile data (e.g., location, age, gender, income, education, marital status, browsing history) (see Appendix C.1 for stimuli).

In the non-customizable RA system conditions, participants were unable to change the selected data used to generate the recommendations. Thus, in the condition where the RA does not use consumers' personal data (n=57), only consumers' stated preferences for the specific search were selected. In the condition where the RA does use consumers' personal data (n=56), both consumers' stated preferences and personal information were selected. In the customizable RA system condition, participants could select which information the RA would use to generate recommendations. 55 participants in the customization condition chose not to give their personal information (i.e., only their stated preferences for the specific search) versus 54 participants who also allowed the use of their personal information. Thus, conditions were organically balanced. Because of our design, we tested for potential selection biases in the RA customization condition (see Appendix D.1). We found no evidence of selection biases in Study 1 based on participants' gender, age, and education.

It should be noted that participants were never exposed to recommendations from the RA. Instead, after being presented with the system settings, they were invited to complete a questionnaire and report their intentions toward the RA (see Appendix E for the measurement scales). This approach ensures that the dependent variables were not influenced by any recommended products or services, which could otherwise have shaped participants' perceptions of the RA. First, we asked them to report their intention to adopt the RA and their WTP annually for its service. Intention to adopt the RA was measured with three items adapted from Komiak and Benbasat (2006). On a 7-point scale (1= Strongly disagree; 7= Strongly agree), participants answered the following items: "I am ready to use this RA personal assistant as a search aid"; "I am willing to let this RA personal assistant assist me in searching online"; "I am willing to use this RA personal assistant as a tool to suggest a number of offerings" ($\alpha = .96$). For WTP annually for this RA service, we used a slider scale ranging from \$0 to \$100; "Knowing that you can use this independent RA personal assistant for many types of searches (e.g., products, services, jobs), how much would you be willing to pay annually for it if it becomes a paid service?".

Subsequently, we asked participants to report their level of sensitivity in providing their personal information online for personalized marketing services (i.e., privacy values). Since our focus is on the design of a more transparent RA system before the generation of the recommendation, we controlled for consumers' sensitivity in providing their personal information online for personalized marketing services by using 10 items adapted from the User Privacy Values Scale (Earp et al., 2005) ($\alpha$ = .88) (e.g., "I mind when a Web site uses my personal information to personalize my browsing experience").

Finally, for the manipulation check, on a 7-point scale (1= Strongly disagree; 7= Strongly agree), we used a single item "I was able to modify the RA personal assistant's system preferences to decide which information would be used to personalize my recommendations" to confirm they perceived being or not in the customizable RA system condition. The questionnaire ended with demographic questions (participants' age, level of education, and gender) used as control variables in our analyses.

***2.5.3 Manipulation check***

Results of a Welch *t*-test revealed that participants in the non-customizable RA system condition (M= 3.47, SD= 2.13) perceived having less ability to modify the RA system than those in the customizable RA system condition (M= 5.42, SD = 1.23, $p < .001$), confirming the successful manipulation of the RA system customizability.

***2.5.4 Hypotheses testing***

First, we test for the main effect of signaling personal data usage by the RA system (use vs. non-use) on consumers' intention to adopt it (H1a). Specifically, consumers are more likely to adopt the RA system when it signals the use of their personal data compared to signaling the non-use of personal data. Results of a Type III GLM reveal a non-significant main effect of signaling personal data usage by the RA on intention to adopt it ($F(1, 214) = .057$, $p = .811$, $\eta^2 = .003$) (see Appendix F for the full model). Thus, H1a is not supported. There is no significant difference between consumers' intention to adopt the RA system when it signals the use of their personal data (M= 5.30, SE = .38) compared to signaling the non-use of their personal data (M= 5.27, SE= .37).

Second, we test for the main effect of signaling personal data usage by the RA system (use vs. non-use) on consumers' WTP for the RA service (H1b). For the variable WTP, we fit a hurdle model (also known as a zero-adjusted model; Stasinopoulos et al., 2024) using a two-part approach. The first component, a binary logistic regression, modeled the probability of being willing to pay (i.e., WTP > $0 vs. WTP = $0). The second component modeled the actual amount participants were willing to pay (from $1 to $100), using only those with WTP > $0. The hurdle model is especially appropriate when a substantial proportion of the sample reports zero WTP, as in our data.

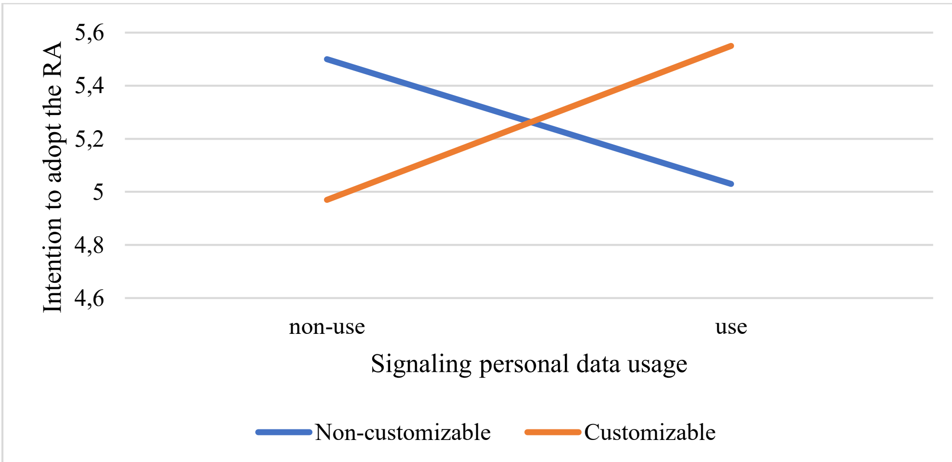
Results of a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > $0 (n=172) vs. WTP = $0 (n=50)) reveal a non-significant main effect of signaling personal data usage on the probability of being willing to pay for the RA service ($F(1, 214) = .022$, $p = .881$, $\eta^2 = .002$) (see Appendix F for the full model). When the RA signals the use of consumers' personal data, the probability of being willing to pay was not higher (M=64.2 %, CI 95 % [36%, 85%]) than when signaling the non-use of personal data (M=63%, IC 95 % [36%, 84%]). Additionally, among those willing to pay for the RA service (n=172), results of a Type III GLM modeling the actual amount participants were willing to pay (from $1 to $100) reveal a non-significant main effect of signaling personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 164) = .230$, $p = .632$, $\eta^2 = .001$) (see Appendix F for the full model). There is no difference between the actual amount participants were willing to pay for the

RA when it signals the use of their personal data (M = 42.7, SE = 4.28) compared to signaling the non-use of personal data (M = 41.1, SE = 4.20). Thus, H1b is not supported.

Third, we test for the interaction between signaling personal data usage by the RA (use vs. non-use) and the RA system customizability (yes vs. no) on consumers' intention to adopt the RA (H2a). Results of a Type III GLM indicate a significant interaction effect between signaling personal data usage by the RA and its customizability on consumers' intention to adopt it ($F$ (1, 213) = 12.614, $p \leq .001$, $\eta^2 = .06$) (See Figure 8) (see Appendix F for the full model). Thus, H2a is supported. When the RA system is customizable, consumers' adoption intentions were higher when it signals the use of their personal data (M = 5.55, SE = .35) compared to signaling the non-use of personal data (M = 4.97, SE = .40, $p = .004$). When the RA system is not customizable, consumers' adoption intentions were lower when it signals the use of their personal data (M = 5.03, SE = .40) compared to signaling the non-use of personal data (M = 5.50, SE = .34, $p = .038$).

Fourth, we test the interaction between signaling of personal data usage (use vs. non-use) and its customizability (yes vs. no) on consumers' willingness to pay for the RA service and the actual amount they are willing to pay (H2b). Results of a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > $0 (n=172) vs. WTP = $0 (n=50)) indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F$(1, 213) = 8.780, $p = .003$, $\eta^2 = .04$; see Appendix F for the full model), providing initial support for H2b.

*Figure 8. Interaction between whether the RA signals the use of consumers' personal data to generate the recommendation and the RA system's customizability on consumers' intention to adopt the RA*




When the RA was customizable, consumers' probability of being willing to pay was higher when the system signals the use of their personal data (M= 76%, CI 95 % [48%, 92%]) compared to signaling the non-use of personal data (M= 50%, CI 95 % [25%, 75%]), $p$ = .030). Conversely, when the RA was not customizable, consumers' probability of being willing to pay was lower when the system signals the use of their personal data (M= 50%, CI 95 % [24%, 76%]) ) compared to signaling the non-use of personal data (M= 73%, IC 95 % [45%, 90%]), $p$=.054), although the effect is marginally significant.

Additionally, results of a Type III GLM modeling the actual amount participants were willing to pay (from $1 to $100) indicate a non-significant interaction effect between signaling personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F$ (1, 163) = 1.941, $p$ = .165, $\eta^2$ = .01) (see Appendix F for the full model). When the RA system is customizable, the actual amount consumers were willing to pay when it signals the use of their personal data (M= 41.7, SE = 4.44) did not significantly differ from when it signals the non-use of personal data (M

= 35.3, SE = 5.11, *p* = .1611). When the RA system is not customizable, consumers' adoption intentions were lower when it signals the use of their personal data (M = 41.2, SE = 5.57) compared to signaling the non-use of personal data (M = 44, SE = 4.44, *p* = .5851). Again, H2b is partially supported, indicating that participants show a higher likelihood of being willing to pay for the RA, but not a higher willingness to pay a greater amount for its service.

***2.5.5 Discussion***

Study 1 shows there is no difference in intention to adopt the RA system and WTP for its services depending on whether the RA signals the use of personal data (H1a, b). In both cases, consumers' intention to use the RA and WTP was high, suggesting that transparency on the level of personalization of the recommendation is quite positive. Specifically, whether the RA signaled the use of only task-specific preferences or a combination of task-specific preferences and personal data did not affect consumers' intention to receive a recommendation from the RA or to pay for its service (H1a, b). This can be attributed to the fact that, when the RA signals the non-use of personal data, the recommendation was still personalized since the RA uses consumers' task-specific preferences. Results could have been different if the non-use of personal data had resulted in generic and non-personalized recommendations (Matt et al., 2013; Yoon et al., 2013).

However, this effect is moderated by the ability to customize or not customize the RA system. Consumers are more likely to adopt the RA and express a higher probability of paying for the service when they are allowed to select the use of their personal data themselves (H2a, b). However, among those willing to pay for the RA service, the actual amount they were ready to pay for it did not differ (H2b). Conversely, when the system does not allow consumers to decide which data will be used to generate the recommendation, being transparent about the fact that it only uses consumers' task-specific preferences and not their personal data also has a positive effect on their intentions (H2a). By controlling for consumers' sensitivity in providing their personal data for marketing purposes, we show that consumers' intentions are impacted by the RA system settings (signaling personal data usage and customizability settings), independently of their individual characteristics.

## 2.6 Study 2

This study aims to test for the moderated mediation path of trust when the RA is customizable (H3) in addition to test the main effect of signaling the use of consumers' personal data on their intentions (H1) and the moderating role of RA system customizability on consumers' intentions to adopt the RA and WTP for it (H2) in a different context.

### *2.6.1 Design and participants*

A 2 (Signaling personal data usage: use vs. non-use) x 2 (RA system customizability: yes vs. no) between-subjects design was used. In total, 394 participants recruited through Prolific (London, United Kingdom) completed an online survey on Qualtrics (Provo, Utah, United States). After participants' removal based on the same criteria used in Study 1, 341 participants remained. Each participant was randomly assigned to one of the three conditions (see Table 12). Participants ranged from 18 to 80 years old (M=39.95, SD =2.99), and 55% were female.

### *2.6.2 Procedure and measurement*

In each condition, participants were told that they had started looking for a hotel for their next vacation. We chose this stimulus based on our pretest presented in Study 1 (see Appendix B). To find highly personalized hotel recommendations, they used an application where an RA helped them find the best hotels across thousands of online platforms. Before the RA presents them with the criteria for identifying their ideal hotel preferences, participants were exposed to the system settings to understand how it identifies the best hotels, as in Study 1 (see Appendix C.2 for stimuli).

The manipulations signaling personal data usage (use vs. non-use) to generate the recommendation, and the RA system's customizability (yes vs. no) were the same as in Study 1. In the non-customizable RA system condition, 66 participants were in the non-personal data used condition and 76 participants were in the personal data used condition. In the customizable RA system condition, 132 participants chose not to give their personal information, versus 67 participants who allowed the use of their personal information. Although the conditions were unbalanced, statistical tests were conducted accordingly (see Appendix A for the data analysis procedure). We found no evidence of selection biases (see Appendix D.2).

Also, the same items as in Study 1 were used to measure the intention to adopt the RA ($\alpha = .96$) and consumers' WTP annually for this RA service (see Appendix E). Again, we control for participants' privacy values ($\alpha = .89$). In this study, we also asked participants to assess their trust in the RA system using nine items from Komiak and Benbasat (2006). We measure the three dimensions of trust, namely competency, benevolence, and integrity (e.g., "The RA personal assistant is like a real expert in assessing products and services,"$\alpha = .94$).

### *2.6.3 Manipulation check*

Results of a Welch *t*-test revealed that participants in the non-customized RA system condition (M = 3.58, SD = 2.24) perceived having less ability to modify the RA system preferences than those in the customized RA system condition (M = 5.86, SD = 1.10, $p < .001$). These results confirm the successful manipulation of the RA system's customizability.

In addition, a manipulation check was conducted to assess whether participants correctly perceived the use of their personal data according to their assigned condition. A chi-square test of independence revealed a significant association between the experimental condition and participants' responses to the manipulation check ($\chi^2(1, N = [341]) = 132.53, p < .001$). In the condition where the RA did not use consumers' personal data, 83.2% of participants responded "no personal data used" to the manipulation check. In contrast, in the condition where the RA used consumers' personal data, 80.5% responded "personal data used." These results confirm that the manipulation was successful.

***2.6.4 Hypotheses testing***

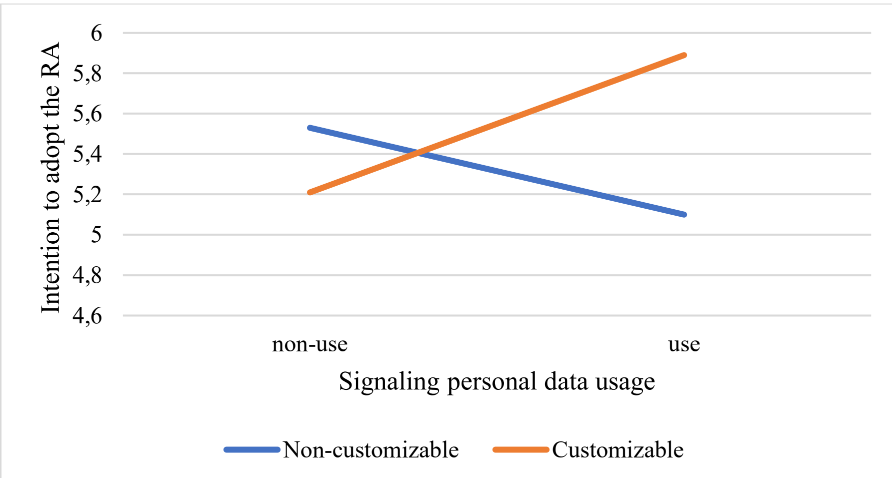
First, we test for the main effect of signaling personal data usage by the RA system (use vs. non-use) on consumers' intention to adopt it (H1a). Results of a Type III GLM reveal a non-significant main effect of signaling personal data usage by the RA on intention to adopt ($F(1, 333) = 1.532$, $p = .217$, $\eta^2 = .009$) (see Appendix G for the full model). There is no significant difference between consumers' intention to adopt the RA system when it signals the use of their personal data (M= 5.45, SE = .39) compared to when it signals the non-use of personal data (M= 5.28, SE= .39). Thus, H1a is again not supported.

Second, we test for the main effect of signaling personal data usage by the RA system on consumers' probability of being willing to pay for the RA service, and on the actual amount they are willing to pay (H1b). Results of a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > \$0 (n=238) vs. WTP = \$0 (n=103)) reveals a significant main effect of signaling personal data usage on the probability of being willing to pay for the RA service ($F(1, 333) = 15.407$, $p \leq .001$, $\eta^2$ =.05; see Appendix G for the full model), providing initial support for H1b. When the RA signals the use of consumers' personal data, WTP was higher (M=68%, CI 95 % [39%, 87%]) than when it signals the non-use of personal data (M=42%, CI 95 % [19%, 68%]).

Additionally, among those willing to pay for the RA service (n=238), results of a Type III GLM modeling the actual amount participants were willing to pay (from $1 to $100) reveal a non-significant main effect of signaling personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 230) = 1.881$, $p$ = .172, $\eta^2 = .01$) (see Appendix G for the full model). There is no difference between the actual amount participants were willing to pay for the RA when it signals the use of their personal data (M= 31, SE = 3.82) compared to when it signals the non-use of personal data (M= 27.3, SE= 3.90). Thus, H1b is partially supported, indicating that participants show a higher likelihood of being willing to pay for the RA, but not a higher willingness to pay a greater amount for its service.

Third, we test for the interaction between signaling personal data usage by the RA (use vs. non-use) and the RA system customizability (yes vs. no) on consumers' intention to adopt the RA (H2a). Results of a Type III GLM indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' intention to adopt it ($F(1, 332) = 16.110$, $p \leq .001$, $\eta^2 = .05$) (See Figure 9) (see Appendix G for the full model). Thus, H2a is again supported. When the RA system is customizable, consumers' adoption intentions were higher when it signals the use of their personal data (M = 5.89, SE = .38) compared to when it signals the non-use of personal data (M = 5.21, SE = .38, $p \leq .001$). When the RA system is not customizable, consumers' adoption intentions were lower when it signals the use of their personal data (M = 5.10, SE = .42) compared to when it signals the non-use of personal data (M = 5.53, SE = .41, $p$ = .071), although this effect is marginally significant.

*Figure 9. Interaction between whether the RA signals the use of consumers' personal data to generate the recommendation and the RA system's customizability on consumers' intention to adopt the RA*




Fourth, we test for the interaction between signaling personal data usage (use vs. non-use) and the RA system customizability (yes vs. no) on consumers' probability of being willing to pay for the RA service, and on the actual amount they are willing to pay (H2b). Results of a binomial logistic regression modeling the probability of being wiling to pay (i.e., WTP > \$0 (n=238) vs. WTP = \$0 (n=103)) indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F(1, 332) = 8.176$, $p = .004$, $\eta^2 = .02$; see Appendix G for the full model), providing initial support for H2b. When the RA system is customizable, consumers' probability of being wiling to pay for the RA service was higher when it signals the use of their personal data (M= 82%, CI 95 % [55%, 95%]) compared to when it signals the non-use of personal data (M = 39%, CI 95 % [18%, 65%]), $p \leq .001$). When the RA system was not customizable, the likelihood of paying did not differ significantly between signaling personal-data use (M = 55%, 95% CI [26%, 80%]) and signaling non-use (M = 48%, 95% CI [22%, 75%]; p = .47).

Additionally, results of a Type III GLM modeling the actual amount participants were willing to pay (from $1 to $100) indicate a non-significant interaction effect between whether RA signals the use of consumers' personal data and RA system customizability on the actual amount consumers were willing to pay ($F$ (1, 229) = 1.249, $p$ = .265, $\eta^2$ = .005) (see Appendix G for the full model). When the RA system is customizable, the difference in the amount consumers were willing to pay when it signals the use of their personal data (M = 31.7, SE = 4.89) compared to when it signals the non-use of personal data (M = 25.4, SE = 4.79, $p$ = .110) is not statistically significant. When the RA system is not customizable, the actual amount consumers were willing to pay when it signals the use of their personal data (M = 29.4, SE = 5.41) was similar to when it signals the non-use of their personal data (M = 29.2, SE = 5.21, $p$ = .945). Again, H2b is partially supported, indicating that participants show a higher likelihood of being willing to pay for the RA, but not a higher willingness to pay a greater amount for its service.

Finally, we test the moderated mediated impact of trust to explain the effect of signaling personal data usage condition, and RA system customizability condition on consumers' intention to adopt the system (H3a), and consumers' WTP (H3b). Results indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on trust toward the RA (β = .857, $t$=3.237, $p$ = .001) (see Appendix G for the full model). For consumers' intention to adopt the RA, results revealed a significant conditional indirect effect in the customizable condition (β = .512, SE = .127, 95% CI = [.291, .769]), supporting H3a, but not in the non-customizable condition (β= -.005, SE = .119, 95% CI = [-.252, .225]).

For the probability of being willing to pay, results revealed a significant conditional indirect effect in the customizable condition (β = .481, SE = .156, 95% CI = [.236, .841]), in support to H3b, but, as expected, not in the non-customizable condition (β= -.004, SE = .114, 95% CI = [-.253, .203]). For the actual amount they are willing to pay, results revealed a significant conditional indirect effect in the customizable condition (β = 3.862, SE = 1.448, 95% CI = [1.242, 6.919]), also in support of H3b, but, as expected, not in the non-customizable condition (β= -.495, SE = 1.551, 95% CI = [-3.842, 2.367]). Thus, H3b is supported.

### *2.6.5 Discussion*

The findings of Study 2 showed that there is no difference in intention to adopt the RA system depending on whether it signals the use of personal data (H1a), corroborating those found in Study 1. However, in Study 2, we found that consumers' likelihood of being willing to pay is higher when the RA signals the use of their personal data compared to when it signals the non-use of their personal data, although it does not seem to impact the actual amount consumers were ready to pay (H1b). This difference in WTP between Study 1 and Study 2 can probably be explained by the type of offering (Study 1, job offers, Study 2, hotel for vacations). Consumers are generally willing to pay more for utilitarian goods (e.g., jobs) than for hedonic ones (e.g., a hotel for vacations) (Okada, 2005). Thus, it can explain the high amount they were willing to pay for the job recommendation, whether the RA signals the use of their personal data. Moreover, results replicated those found in Study 1, showing that consumers are more likely to adopt the RA system and have a higher probability of being willing to pay annually for its service when they are allowed to select by themselves the use of their personal data (H2a, b). When the system does not allow consumers to decide which data will be used to generate the recommendation, consumers did not seem to react differently whether the RA signals the use of their personal data (H2a, b). This can be explained by the fact that trust is activated only when the RA is customizable. In line with H3, consumers who provided their personal data were allowed to control which data would be used to generate recommendations trusted the RA more than those who did not allow such use. In turn, higher trust in the RA explained consumers' intention to adopt the RA and WTP for it.

## 2.7 Study 3

This study aims to test the mediated moderating effect of trust toward the RA (H3) and privacy concerns (H4) to explain the interaction between whether the RA signals personal data usage (use vs. non-use) to generate the recommendation and the RA system customizability (yes vs. no) on consumers' intentions (H2).

### *2.7.1 Design and participants*

A 2 (Signaling personal data usage: use vs. non-use) x 2 (RA system customizability: yes vs. no) between-subjects design was used. In total, 430 participants recruited through Prolific (London, United Kingdom) completed an online survey on Qualtrics (Provo, Utah, United States). After participants' removal (same procedure as previous studies), 382 participants remained. Each participant was randomly assigned to one of the three conditions (see Table 12). Participants ranged from 18 to 69 years old (M = 34.96, SD = 11.56), and 59 % were female.

### *2.7.2 Procedure and measurement*

The procedure and context were the same as in Study 2 (see Appendix C.2 for stimuli). In the non-customizable RA system condition, 95 participants were in the non-personal data used condition, and 65 participants were in the personal data used condition. In the customizable RA system condition, 139 participants chose not to give their personal information, versus 83 participants who allowed the use of their personal information. Although the conditions were not evenly balanced, we applied appropriate statistical tests to account for this (see Appendix A for details on the data analysis procedure). We found no evidence of selection bias in Study 3 (see Appendix D.3).

Also, the same items were used to measure the intention to adopt the RA ($\alpha = .94$) and consumers' WTP annually for this RA service, and to control for privacy values ($\alpha = .89$) (see Appendix E). To measure privacy concerns, we adapted the scale from Dinev and Hart (2006), using 3-items Likert scale (1= Strongly disagree; 7= Strongly agree) (e.g., "I am concerned that the information I submit to the RA personal assistant could be misused") ($\alpha = .93$). As in Study 2, we also measure the three dimensions of trust ($\alpha = .94$). For control purposes, we also asked whether participants had experienced a data breach in the past. Thus, we asked them, "Have you ever been the victim of a data leak and/or a confidentiality incident with a company to which you have provided personal information (Yes (54%)/No (46%))?", and whether they live in California (Yes (13%) / No (87%)) (i.e., presence of CCPA and CPRA). To enhance the readability of our results, the full models including control variables are provided in Appendix H.

### *2.7.3 Manipulation check*

Results of a Welch Two Sample *t*-test revealed that participants in the non-customizable RA system condition (M = 3.66, SD = 2.05) perceived having less ability to modify the RA system than those in the customizable RA system condition (M = 5.57, SD = 1.21, $p$ <.001). These results confirm the successful manipulation of the RA system's customizability.

A manipulation check was conducted to assess whether participants correctly perceived the use of their personal data according to their assigned condition. A chi-square test of independence revealed a significant association between the experimental condition (signaling personal data usage: use vs. non-use) and participants' responses to the manipulation check ($\chi^2(1, N = [382]) = [126], p < .001$). In the condition where the RA did not use consumers' personal data, 84.2% of participants responded "no personal data used" to the manipulation check. In contrast, in the condition where the RA used consumers' personal data, 73.7% responded "personal data used." These results confirm that the manipulation was successful.

### *2.7.4 Hypotheses testing*

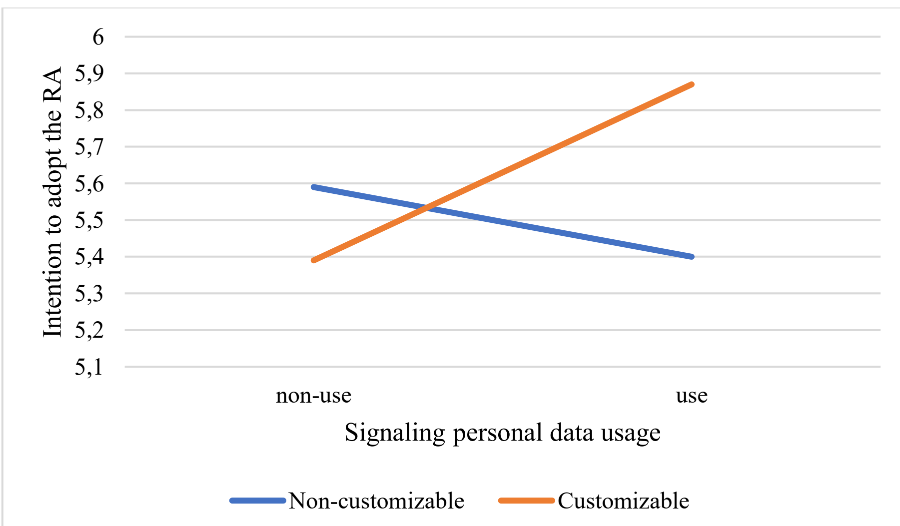
First, we test for the main effect of signaling personal data usage by the RA system (use vs. non-use) on consumers' intention to adopt it (H1a). A Type III GLM reveals a non-significant main effect of signaling personal data usage by the RA on intention to adopt ($F(1, 372) = 2.489$, $p = .115$, $\eta^2 = .006$) (see Appendix H for the full model). There is no difference between consumers' intention to adopt the RA system when it signals the use of their personal data (M= 5.59, SE = .29) compared to when it signals the non-use of their personal data (M= 5.39, SE= .29). Thus, H1a again is not supported.

Second, we test for the main effect of signaling personal data usage by the RA system (use vs. non-use) on consumers' probability of being willing to pay for the RA service and on the actual amount they are willing to pay (H1b). Results of a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > \$0 (n=303) vs. WTP = \$0 (n=79)) reveal a non-significant main effect of signaling personal data usage on the probability of being willing to pay for the RA service ($F(1, 372) = .962$, $p = .327$, $\eta^2 = .004$) (see Appendix H for the full model), while controlling for RA system customizability ($F (1, 372) = 2.063$, $p = .152$, $\eta^2 = .004$). The probability of being willing to pay when the RA signals the use of consumers' personal data (M=58%, CI 95 % [25%, 85%]) is higher than when it signals the non-use of consumers' personal data (M=51%, CI 95 % [20%, 81%]), although the difference is non-significant.

Additionally, among those willing to pay for the RA service (n=303), results of a Type III GLM modeling the actual amount participants were willing to pay (from \$1 to \$100) reveal a significant main effect of signaling personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 293) = 6.359$, $p = .012$, $\eta^2 = .03$; see Appendix H for the full model), providing some support for H1b. When the RA signals the use of consumers' personal data, the actual amount participants were willing to pay was higher (M= 19.4, SE = 4.27) than when it signals the non-use of personal data (M= 13.1, SD= 3.95). Thus, H1b is partially supported: participants do not show a higher likelihood of being willing to pay for the RA; however, when they are willing to pay, they exhibit a greater willingness to pay a higher amount for its service.

Third, we test for the interaction between signaling personal data usage by the RA and the RA system customizability on consumers' intention to adopt the RA (H2a). Results of a Type III GLM indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' intention to adopt it ($F (1, 371) = 7.164$, $p = .008$, $\eta^2 = .02$; see Figure 10; see Appendix H for the full model). Thus, H2a is again supported. When the RA system is customizable, consumers' adoption intentions were higher when it signals the use of their personal data (M = 5.87, SE = .27) compared to when it signals the non-use of their personal data (M = 5.39, SE = .28, $p \leq .001$). When the RA system is not customizable, consumers' adoption intentions were lower when it signals the use of their personal data (M = 5.40, SE = .29) compared to when it signals the non-use of personal data (M = 5.59, SE = .28, $p = .385$), although this effect is non-significant.

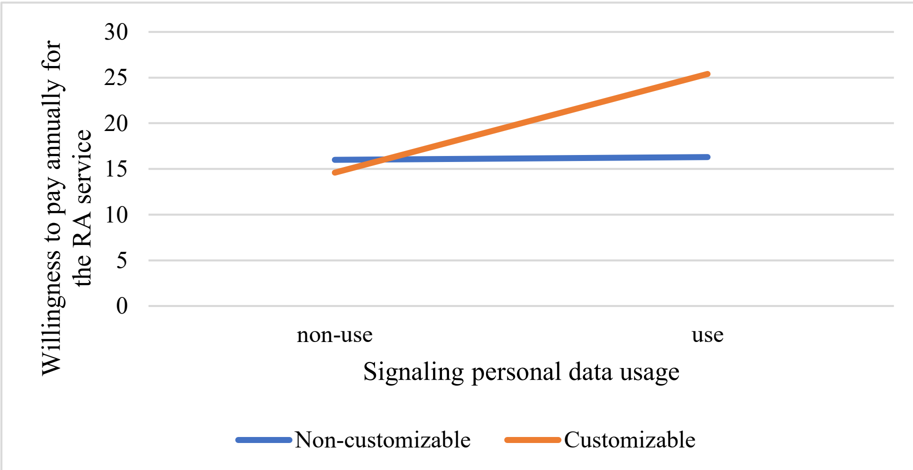
*Figure 10. Interaction between whether the RA signals the use of consumers' personal data to generate the recommendation and the RA system's customizability on consumers' intention to adopt the RA*




Fourth, we test for the interaction between signaling personal data usage by the RA and the RA system customizability on consumers' probability of being willing to pay for the RA service, and on the actual amount they are willing to pay (H2b). Results of a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > \$0 (n=303) vs. WTP = \$0 (n=79)) indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F$(1, 371) = 5.654, $p$ = .018, $\eta^2$ = .01; see Appendix H for the full model). Thus, it provides support for H2b. In the customizable RA condition, consumers have a higher WTP when the RA signals the use of their personal data (M= 66%, CI 95 % [30%, 90%]) compared to when it signals the non-use of personal data (M= 46%, CI 95 % [17%, 78%]), $p$ = .034). In the non-customizable RA condition, consumers have a lower WTP when the RA signals the use of their personal data (M= 55%, CI 95 % [21%, 85%]) compared to when it signal the non-use of personal data (M= 68%, CI 95 % [31%, 91%]), $p$ = .234), although the difference is non-significant.

Additionally, results of a Type III GLM modeling the actual amount participants were willing to pay (from $1 to $100) indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F$ (1, 292) = 4.395, $p$ = .037, $\eta^2$ = .01; see Figure 11; see Appendix H for the full model). Thus, H2b is supported. When the RA system is customizable, the actual amount consumers were willing to pay when it signals the use of their personal data (M= 25.4, SE = 5.25) was higher than when it signals the non-use of their personal data (M = 14.6, SE = 4.08, $p$ = .003). When the RA system is not customizable, the actual amount consumers were willing to pay when it signals the use of their personal data (M = 16.3, SE = 4.29) was not significantly higher than when it signals the non-use of their personal data (M = 16.0, SE = 4.45, $p$ = .926.

*Figure 11. Interaction between whether the RA signals personal data usage to generate the recommendation and the RA system's customizability on the actual amount consumers were willing to pay (n = 303)*




Finally, we test the moderated mediated impact of trust to explain the effect of signaling personal data usage in the RA system customizability condition on consumers' intention to adopt the system (H3a), and on consumers' WTP (H3b). Results of a moderated mediation model (PROCESS Model 7; Hayes, 2022) indicate a marginally significant interaction effect between signaling personal data usage by the RA and RA system customizability on trust toward the RA (β = .502, *t* = 1.962, *p* = .051; see Appendix H for the full model). For consumers' intention to adopt the RA, results revealed a significant conditional indirect effect in the customizable condition (β = .306, SE = .097, 95% CI = [.125, .515]), supporting H3a, but, as expected, not in the non-customizable condition (β= .049, SE = .094, 95% CI = [-.126, .230]).

For the probability of being willing to pay through the path of trust, results revealed a significant conditional indirect effect in the customizable condition (β = .336, SE = .131, 95% CI = [.127, .644]), providing initial support for H3b, but not in the non-customizable condition (β= .035, SE = .111, 95% CI = [-.204, .239]). For the actual amount they are willing to pay through the path of trust, results revealed a significant conditional indirect effect in the customizable condition (β = 3.770, SE = 1.284, 95% CI = [1.526, 6.660]), confirming the support of H3b, but, as expected, not in the non-customizable condition (β= 1.124, SE = 1.205, 95% CI = [-1.332, 3.458]).

We also want to test the moderated mediated impact of privacy concerns to explain the effect of signaling personal data usage and the RA system non-customizability on consumers' intention to adopt the system (H4a), and on consumers' WTP (H4b). Results indicated a significant interaction between signaling personal data usage and RA system customizability on privacy concerns (β = –.593, $t$ = –2.266, $p$ = .024) (see Appendix H for the full model). However, both in the customizable and non-customizable conditions, the conditional indirect effect was not significant ($\beta_{customizable}$= .011, SE = .016, 95% CI = [-.015, .050]; ($\beta_{non\text{-}customizable}$ = -.009, SE = .015, 95% CI = [-.050, .012]). Thus, H4a is not supported.

For the probability of being willing to pay through the path of privacy concerns, both in the customizable and non-customizable conditions, the conditional indirect effect was not significant ($\beta_{customizable}$= -.037, SE = .054, 95% CI = [-.157, .065]; ($\beta_{non\text{-}customizable}$ = .032, SE = .052, 95% CI = [-.067, .142]). For the actual amount they are willing to pay through the path of privacy concerns, both in the customizable and non-customizable conditions, the conditional indirect effect was not significant ($\beta_{customizable}$= -.576, SE = .435, 95% CI = [-1.452, .248]; ($\beta_{non\text{-}customizable}$ = .765, SE = .598, 95% CI = [-.237, 2.070]). Thus, H4b is not supported.

### *2.7.5 Discussion*

The findings of Study 3 replicated those of Study 2 (H1, H2, H3). Although the effect of privacy concern appeared to align with expectations in explaining the mechanism within the non-customizable condition, it was not statistically significant (H4). As the chosen stimulus (i.e., hotel and job) may influence consumer responses, we use another product category in the next study, namely cars. This choice was based on our pretest presented in Study 1, as well as the literature showing that utilitarian and hedonic products can influence consumers' responses such as WTP (Okada, 2005). A car is a product category that is more neutral since it can be perceived as both utilitarian and hedonic (Dhar & Wertenbroch, 2000).

## 2.8 Study 4

This study aims to retest the mediating role of trust (H3) and privacy concern (H4) as a mechanism explaining the interaction between whether the RA signals the use of consumers' personal data to generate the recommendation and the RA system customizability on consumers' intentions (H2) in another consumption context (i.e., shopping for a car). Finally, we want to rule out an alternative explanation to privacy concerns, namely, privacy fatigue, which is a sense of weariness and cynicism toward privacy issues, in which consumers believe that there is no effective means of managing their personal information on the Internet (Choi et al., 2018; Kawaf et al., 2024). Unlike privacy concerns, which reflect active worry about data protection, privacy fatigue reflects a sense of disengagement or apathy that leads consumers to withdraw from adopting protective privacy behaviors (Choi et al., 2018).

### *2.8.1 Design and participants*

We use a 2 (Signaling personal data usage: use vs. non-use) x 2 (RA system customizability: yes vs. no) between-subjects design. In total, 445 participants recruited through Prolific (London, United Kingdom) completed an online survey on Qualtrics (Provo, Utah, United States). After the removal of the participants (using the same procedure as in previous studies), 421 participants remained. Each participant was randomly assigned to one of the three conditions (see Table 12). Participants ranged from 18 to 77 years old (M= 36.71, SD = 12.56), and 56 % were female.

### *2.8.2 Procedure and measurement*

In each condition, participants were told they had started looking for a new car (see Appendix C.3 for stimuli). In the non-customizable RA system condition, 74 participants were in the non-personal data used condition, and 76 participants were in the signaling personal data usage condition. In the customizable RA system condition, 110 participants chose not to give their personal information, versus 106 participants who allowed the use of their personal information. We found no evidence of selection bias in Study 4 (see Appendix D.4).

Also, the same items as in previous studies were used to measure the intention to adopt the RA ($\alpha$ = .95) and consumers' WTP for this service as dependant variables, trust toward the RA ($\alpha$ = .92), and privacy concern ($\alpha$ = .94), as the mediators and privacy values ($\alpha$ = .85) as control variable (see Appendix E). To measure privacy fatigue, we adapted the scale from Choi et al. (2018), using a 7-point Likert scale (e.g., "I feel emotionally drained from dealing with privacy issues in an online environment;" $\alpha$ = .73).

Finally, we asked participants if they had experienced a data breach in the past (Yes (54%)/No (46%))?", and whether they live in California state (Yes (11%) / No (89%)). To enhance the readability of our results, the full models including control variables are provided in Appendix I.

### *2.8.3 Manipulation check*

Results of a *t*-test revealed that participants in the non-customized RA system condition (M = 3.73, SD = 2.02) perceived having less ability to modify the RA system than those in the customized RA system condition (M = 5.67, SD = 1.12, $p < .001$). These results confirm the successful manipulation of the RA system's customizability.

A chi-square test of independence revealed a significant association between the experimental condition (signaling personal data usage) and participants' responses to the manipulation check ($\chi^2(1, N = [421]) = 177.02, p < .001$). In the condition where the RA did not use consumers' personal data, 84.7% of participants responded "no personal data used" to the manipulation check, whereas in the condition where the RA used consumers' personal data, 80.6% responded "personal data used." These results confirm that the manipulation was successful.

### *2.8.4 Hypotheses testing*

First, we test for the main effect of signaling personal data usage by the RA system (use vs. non-use) on consumers' intention to adopt it (H1a). Results of a Type III GLM reveal a non-significant main effect of signaling personal data usage by the RA on intention to adopt ($F(1, 411) = .110$, $p = .741$, $\eta^2 \leq .001$) (see Appendix I for the full model). There is no difference between consumers' intention to adopt the RA system when it signals the use of their personal data (M= 4.80, SE = .42) compared to when it signals the non-use of their personal data (M= 4.84, SE= .42). Thus, H1a is again not supported.

Second, we test for the main effect of signaling personal data usage by the RA system on consumers' probability of being willing to pay for the RA service, and on the actual amount they are willing to pay (H1b). Results of a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > \$0 (n=343) vs. WTP = \$0 (n=78)) reveal a marginal significant main effect of signaling personal data usage on the probability of being willing to pay for the RA service ($F(1, 411) = 3.249$, $p = .072$, $\eta^2 = .010$; see Appendix I for the full model). The probability of being willing to pay when the RA signals the use of consumers' personal data is higher (M=74%, CI 95 % [46%, 90%]) than when it signals the non-use of consumers' personal data (M= 63%, CI 95 % [36%, 84%]). Additionally, among those willing to pay for the RA service (n=343), results of a Type III GLM modeling the actual amount participants were willing to pay (from \$1 to \$100) reveal a significant main effect of signaling personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 333) = 7.955$, $p = .005$, $\eta^2 = .030$; see Appendix I for the full model). When the RA signals the use of consumers' personal data, the actual amount participants were willing to pay was higher (M= 27.9, SE = 3.83) than when it signals the non-use of personal data (M= 21.3, SE= 3.38). Thus, H1b is partially supported, indicating that participants show a slightly higher likelihood of being willing to pay for the RA, and a higher willingness to pay a greater amount for its service

Third, we test for the interaction between signaling personal data usage by the RA and the RA system customizability on consumers' intention to adopt the RA (H2a).

Results of a Type III GLM indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' intention to adopt it ($F(1, 410) = 7.775$, $p = .006$, partial $\eta^2 = .020$; see Appendix I for the full model), supporting H2a. When the RA system is customizable, consumers' adoption intentions were higher when it signals the use of their personal data (M = 4.98, SE = .42) compared to when it signals the non-use of their personal data (M = 4.79, SE = .42, $p = .131$), although this difference is non-significant. When the RA system is not customizable, consumers' adoption intentions were lower when it signals the use of their personal data (M = 4.58, SE = .43) compared to when it signals the non-use of their personal data (M = 5.01, SE = .43, $p = .036$).

Fourth, we test for the interaction between signaling personal data usage by the RA and the RA system customizability on consumers' WTP for the RA service (H2b). Results of a binomial logistic regression modeling the WTP (i.e., WTP > \$0 (n=343) vs. WTP = \$0 (n=78)) indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F(1, 410) = 3.953$, $p = .048$, partial $\eta^2 = .009$; see Appendix I for the full model), providing initial support for H2b. In the customizable RA condition, consumers have a higher WTP when the RA signals the use of their personal data (M= 80%, CI 95 % [52%, 93%]) compared to when it signals the non-use of their personal data (M=60%, CI 95 % [32%, 83%], $p = .010$). In the non-customizable RA condition, consumers have a lower WTP when the RA signals the use of their personal data (M= 67%, CI 95 % [37%, 88%])) compared to when it signals the non-use of their personal data (M= 71%, CI 95 % [42%, 89%], $p = .677$), although the difference is non-significant.

Additionally, results of Type III GLM modeling the actual amount participants were willing to pay (from \$1 to \$100) indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F(1, 332) = 7.514$, $p = .007$, $\eta^2 = .020$; see Appendix I for the full model), confirming the support of H2b. When the RA system is customizable, the actual amount consumers were willing to pay when it signals the use of their personal data (M= 31.4, SE = 3.10) was higher than when it signals the non-use of their personal data (M = 20.1, SE = 2.24, $p \leq .001$). When the RA system is not customizable, the actual amount consumers were willing to pay when it uses their personal data (M = 21.9, SE = 3.42) was lower than when it does not use their personal data (M = 23.6, SE = 3.11, $p = .668$), although this effect is non-significant.

We test the moderated mediated impact of trust to explain the effect of signaling personal data usage in the RA system customizability condition on consumers' intention to adopt the system (H3a), and consumers' WTP for the service (H3b). First, a moderated mediation model (PROCESS Model 7; Hayes, 2022) indicates a significant interaction effect between signaling personal data usage by the RA and RA system customizability on trust toward the RA ($\beta = .526$, $t = 2.403$, $p = .017$; see Appendix I for the full model). For consumers' intention to adopt the RA, results revealed a significant conditional indirect effect in the customizable condition ($\beta = .146$, SE = .064, 95% CI = [.026, .285]), supporting H3a, but not in the non-customizable condition ($\beta$= -.093, SE = .089, 95% CI = [-.275, .076]).

For the probability of being willing to pay through the path of trust, results revealed a significant conditional indirect effect in the customizable condition ($\beta = .2486$, SE = .1098, 95% CI = [.044, .4721]), providing initial support for H3b, but not in the non-customizable condition (β= -.1577, SE = .1630, 95% CI = [-.5223, .1249]). For the actual amount they are willing to pay through the path of trust, both in the customizable and non-customizable conditions, the conditional indirect effect was not significant ($\beta_{customizable}$= 2.157, SE = 1.199, 95% CI = [-.210, 4.516]; ($\beta_{non\text{-}customizable}$ = -1.387, SE = 1.712, 95% CI = [-4.841, 1.716]). Thus, H3b is partially supported.

We test the moderated mediated impact of privacy concerns to explain the effect of signaling personal data usage in the RA system non-customizability condition on consumers' intention to adopt the system (H4a), and WTP (H4b). Results indicated a significant interaction between signaling personal data usage and RA system customizability on privacy concerns (β = –.895, $t$ = –3.258, $p$ = .001) (see Appendix I for the full model). For consumers' intention to adopt the RA, results revealed a significant conditional indirect effect in the non-customizable condition (β = -.067, SE = .035, 95% CI = [-.146, -.014]), supporting H4a, but not in the customizable condition, as expected (β= .021, SE = .018, 95% CI = [-.009, .065]).

For the probability of being willing to pay through the path of privacy concerns, both in the customizable and non-customizable conditions, the conditional indirect effect was not significant ($\beta_{customizable}$= -.0262, SE = .0345, 95% CI = [-.1075, .0335]; ($\beta_{non\text{-}customizable}$ = .0827, SE = .0901, 95% CI = [-.0796, .2732]). For the actual amount they are willing to pay through the path of privacy concerns, both in the customizable and non-customizable conditions, the conditional indirect effect was not significant ($\beta_{customizable}$= .044, SE = .184, 95% CI = [-.257, .499]; ($\beta_{non\text{-}customizable}$ = -.343, SE = .758, 95% CI = [-2.089, 1.052]). Thus, H4b is not supported.

### *2.8.5 Rule out an alternative explanation: mediating role of privacy fatigue*

Next, we examined the indirect effect of signaling personal data usage by the RA and RA system customizability on consumers' adoption through their level of privacy fatigue, privacy concern, and trust in a PROCESS model (Model 7, 5,000 bootstrap sample; Hayes, 2022). Results suggest a non-significant interaction between signaling personal data usage by the RA and RA system customizability on privacy fatigue ($\beta = .232$, $t = 1.058$, $p = .291$) (see Appendix I for the full model). Privacy concerns and trust seem to be relevant mediators to explain the effect of signaling personal data usage by the RA and RA system customizability on our variables of interest.

### *2.8.6 Discussion*

The findings of Study 4 mainly replicated those of previous studies (see Table 13). Moreover, we found that when the RA system is not customizable, consumers express more privacy concerns when it signals the use of their personal data compared to when it does not, which in turn explains why they have lower adoption intentions for its services (H4a). Results also show that privacy fatigue does not explain their behavioral intentions toward the RA system, both in the customizable and non-customizable conditions. Table 13 provides a summary of the results of the studies.

*Table 13. Overview of results across studies*

| | **Study 1** | **Study 2** | **Study 3** | **Study 4** |
|---|---|---|---|---|
| **H1a** | Not supported | Not supported | Not supported | Not supported |
| **H1b** | Not supported | *Partially supported*. Signaling personal data usage increases consumers' likelihood of paying for the RA but does not increase how much those who are willing to pay are ready to spend. | *Partially supported*. Signaling personal data usage does not increase consumers' likelihood of paying for the RA, but it does increase how much those who are willing to pay are ready to spend. | Supported. |
| **H2a** | Supported | Supported | Supported | Supported |

| | | | | |
|---|---|---|---|---|
| **H2b** | *Partially supported.* The likelihood of paying for the RA is impacted by whether the RA signals personal data usage and whether the RA system is customizable, but not the actual amount that those who are willing to pay are ready to spend. | *Partially supported.* The likelihood of paying for the RA is impacted by whether the RA signals personal data usage and whether the RA system is customizable, but not the actual amount that those who are willing to pay are ready to spend. | Supported | Supported |
| **H3a** | | Supported | Supported | Supported |
| **H3b** | | Supported | Supported | *Partially supported*. Trust mediates the relationship between signaling personal data usage when the RA is customizable on consumers' likelihood of paying for the RA, but not for the actual amount that those who are willing to pay are ready to spend. |
| **H4a** | | | Not supported | Supported |
| **H4b** | | | Not supported | Not supported |

## 2.9 General discussion

Contrary to our expectations, the results of four studies indicate that, in a concrete purchase context on a retailer website, being more transparent about whether personal data are used by the RA prior to generating the recommendation has no significant effect on consumers' intention to adopt it, regardless of whether it relies on consumers' personal data or not (H1a). Interestingly, in both situations, consumers express high levels of intention to adopt the RA. This may be because, even without using personal data, the RA still delivered personalized recommendations based on consumers' task-specific preferences (Matt et al., 2013; Yoon et al., 2013).

Additionally, we found that in some contexts, consumers have a higher WTP for the RA service (H1b) when it signals personal data usage. However, these results strongly depend on the purchase context. For instance, only Study 4, where participants were searching for a product (i.e., a car), found that when the RA signaled personal data usage, consumers were not only more likely to pay for the RA, but also willing to spend more on it to receive its services. In contrast, when the shopping context involved a service, the findings were mixed: sometimes signaling data usage had no impact on consumers' WTP (Study 1, job offer), while in other cases it affected either the likelihood of paying, or the actual amount consumers were willing to spend (Studies 2 and 3, hotel). All in all, these findings regarding H1a and H1b tend to provide support to previous research showing that consumers see value in personalization in a service context (Awad & Krishnan, 2006; Karwatzki et al., 2017), but not necessarily on the level of personalization (i.e., use or non-use of personal data).

In line with past research on the interplay between transparency about personal data use and perceived control over one's data (Bornschein et al., 2020), we investigate when transparency about data use increases the adoption of RAs. We find that the presence or absence of customizable settings can amplify or diminish the impact of signaling personal data usage before the RA generates a recommendation. In our research, control was operationalized through customizable parameters, allowing consumers to decide whether they agree or not to the use of their personal data by the RA in a specific shopping context. Specifically, our results showed that consumers' intention to adopt the RA when it signals personal data usage was conditional on the presence of customizable parameters (H2a). Thus, consumers' intentions to adopt the RA were higher when they self-selected the use of their personal data (i.e., when the RA was customizable) compared to when they did not permit such use, allowing only their task-specific preferences to be used. Except for Study 3, where no difference was found, consumers' adoption intentions were lower when the RA signaled the use of personal data without the possibility of adjusting these settings (i.e., when the RA was not customizable) compared to when it signaled the non-use of personal data.

The effects of signaling personal data usage and RA system customizability on consumers' WTP appear to point in the same direction, although their interpretation requires nuance (H2b). Across the four studies, consumers' likelihood of paying for the RA was higher when they self-selected the use of their personal data (i.e., when the RA was customizable) compared to when they did not allow such use. However, only Studies 3 and 4 found that the actual amount consumers were willing to pay for the RA service was higher under self-selection of personal data use than when such use was not allowed. Moreover, when the RA was not customizable, neither the likelihood of paying for the RA nor the actual amount consumers were willing to pay differed significantly. Overall, consumers were generally more likely to pay than not to pay for the RA service, regardless of whether it signaled the use of personal data, and were quite interested in paying a reasonable amount for it.

When the RA is customizable, we found that consumers experienced a higher level of trust toward the RA when it uses their personal data compared to when it does not, which in turn, explained intentions to adopt (H3a), and WTP for its service (H3b). This is in line with past research showing that trust was the main driver of information disclosure (Wang et al., 2025) and intentions to adopt RAs (Ebrahimi et al., 2022). It also supports the perspective that consumers having higher trust in the RA when disclosing their personal data see higher benefit in using it (Huang et al., 2024).

Conversely, in the absence of customizable settings, our results showed that consumers experience higher privacy concerns when the RA uses their personal data compared to when it does not, which, in turn, explained consumers' intention to adopt the RA (H4a). However, this result was found only in Study 4 (shopping for a car), but not in Study 3 (shopping for a hotel stay). It tends to corroborate Lambillotte et al. (2022), showing that higher levels of personalization lead to a perceived loss of control, increasing privacy concerns. Moreover, privacy fatigue was not an alternative explanation for privacy concerns. It means that transparency about the use of personal data leads to more engagement from consumers to adopt coping behaviors to protect their online privacy (Choi et al., 2018).

However, privacy concerns did not explain why, in the absence of customizable settings, consumers have a lower probability of being willing to pay for the RA and were ready to pay less for its service (H4b). In fact, privacy concern was not a predictor of WTP. This is in line with prior studies showing that trust can be a predictor of WTP, but privacy concern is not. For instance, Schreiner and Hess (2015) have shown that perceived privacy risk is not enough to have an impact on consumers' WTP. In fact, consumers are willing to pay for a personalized service if they see a benefit in it. Thus, even if personal data is used when the RA is not customizable, it increases privacy concerns; consumers potentially acknowledge the added value of such personalized service.

#### *2.9.1 Theoretical contributions*

This research makes three contributions to the literature on RA input design (e.g., Xu et al., 2014) and personal-data privacy in marketing (Bornschein et al., 2020; Martin et al., 2017; Martin & Murphy, 2017; Quach et al., 2022; Schweidel et al., 2022). First, we enrich the Signaling Theory (Spence, 1973, 2002), which posits that transparent cues reduce information asymmetry and thereby foster trust. By doing so, we contribute to reducing the gap in the literature regarding RA input design, since we observed that most of the focus has been on output design or RA engine (e.g., Ebrahimi et al., 2022; Wang & Benbasat, 2007). However, our findings showed that a positive effect, such as heightened intention to adopt the RA and pay for its service, emerges when the RA is transparent about the personal data it uses, but this effect is contingent on consumer control. Specifically, when transparency about personal data used is paired with customizable parameters, it becomes a positive signal for consumers who communicate higher intentions to adopt the RA and WTP for it. Conversely, when system transparency about personal data used is unaccompanied by customizable parameters, it becomes a negative signal, reducing consumers' intentions to adopt the RA and WTP for it. Thus, we advance Signaling Theory from a static cue model to a dynamic, conditional signaling framework for digital service design.

Second, we contribute to the transparency (i.e., visibility) versus choice debate (e.g., Acquisti et al., 2015; Bornschein et al., 2020) in the personal data usage phase by explaining consumers' responses to transparency in the absence or presence of customizable parameters. Consistent with Bornschein et al. (2020) studying visibility and control in the personal data collection phase through cookie notices, transparency alone only affects risk perception, privacy concerns in our research, while transparency and control explain consumers' intentions through trusting beliefs toward the RA. Thus, control makes consumers more confident in the use of their personal data by the RA, which in turn explains consumers’ positive intentions toward it compared to when it uses only explicit preferences. For its part, when customizable parameters are absent, transparency alone leads consumers to experience more privacy concerns when the RA shows the use of personal data for recommendation generation, compared to when it only uses explicitly reported preferences (Lambillotte et al., 2022).

Finally, our third contribution speaks to the literature about personal data management beyond the cookie notice. Since the advent of new privacy legislations, much research has been done to understand the influential impact of cookie notices on consumers' perceptions and behaviors (Bauer et al., 2021; Habib et al., 2022; Santos et al., 2021; Strycharz et al., 2021). Thus, the literature has primarily focused on personal data collection and consumers' willingness to disclose such data at the beginning of the navigation process on a retailer's website (e.g., Miyazaki, 2008). Our research allows a better understanding of consumer intentions regarding the use of their personal data during navigation, namely when the RA signals to consumers which data will be used for a concrete product or service search. So far, consumers have very few possibilities to assess which data a retailer has about them, which limits their understanding of how recommendations were generated (Yeomans et al., 2019). Our research proposes an accessible and transparent setting for RA, showing consumers which data, previously collected about them, will be used to generate the recommendation. Our results showed that, as in a data usage context, transparency alone (e.g., visibility) can backfire when the RA shows that personal data will be used, without allowing consumers to act on it, even if they have already agreed to provide their personal data.

### *2.9.2 Implications for managers and policy makers*

From a managerial perspective, our research offers two main insights for service providers using RAs navigating a landscape of laws and regulations aimed at safeguarding consumer privacy in the realm of content personalization (Felzmann et al., 2019; Quach et al., 2022). Indeed, these regulatory requirements in different countries emphasize the need for the development of RA systems that are manageable by individuals and stress the importance of transparency about personal data usage. So far, we have only observed consumers' control and visibility over their personal data for personalized content for advertising purposes, such as the Google ads settings example (Google, 2022). Specifically, in 2022, Google adopted a new ad transparency policy by introducing the Google Ads Settings platform. This initiative provides consumers with increased visibility and control over the content they are exposed to and the reasons behind being targeted by specific advertisers. Consumers can customize their advertising experience by selecting which retailers or types of content they want to be exposed to, influencing how Google determines which ads to display. Additionally, consumers have access to their personal information (e.g., marital status, income, education) and can modify this information to ensure accuracy or opt out, instructing Google not to create profiles based on this information.  Our research shed light on the effect of such a transparent and controllable system for RA on retailers' websites. Specifically, we proposed a way for retailers to give consumers more control and visibility regarding their personal data to act on the RA and its recommendations, ensuring that this benefits both consumers and retailers. Thus, our research proposes that if the RA must rely on consumers' personal data to generate personalized recommendations, the presence of customizable parameters is of importance to increase consumers' trust, intention to adopt the RA, and WTP to pay for it. Conversely, if the RA relies only on consumers' direct input (i.e., task-specific preferences), there is no need to add these additional customizable parameters (e.g., discussion with a chatbot).

Additionally, this research can help retailers show consumers the benefits of using their personal data for service personalization. We propose an RA input design that clearly signals the data collected and its purpose. Given that insufficient personal data on retailers' platforms can reduce recommendation quality (Sun et al., 2024), our findings show that transparent RA settings with customizable parameters can encourage consumers to recognize the value of allowing their data to be used. Notably, this design did not trigger privacy fatigue, which is a disengagement from privacy-protective behaviours often seen with cookie notices. Thus, it offers a potential solution to address the lack of informed consent at the start of online navigation (EMarketer, 2024; Kulyk et al., 2020).

Finally, from a policymaker's perspective, our results highlight the need to ensure that control parameters are real, rather than providing consumers with a false sense of security in allowing the use of their personal data for specific contexts. Moreover, prospective transparency without customizable parameters can serve to enhance consumer awareness and encourage the adoption of protective behaviors, especially in contrast to the prevailing sense of privacy fatigue, which is particularly evident during the collection of personal data (Choi et al., 2018; Kulyk et al., 2020; Liu et al., 2023).

### *2.9.3 Limitations and future research*

In this research, we first acknowledged that consumers' privacy concerns and their intention to disclose information are significantly influenced by trust in the firm and its management of personal information (e.g., concerns about whether firms will share their information with other entities) (Ebrahimi et al., 2022; Swani et al., 2021; Wang & Benbasat, 2007). Therefore, future research should use actual retailers with varying levels of consumer trust.

Second, in our experiments, participants were never exposed to recommendations from the RA. Yet consumers' responses to an RA, such as their intention to adopt it or their WTP for it, may be influenced by the quality of its recommendations (Blut et al., 2023). Future research should therefore examine the proposed RA input design in contexts where consumers are exposed to both high- and low-quality recommendations and explore how they respond.

Third, while this research provides valuable insights into the positive impact of personal data use, it assumes that consumers are willing to explore the RA's transparency settings. Given that many consumers often neglect website settings (e.g., accepting or declining cookies), even when prompted, it would be worthwhile to explore strategies that encourage greater engagement with these settings. Moreover, our findings stem from a controlled experimental environment in which participants interacted with a single website. In real-world contexts, consumers repeatedly face decisions about data usage and cookie settings across multiple websites. Future research could examine whether repeated exposure to such customizable parameters leads to user fatigue over time, potentially influencing trust and willingness to engage with RA personalization settings.

In line with the above, we assume that consumers have already accepted or declined the collection of their personal data. Future research should examine consumers' behaviours on a retailer's website across the entire process: from agreeing to data collection to the RA's subsequent use of that data. A field experiment could provide more realistic behavioural data, as our study focused primarily on consumers' intentions to adopt the RA and their WTP.

Finally, while we captured some behavioural responses through the RA system's customisability condition, further research should directly assess behavioural outcomes from this design. In our study, consumers in the customisable RA condition self-assigned themselves to the personal data condition; although we found no evidence of selection bias, other studies have reported unbalanced conditions due to self-assignment. Additional work could employ a scenario in which consumers consider customisable parameters that allow them to modify the data used by the RA (Bornschein et al., 2020; Zhang & Sundar, 2019). It would also be valuable to investigate how implementing such a system during the data-use phase influences the data-collection phase in subsequent website visits (Puntoni et al., 2021; van Ooijen & Vrabec, 2019), and whether it increases consumers' perceived benefits or perceived risks of providing their personal data (Dinev & Hart, 2006). As proposed by Yoo et al. (2025), the use of large multimodal models (LMMS) like ChatGPT or other GenAI tools can help build more realistic experimental designs for researchers.

**Statement:** During the preparation of this work, the authors used ChatGPT-5 and Grammarly for copy-editing, after which, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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# Appendix

## *Appendix A. Data analysis*

All analyses were conducted in R version 4.4.2 (R Core Team, 2024). In each study, participants were removed based on the same four criteria. First, they failed to complete the survey. Second, they failed the attention check (i.e., "For attention check, please select 'Strongly agree'"). Third, we removed participants with missing data in our control variables (i.e., age and education). Four, after applying the previous two criteria, we removed participants with unusually long completion times, defined as exceeding the mean completion time by more than two standard deviations.

Due to the RA system's customizability, which allowed participants to self-select into conditions, some studies resulted in an unbalanced 2×2 design. Thus, we conducted General Linear Models (GLMs) using Type III sums of squares with the *car* (Fox & Weisberg, 2019), *lmtest* (Zeileis & Hothorn, 2002), and *effectsize* (Ben-Shachar et al., 2020) packages. Type III GLMs (Gaussian family) do not assume equal group sizes or normality of the predictors, making them appropriate for testing interaction effects in unbalanced designs. Potential violations of the homoskedasticity assumption were addressed using heteroskedasticity-consistent standard errors (White's estimator). Specifically, we used the HC3 estimator[1], which provides a conservative correction suitable for small to moderate samples (Hayes & Cai, 2007). Model assumptions were

[1] Robust standard errors (HC3) were applied to all general linear models to account for potential heteroskedasticity and high-leverage observations, except in Study 3 for testing H1b and H2b, where a single extreme hat value was identified. In this case, an alternative robust estimation approach (HC1) was used to ensure accurate inference.

checked via visual inspection of residuals and the studentized Breusch-Pagan test (Breusch & Pagan, 1979).

For pairwise comparisons and estimated means, we used the *emmeans* package (Lenth et al., 2018). Estimated Marginal Means (EMMeans) were used to adjust group means based on covariates included in the model, ensuring consistency with the structure of the fitted model. EMMeans are particularly suitable for unbalanced designs, as they estimate group means as if the design were balanced (Lenth et al., 2025).

For the variable WTP, we fit a hurdle model (also known as a zero-adjusted model; Stasinopoulos et al., 2024) using a two-part approach. The first component, a binary logistic regression, modeled the probability of being willing to pay (i.e., WTP > $0 vs WTP = $0). The second component modeled the actual amount participants were willing to pay (from $1 to $100), using only those with WTP > $0. The hurdle model is especially appropriate when a substantial proportion of the sample reports zero willingness to pay, as in our data.

Finally, to perform our moderated mediations (H3-H4), we used the PROCESS macro for R, version 4.3 (Hayes, 2022).

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***Appendix B. Pretest stimuli***

According to the GDPR and other data protection laws (e.g., California Consumer Privacy Act (CCPA)), consumers' personal data should be collected only when it is relevant for the purpose for which it is being processed. Therefore, we conducted a pre-test to explore various products and services that consumers find useful to provide their personal data. In total, 53 participants recruited on Prolific (London, United Kingdom) completed an online survey on Qualtrics (Provo, Utah, United States). Participants ranged from 19 to 70 years old (M= 40.58, SD = 14.52), and 60.4% were female. Twenty-three products and services were tested in this pretest. We relied on past studies on RAs and on the privacy concerns literature to choose these offerings (e.g., Chellappa & Sin, 2005). We asked participants, "How likely are you to share your personal information (e.g., age, gender, location, time zone, browsing, and purchase history) to receive highly personalized recommendations for these products and services?" (1= Very much unlikely; 7= Very much likely).

Products and services that scored the highest were Jobs (M= 4.73, SD = 2.04), Apartments (M= 4.10, SD = 1.99), Smartphones (M= 4.06, SD = 2.04), Restaurant (M= 4.06, SD = 1.96), Financial services (M= 4.02, SD = 2.05), Hotels (M= 4.00, SD = 2.02) and Cars (M= 3.92, SD = 1.97) (see Table 14 for means for products and services in the pre-test). The relatively low average scores for participants' willingness to provide personal data for recommendations on these product and service types can be explained by the fact that these offerings were presented without context (e.g., on a website and without a scenario).

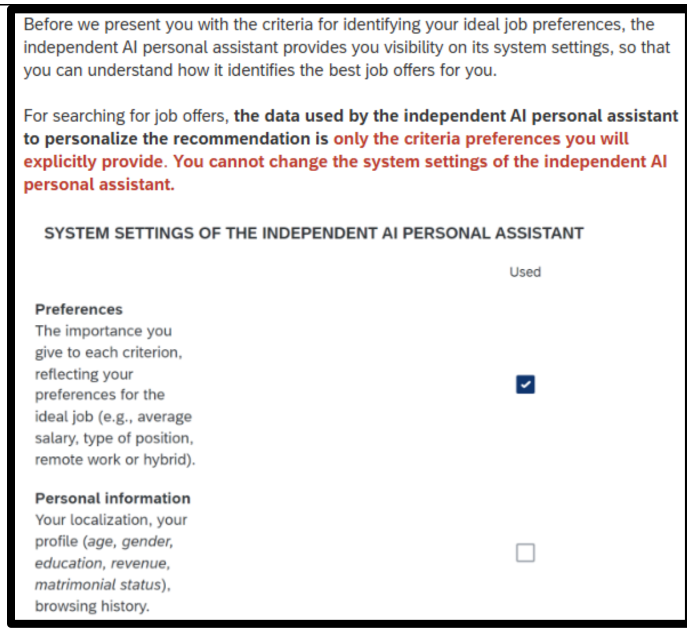
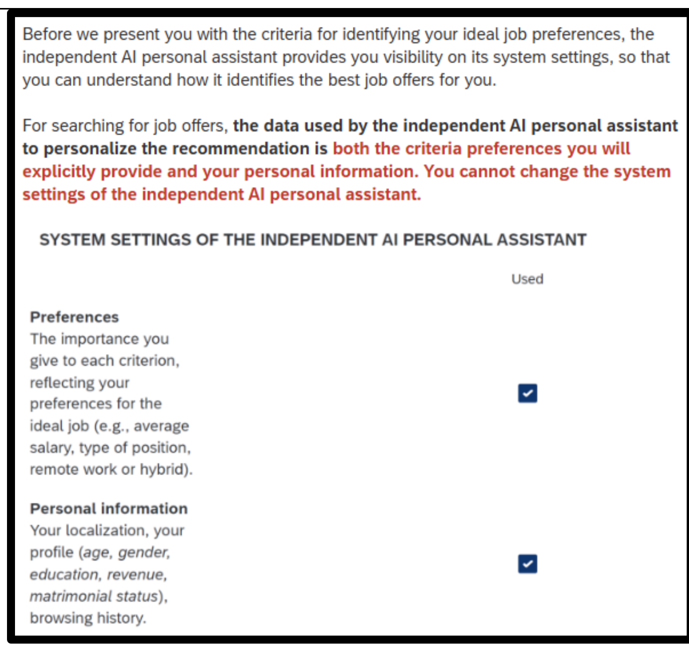
*Table 14. Means for products and services in the pre-test*

| Stimulus | M | SD |
|---|---|---|
| Jobs | 4.73 | 2.04 |
| Apartment | 4.10 | 1.99 |
| Smartphone | 4.06 | 2.04 |
| Restaurant | 4.06 | 1.96 |
| Financial service | 4.02 | 2.05 |
| Hotel | 4.00 | 2.02 |
| Car | 3.92 | 1.97 |
| Book | 3.90 | 2.06 |
| Movie | 3.89 | 1.93 |
| Sneakers | 3.89 | 2.08 |
| Music | 3.85 | 1.94 |
| Laptop | 3.83 | 1.97 |
| Vitamin | 3.61 | 2.14 |
| Sport equipment | 3.19 | 2.07 |
| Cosmetic | 3.16 | 2.03 |
| Meal Kit | 3.12 | 1.99 |
| Washing machine | 3.02 | 2.02 |
| Sweaters | 2.98 | 2.07 |
| Digital camera | 2.92 | 1.98 |
| Coffee machine | 2.90 | 1.99 |
| Wine | 2.80 | 1.87 |
| Oven | 2.69 | 1.87 |

## References

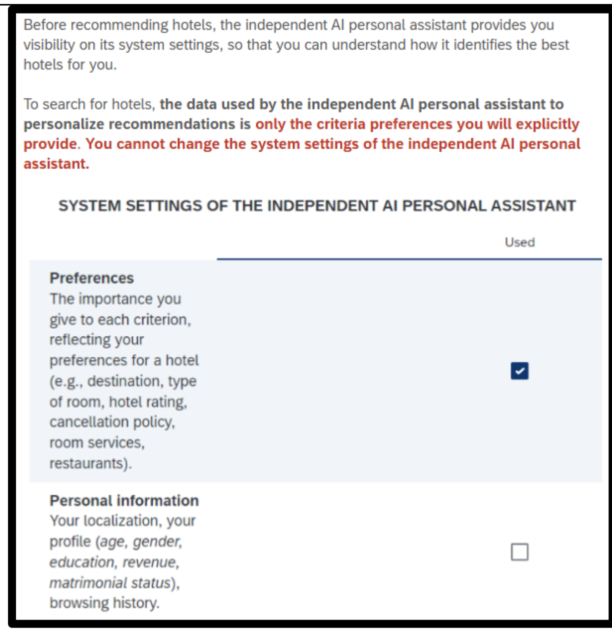
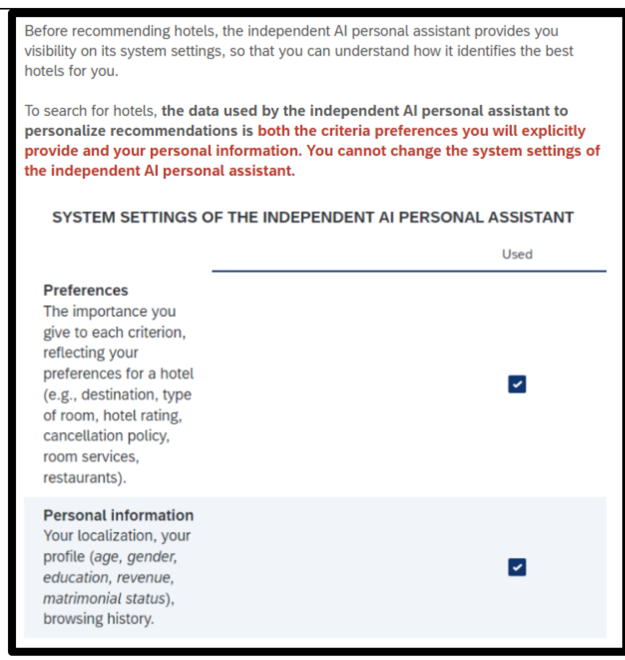
Chellappa, R. K., & Sin, R. G. (2005). Personalization versus Privacy: An Empirical Examination of the Online Consumer's Dilemma. *Information Technology and Management*, *6*(2-3), 181-202. https://doi.org/10.1007/s10799-005-5879-y

*Appendix C.1. Stimuli used in Study 1*

| | |
|---|---|
| ***Condition: Signaling personal data non-use, Non-customized RA system*** | <br>Before we present you with the criteria for identifying your ideal job preferences, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best job offers for you.<br>For searching for job offers, **the data used by the independent AI personal assistant to personalize the recommendation is only the criteria preferences you will explicitly provide. You cannot change the system settings of the independent AI personal assistant.**<br>SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT<br>Used<br>**Preferences**<br>The importance you give to each criterion, reflecting your preferences for the ideal job (e.g., average salary, type of position, remote work or hybrid).<br>**Personal information**<br>Your localization, your profile (*age, gender, education, revenue, matrimonial status*), browsing history. |
| ***Condition: Signaling personal data use, Non-customized RA system*** | <br>Before we present you with the criteria for identifying your ideal job preferences, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best job offers for you.<br>For searching for job offers, **the data used by the independent AI personal assistant to personalize the recommendation is both the criteria preferences you will explicitly provide and your personal information. You cannot change the system settings of the independent AI personal assistant.**<br>SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT<br>Used<br>**Preferences**<br>The importance you give to each criterion, reflecting your preferences for the ideal job (e.g., average salary, type of position, remote work or hybrid).<br>**Personal information**<br>Your localization, your profile (*age, gender, education, revenue, matrimonial status*), browsing history. |

| | |
|---|---|
| ***Condition: Customizable RA system condition, participants decided whether to consent to the use of their personal data*** | Before we present you with the criteria for identifying your ideal job preferences, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best job offers for you.<br><br>For searching for job offers, **you can customize the system settings of the independent AI personal assistant. To do so, you must authorize the use of the information that the independent AI personal assistant may use to generate the recommendations. Please, select the information you want to be used by the independent AI personal assistant to find you job offers.**<br><br>SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT<br><br>Used<br>**Preferences** The importance you give to each criterion, reflecting your preferences for the ideal job (e.g., average salary, type of position, remote work or hybrid). ☐<br>**Personal information** Your localization, your profile (*age, gender, education, revenue, matrimonial status*), browsing history. ☐ |

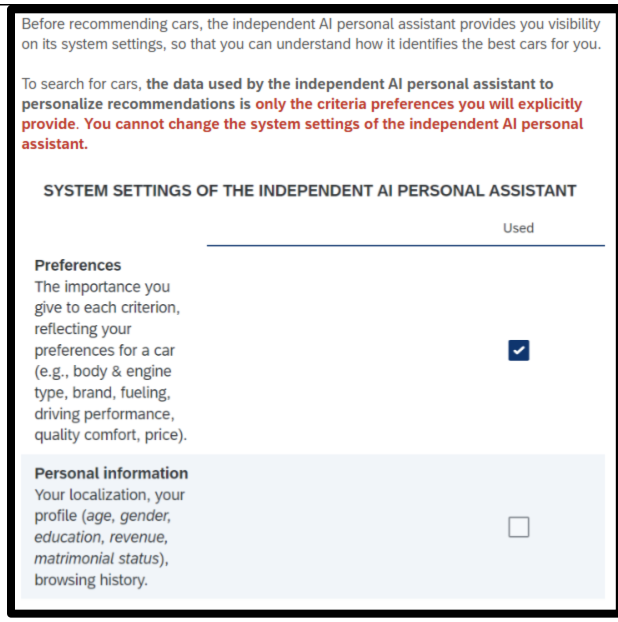
*Appendix C.2. Stimuli used in Studies 2-3*

<table>
<tr>
<td>Condition: Signaling personal data non-use, Non-customized RA system</td>
<td>
Before recommending hotels, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best hotels for you.<br><br>
To search for hotels, the data used by the independent AI personal assistant to personalize recommendations is only the criteria preferences you will explicitly provide. You cannot change the system settings of the independent AI personal assistant.<br><br>
SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT<br>
Used<br>
Preferences The importance you give to each criterion, reflecting your preferences for a hotel (e.g., destination, type of room, hotel rating, cancellation policy, room services, restaurants). ☑<br>
Personal information Your localization, your profile (age, gender, education, revenue, matrimonial status), browsing history. ☐</td>
</tr>
<tr>
<td>Condition: Signaling personal data use, Non-customized RA system</td>
<td>
Before recommending hotels, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best hotels for you.<br><br>
To search for hotels, the data used by the independent AI personal assistant to personalize recommendations is both the criteria preferences you will explicitly provide and your personal information. You cannot change the system settings of the independent AI personal assistant.<br><br>
SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT<br>
Used<br>
Preferences The importance you give to each criterion, reflecting your preferences for a hotel (e.g., destination, type of room, hotel rating, cancellation policy, room services, restaurants). ☑<br>
Personal information Your localization, your profile (age, gender, education, revenue, matrimonial status), browsing history. ☑</td>
</tr>
</table>

<table>
<tr>
<td>Condition: Customizable RA system condition, participants decided whether to consent to the use of their personal data</td>
<td>
Before recommending hotels, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best hotels for you.
To search for hotels, you can customize the system settings of the independent AI personal assistant. To do so, you must authorize the use of the information that the independent AI personal assistant may use to generate recommendations. Please, select the information you want to be used by the independent AI personal assistant to recommend you hotels.
SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT
<table>
<tr><th></th><th>Used</th></tr>
<tr><td>Preferences<br>The importance you give to each criterion, reflecting your preferences for a hotel (e.g., destination, type of room, hotel rating, cancellation policy, room services, restaurants).</td><td>☐</td></tr>
<tr><td>Personal information<br>Your localization, your profile (age, gender, education, revenue, matrimonial status), browsing history.</td><td>☐</td></tr>
</table>
</td>
</tr>
</table>

*Appendix C.3. Stimuli used in Study 4*

***Condition: Signaling personal data non-use, Non-customized RA system***

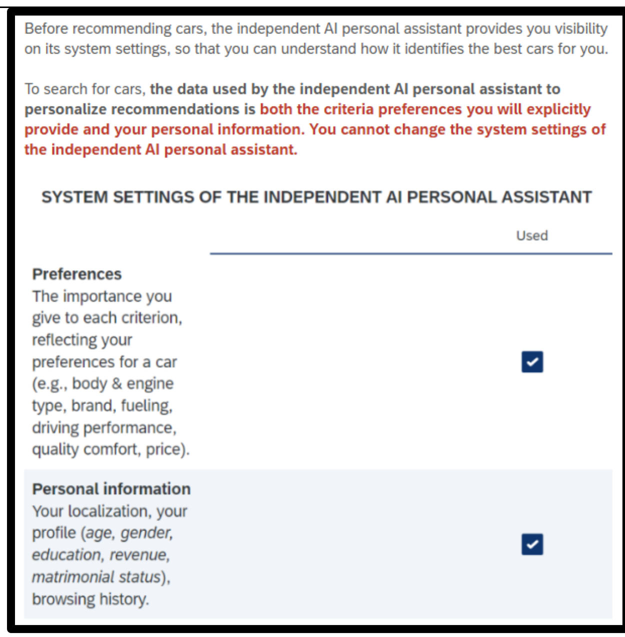

Before recommending cars, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best cars for you.

To search for cars, **the data used by the independent AI personal assistant to personalize recommendations is only the criteria preferences you will explicitly provide. You cannot change the system settings of the independent AI personal assistant.**

SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT

| | Used |
|---|---|
| **Preferences**<br>The importance you give to each criterion, reflecting your preferences for a car (e.g., body & engine type, brand, fueling, driving performance, quality comfort, price). | ☑ |
| **Personal information**<br>Your localization, your profile (*age, gender, education, revenue, matrimonial status*), browsing history. | ☐ |

***Condition: Signaling personal data use, Non-customized RA system***

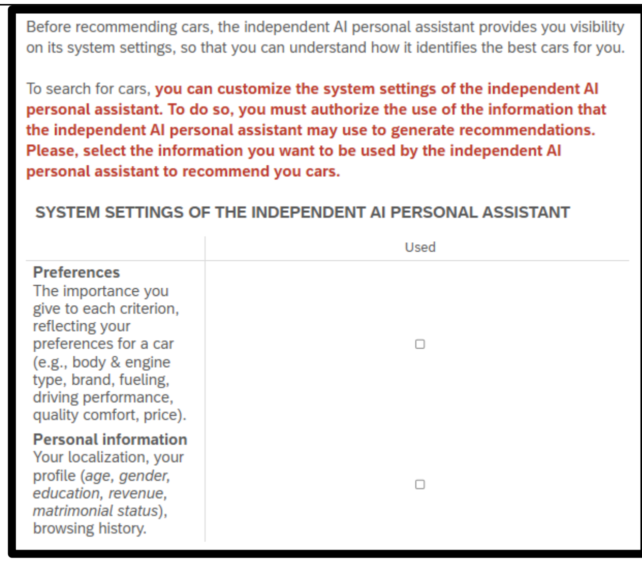

Before recommending cars, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best cars for you.

To search for cars, **the data used by the independent AI personal assistant to personalize recommendations is both the criteria preferences you will explicitly provide and your personal information. You cannot change the system settings of the independent AI personal assistant.**

SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT

| | Used |
|---|---|
| **Preferences**<br>The importance you give to each criterion, reflecting your preferences for a car (e.g., body & engine type, brand, fueling, driving performance, quality comfort, price). | ☑ |
| **Personal information**<br>Your localization, your profile (*age, gender, education, revenue, matrimonial status*), browsing history. | ☑ |

***Condition: Customizable RA system condition, participants decided whether to consent to the use of their personal data***



Before recommending cars, the independent AI personal assistant provides you visibility on its system settings, so that you can understand how it identifies the best cars for you.

To search for cars, **you can customize the system settings of the independent AI personal assistant. To do so, you must authorize the use of the information that the independent AI personal assistant may use to generate recommendations. Please, select the information you want to be used by the independent AI personal assistant to recommend you cars.**

SYSTEM SETTINGS OF THE INDEPENDENT AI PERSONAL ASSISTANT

| | Used |
|---|---|
| **Preferences** The importance you give to each criterion, reflecting your preferences for a car (e.g., body & engine type, brand, fueling, driving performance, quality comfort, price). | ☐ |
| **Personal information** Your localization, your profile (*age, gender, education, revenue, matrimonial status*), browsing history. | ☐ |

***Appendix D.1. Selection bias tests for Study 1***

In the RA customizability condition, we test whether there were any participants' characteristics, such as age, gender, and education, that could have impacted the decision to provide or withhold their personal data. Thus, we selected only participants in the customizable system setting condition to perform tests (n=109).

Results of a binomial logistic regression with signaling personal data usage by the RA system (use vs. non-use) as the dependent variable and age as the independent variable revealed a non-significant effect ($b$ = -.023, SE = .014, $p$ = .095). Moreover, a Chi-square test revealed a non-significant effect of signaling personal data usage by the RA system (use vs. non-use) on education ($\chi^2(2, N = [109]) = 5.338$, $p$ =.069), on women ($\chi^2(1, N = [109]) = .092$, $p$ = .762), and on men ($\chi^2(1, N = [109]) = .014$, $p$ = .907). A Fisher's Exact Test also revealed a non-significant effect of signaling personal data usage on other genders than men and women ($p$ =1). Thus, in Study 1, there is no evidence of selection bias based on age, gender (women, men, other), and education (less than high school degree (1), high school/GED degree (2), bachelor's degree (3), and graduate degree (4)).

### ***Appendix D.2. Selection bias tests for Study 2***

As in Study 1, we selected only participants in the customizable system setting condition to perform tests (n=199). Results of a binomial regression with signaling personal data usage by the RA system (use vs. non-use) as the dependent variable and age as an independent variable revealed a non-significant effect ($b$ = -.025, SE = .013, $p$ = .055). Moreover, a Chi-square test revealed a non-significant effect of the signaling personal data usage condition (use vs. non-use) on education ($\chi^2(2, N = [199]) = 5.751$, $p$ =.056), on women ($\chi^2(1, N = [199]) = 2.095$, $p$ = .148), and on men ($\chi^2(1, N = [199]) =$ 2.433, $p$ = .119). A Fisher's Exact Test also revealed a non-significant effect of signaling personal data usage on other genders than men and women ($p$ =.666). Again, there is no evidence of selection bias.

***Appendix D.3. Selection bias tests for Study 3***

In the customizable RA system condition, we test if there were any participants' characteristics, such as age, gender, and education, that could have impacted the decision to provide or withhold their personal data to the RA. Additionally, in Study 3, we tested whether participants came from California, since this state has implemented privacy data regulations (i.e., California Privacy Rights Act (CPRA)). Thus, we selected only participants in the customizable system condition to perform tests (n=222).

Results of a binomial regression with signaling personal data usage by the RA system (use vs. non-use) as the dependent variable and age as the independent variable revealed a non-significant effect ($b$ = -.007, SE = .012, $p$ = .545). Moreover, a Chi-square test revealed a non-significant effect of the signaling personal data usage condition (use vs. non-use) on education ($\chi^2(3, N = [222])) = .799, p =.850$), on women ($\chi^2(1, N = [222]) = 2.23, p = .135$), and on men ($\chi^2(1, N = [222]) = 2.904, p = .088$). A Fisher's Exact Test also revealed a non-significant effect of signaling personal data usage on other genders than men and women ($p$ =.53). Whether they are based in California or not ($\chi^2(1, N = [222]) \leq .001, p = .1$) and experience a data breach in the past ($\chi^2(1, N = [222]) = 1.568, p =.211$) didn't have any significant effect also. Thus, there is no evidence that consumers' characteristics could have an impact on the results of this study.

In this study, in addition to testing for additional variables that might lead to selection bias in the customizable RA system condition (i.e., whether participants have experienced a data breach with a company in the past), we also test for the selection bias for participants in the non-customizable RA system condition, since they were unable to change the data used. Therefore, we want to check, for the non-customizable condition, whether the proportion of participants who would or would not have provided their personal data would have been the same if these participants had had the choice to customize the RA system settings. Thus, we selected only participants in the non-customized RA system condition (n=160). A Chi-square test revealed a non-significant effect of the data used by the RA when the system imposed it compared to which data participants would have deliberately provided to the RA ($\chi^2(1, N = [152])$), $p = .6965$). Thus, the proportion of participants who would have provided their personal data or not would have been the same, regardless of whether it was imposed or voluntary.

***Appendix D.4. Selection bias tests for Study 4***

In the customizable RA system condition, we test if there were any participants' characteristics, such as age, gender, education, and whether they live in California or not, that could have impacted their decision to provide or withhold their personal data. Thus, we selected only participants in the customizable system condition to perform tests (n=271).

Results of a binomial regression with signaling personal data usage by the RA system (use vs. non-use) as the dependent variable and age as the independent variable revealed a non-significant effect ($b$ = .012, SE = .009, $p$ = .218). Moreover, a Chi-square test revealed a non-significant effect of the signaling personal data condition (use vs. non-use) on education ($\chi^2(2, N = [271])$ ) = .772, $p$ =.680), on women ($\chi^2(1, N = [271])$ = 2.211, $p$ = .137), and on men ($\chi^2(1, N = [271])$ = 3.219, $p$ = .0728). A Fisher's Exact Test also revealed a non-significant effect of signaling personal data usage on other genders than men and women ($p$ =0.274). Whether they are based in California or not ($\chi^2(1, N = [271])$ = .3.40, $p$ = .0652) and experience a data breach in the past ($\chi^2(1, N = [271])$ = .226, $p$ =.635) didn't have any significant effect also. Thus, there is no evidence that consumers' characteristics could have an impact on the results of this study.

Additionally, we selected only participants in the non-customized RA system condition (n=150). A Chi-square test revealed a non-significant effect of the data used by the RA when it was imposed by the system compared to which data participants would have deliberately provided to the RA ($\chi^2(1, N = [146])$) = .005, $p$ = .943). Thus, the proportion of participants who would have provided their personal data or not would have been the same, regardless of whether it was imposed or voluntary.

***Appendix E. Measurement scale and reliability score per study***

*Table 15. Measurement scale and reliability score per study*

| Constructs | Items | Reliability score |
|---|---|---|
| **Study 1** | | |
| *Intention to adopt the RA*, three items adapted from Komiak and Benbasat (2006). | I'm ready to use this RA personal assistant as a search aid | α = .973 |
| | I am willing to let this RA personal assistant assist me in searching online | |
| | I am willing to use this RA personal assistant as a tool to suggest a number of offerings<br><br>(1= Strongly disagree; 7 = strongly agree) | |
| Willingness to pay for the RA | Knowing that you can use this independent RA personal assistant for many types of searches (e.g., products, services, jobs), how much would you be willing to pay annually for it if it becomes a paid service?<br><br>($1 to $100 slider scale) | |
| *Privacy values*, 10 items adapted from the User Privacy Values Scale (Earp et al., 2005) | I mind when a Web site uses my personal information to personalize my browsing experience. | α = .875 |
| | I mind when a Web site uses cookies to personalize my browsing experience (A cookie is information that a Web site puts on your hard disk so that it can remember something about you at a later time). | |
| | I mind when a Web site uses my purchasing history to personalize my browsing experience. | |
| | I mind when my personal information is used for marketing or research activities. | |
| | I mind when a Web site monitors my purchasing patterns. | |
| | I want the option to decide how my personal information is used. | |
| | I want a Web site to disclose how my personal information will be used. | |

| | | |
|---|---|---|
| | I want a Web site to inform me before using my personal information in a manner that it had not previously disclosed to me. | |
| | I want a Web site to allow me to check my personal information for accuracy. | |
| | I want a Web site to allow me to modify my personal information.<br><br>(1= Strongly disagree; 7 = strongly agree) | |
| **Study 2** | | |
| Intention to adopt the RA | Same as in Study 1. | α = .961 |
| Willingness to pay for the RA | Same as in Study 1. | |
| Privacy values | Same as in Study 1. | α = .885 |
| *Trust in the RA*, nine items from Komiak and Benbasat (2006). | The RA personal assistant is like a real expert in assessing products and services | α = .943 |
| | The RA personal assistant has the expertise to understand my needs and preferences | |
| | The RA personal assistant has the ability to understand my needs and preferences | |
| | The RA personal assistant puts my interest first | |
| | The RA personal assistant keeps my interests in its mind | |
| | The RA personal assistant wants to understand my needs and preferences | |
| | The RA personal assistant provides unbiased product recommendations | |
| | The RA personal assistant is honest | |
| | I Consider the RA personal assistant to be of integrity | |
| **Study 3** | | |
| Intention to adopt the RA | Same as in Study 1. | α = .943 |
| Willingness to pay for the RA | Same as in Study 1. | |
| Privacy values | Same as in Study 1. | α = .885 |
| Trust in the RA | Same as in Study 2. | α = .936 |
| *Privacy concerns*, three items from Dinev and Hart (2006). | I am concerned that the information I submit to the RA personal assistant could be misused. | α = .927 |
| | I am concerned about providing personal information to the RA personal assistant, because of what others might do with it. | |
| | I am concerned about providing personal information to the RA personal assistant, because it could be used in a way I did not foresee. | |

| | | |
|---|---|---|
| | (1= Strongly disagree; 7 = strongly agree) | |
| **Study 4** | | |
| Intention to adopt the RA | Same as in Study 1. | α = .95 |
| Willingness to pay for the RA | Same as in Study 1. | |
| Trust in the RA | | α = .921 |
| Privacy values | Same as in Study 1. | α = .853 |
| Privacy concerns | Same as in Study 4. | α = .938 |
| *Privacy fatigue*, three items from Choi et al., (2018). | I have become less interested in online privacy issues. | α = .731 |
| | I have become less enthusiastic in protecting personal information like the one provided to the RA personal assistant. | |
| | I doubt the significance of online privacy issues more often.<br><br>(1= Strongly disagree; 7 = strongly agree) | |

***Appendix F. Results of the full models executed in Study 1***

***Testing for H1a*.**

A Type III GLM was performed with signaling personal data usage by the RA (use vs. non-use) as the independent variable, and consumers' intention to adopt the RA as the dependent variable. We also included in the model RA system customizability, gender, education, age, and privacy values. Results revealed a non-significant main effect of personal data usage by the RA on intention to adopt ($F(1, 214) = 0.057$, $p = 0.811$, $\eta^2 = 0.003$) while controlling for RA system customizability ($F(1, 214) = .017$, $p = 0.895$, $\eta^2 \leq .001$), age ($F(1, 214) = 1.881$, $p = .172$, $\eta^2 = 0.007$), education ($F(1, 214) = 4.542$, $p = .034$, $\eta^2 = .02$), gender ($F_{other}(1, 214) = 3.105$, $p = .079$, $\eta^2 = .02$; $F_{man}(1, 214) = 2.724$, $p = .100$, $\eta^2 = .02$) and privacy values ($F(1, 214) = 5.661$, $p = .034$, $\eta^2 = .03$).

***Testing for H1b.***

A binomial logistic regression was performed, modeling the probability of being willing to pay (i.e., WTP > \$0 (n=172) vs. WTP = \$0 (n=50)) as the dependent variable, and signaling personal data usage by the RA (use vs. non-use) as the independent variable. We also included in the model RA system customizability, gender, education, age, and privacy values. Results revealed a non-significant main effect of personal data usage on the probability of being willing to pay for the RA service ($F(1, 214) = .022$, $p = 0.881$, $\eta^2 = .002$) while controlling for RA system customizability ($F(1, 214) = .000$, $p = 0.992$, $\eta^2 \leq .001$), age ($F(1, 214) = .370$, $p = .543$, $\eta^2 = 0.002$), education ($F(1, 214) = 7.899$, $p = .005$, $\eta^2 = .03$), gender ($F_{other}(1, 214) = 2.410$, $p = .122$, $\eta^2 = .02$; $F_{man}(1, 214) = .000$, $p = .992$, $\eta^2 \leq .001$) and privacy values ($F(1, 214) = 1.133$, $p = .288$, $\eta^2 = .005$).

Among those willing to pay for the RA service (n=172), a Type III GLM was performed, modeling the actual amount participants were willing to pay (from \$1 to \$100) as the dependent variable, and signaling personal data usage by the RA (use vs. non-use) as the independent variable. We also included in the model RA system customizability, gender, education, age, and privacy values. Results revealed a non-significant main effect of personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 164) = 0.230$, $p = 0.632$, $\eta^2 = 0.001$), ) while controlling for RA system customizability ($F(1, 164) = 1.498$, $p = 0.223$, $\eta^2 = .010$), age ($F(1, 164) = .133$, $p = .715$, $\eta^2 = 0.001$), education ($F(1, 164) = 1.192$, $p = .715$, $\eta^2 = .006$), gender ($F_{other}(1, 164) = 3.286$, $p = .072$, $\eta^2 = .020$; $F_{man}(1, 164) = .931$, $p = .336$, $\eta^2 = .003$) and privacy values ($F(1, 164) = .704$, $p = .403$, $\eta^2 = .004$).

***Testing for H2a.***

A Type III GLM was conducted, with the intention to adopt the RA as the dependent variable, and signaling personal data usage by the RA and RA system customizability as the independent variables. We also included in the model gender, education, age, and privacy values. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' intention to adopt it ($F$ (1, 213) = 12.614, $p \leq .001$, $\eta^2 = 0.06$) (See Figure 2), while controlling for participant's privacy values ($F$ (1, 213) = 4.073, $p = 0.045$, $\eta^2 = 0.03$), participants' age ($F(1, 213) = 2.934$, $p = 0.088$, $\eta^2 = 0.0079$), gender, ($F_{\text{other}}$ (1, 213) = 3.671, $p = 0.057$, $\eta^2 = 0.020$), ($F_{man}$ (1, 213) = 2.823, $p = 0.094$, $\eta^2 = 0.02$) and education ($F$ (1, 213) = 4.356, $p = 0.038$, $\eta^2 = 0.02$).

***Testing for H2b.***

A binomial logistic regression was conducted, modeling the probability of being willing to pay (i.e., WTP > $0 (n=172) vs WTP = $0 (n=50)) as the dependent variable, and signaling personal data usage by the RA and RA system customizability as independent variables. We also included in the model gender, education, age, and privacy values. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F$(1, 213) = 8.780, $p$ = .003, $\eta^2$ = .04), while controlling for participant's privacy values ($F$ (1, 213) = .630, $p$ = .428, $\eta^2$ = .006), participants' age ($F$(1, 213) = .858, $p$ = .355, $\eta^2$ = .002), gender, ($F_{\text{other}}$ (1, 213) = 2.782, $p$ = .097, $\eta^2$ = .02), ($F_{man}$ (1, 213) = .004, $p$ = .950, $\eta^2 \leq .001$), and education ($F$ (1, 213) = 8.044, $p$ = .005, $\eta^2$ = .04).

A Type III GLM was conducted, modeling the actual amount participants were willing to pay (from $1 to $100) as the dependent variable, and signaling personal data usage by the RA and RA system customizability as the independent variables. We also included in the model gender, education, age, and privacy values. Results indicate a non-significant interaction effect between personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F$ (1, 163) = 1.941, $p$ = .165, $\eta^2$ = .01), while controlling for participant's privacy values ($F$ (1, 163) = 0.605, $p$ = .438, $\eta^2$ = .004), participants' age ($F$(1, 163) = .247, $p$ = .620, $\eta^2$ = .001), gender, ($F_{\text{other}}$ (1, 163) = 2.768, $p$ = .098, $\eta^2$ = .02), ($F_{man}$ (1, 163) = .856, $p$ = .356, $\eta^2$ = .003) and education ($F$ (1, 163) = 1.081, $p$ = .300, $\eta^2$ = .006).

***Appendix G. Results of the full models executed in Study 2***

***Testing for H1a*.**

A Type III GLM was performed with signaling personal data usage by the RA (use vs. non-use) as the independent variable, and consumers' intention to adopt the RA as the dependent variable. We also included in the model RA system customizability, gender, education, age, and privacy values. Results revealed a non-significant main effect of personal data usage by the RA on intention to adopt ($F(1, 333) = 1.532$, $p = .217$, $\eta^2 = 0.009$), while controlling for RA system customizability ($F(1, 333) = .737$, $p = .391$, $\eta^2 =.004$), age ($F(1, 333) = .636$, $p =.426$, $\eta^2 \leq .001$), education ($F(1, 333) = .737$, $p = .391$, $\eta^2 = .003$), gender ($F_{other}(1, 333) = 1.079$, $p = .3$, $\eta^2 = .006$; $F_{man}(1, 333) = 1.311$, $p = .253$, $\eta^2 = .006$) and privacy values ($F(1, 333) = 12.23$, $p \leq .001$, $\eta^2 = .04$).

***Testing for H1b.***

A binomial logistic regression was performed, modeling the probability of being willing to pay (i.e., WTP > \$0 (n=238) vs WTP = \$0 (n=103)) as the dependent variable, and signaling personal data usage by the RA (use vs. non-use) as the independent variable. We also included in the model RA system customizability, gender, education, age, and privacy values. Results revealed a significant main effect of personal data usage on the probability of being willing to pay for the RA service ($F(1, 333) = 15.407$, $p \leq .001$, $\eta^2 =.05$), while controlling for RA system customizability ($F(1, 333) = .227$, $p = .634$, $\eta^2 \leq .001$), age ($F(1, 333) = .183$, $p =.669$, $\eta^2 = .001$), education ($F(1, 333) = 2.37$, $p = .125$, $\eta^2 = .007$), gender ($F_{other}(1, 333) = 3.342$, $p = .068$, $\eta^2 = .01$; $F_{man}(1, 333) = 5.064$, $p = .025$, $\eta^2 = .01$) and privacy values ($F(1, 333) = 3.752$, $p = .054$, $\eta^2 = .01$).

Among those willing to pay for the RA service (n=238), we conducted a type III GLM modeling the actual amount participants were willing to pay (from \$1 to \$100) as the dependent variable, and signaling personal data usage by the RA (use vs. non-use) as the independent variable. We also included in the model RA system customizability, gender, education, age, and privacy values. Results revealed a non-significant main effect of personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 230) = 1.881$, $p = .172$, $\eta^2 = .01$), while controlling for RA system customizability ($F(1, 230) = .132$, $p = .717$, $\eta^2 \leq .001$), age ($F(1, 230) = .187$, $p =.666$, $\eta^2 = .001$), education ($F(1, 230) = 1.348$, $p = .247$, $\eta^2 = .007$), gender ($F_{other}(1, 230) = .319$, $p = .573$, $\eta^2 = .001$; $F_{man}(1, 230) = 5.328$ $p = .022$, $\eta^2 = .02$) and privacy values ($F(1, 230) = .038$, $p = .846$, $\eta^2 \leq .001$).

***Testing for H2a.***

A Type III GLM was conducted using signaling personal data usage by the RA and RA system customizability as independent variables, and intention to adopt as the dependent variable. We used participants' privacy values, age, gender, and education as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' intention to adopt it ($F$ $(1, 332) = 16.110$, $p \leq .001$, $\eta^2 = .05$), while controlling for participant's privacy values ($F$ $(1, 332) = 11.232$, $p \leq .001 \eta^2 = .04$), participants' age ($F(1, 332) = 1.216$, $p = .271$, $\eta^2 \leq .001$), gender, ($F_{\text{other}}$ $(1, 332) = .823$, $p = .365$, $\eta^2 = .006$), ($F_{man}$ $(1, 332) = .988$, $p = .321$, $\eta^2 = .007$) and education ($F$ $(1, 332) = .211$, $p = .647$, $\eta^2 = .003$).

***Testing for H2b.***

A binomial logistic regression was performed, modeling the probability of being willing to pay (i.e., WTP > \$0 (n=238) vs WTP = \$0 (n=103)) as the dependent variable, and signaling personal data usage and RA system customizability as independent variables. We also included in the model gender, education, age, and privacy values. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F$(1, 332) = 8.176, $p$ = .004, $\eta^2$ = .02), while controlling for participant's privacy values ($F$ (1, 332) = 3.347, $p$ = .068, $\eta^2$ = .01), participants' age ($F$(1, 332) = .069, $p$ = .793, $\eta^2$ = .001), gender, ($F_{\text{other}}$ (1, 332) = 3.09, $p$ = .08, $\eta^2$ = .01), ($F_{man}$ (1, 332) = 5.653, $p$ = .018, $\eta^2$ = .01) and education ($F$ (1, 332) = 1.611, $p$ = .205, $\eta^2$ = .007).

A Type III GLM was performed, modeling the actual amount participants were willing to pay (from \$1 to \$100) as the dependent variable, and signaling personal data usage and RA system customizability as the independent variables. We also included in the model gender, education, age, and privacy values. Results indicate a non-significant interaction effect between personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F$ (1, 229) = 1.249, $p$ = .265, $\eta^2$ = .005), while controlling for participant's privacy values ($F$ (1, 229) = .053, $p$ = .818, $\eta^2$ $\leq$.0001), participants' age ($F$(1, 229) = .284, $p$ = .595, $\eta^2$ = .001), gender, ($F_{\text{other}}$ (1, 229) = .288, $p$ = .592, $\eta^2$ = .001), ($F_{man}$ (1, 229) = 5.016, $p$ = .026, $\eta^2$ = .02) and education ($F$ (1, 229) = 1.065, $p$ = .303, $\eta^2$ = .007).

***Testing for H3.***

We tested the moderated mediated impact of trust to explain the effect of signaling personal data usage. Specifically, when the RA system is customizable, signaling the use of consumers' personal data will lead to higher trust in the RA system compared to when signaling the non-use of personal data, which in turn increases consumers' intention to adopt it, probability of being willing to pay for it, and the actual amount they are willing to pay for it also. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on trust toward the RA ($\beta$ = .857, $t$=3.237, $p$ = .001), while controlling for privacy values ($\beta$ = .862, $t$= 3.2, $p$ = .002), participants' age ($\beta$= -.003, $t$= -0.601, $p$ = .548), gender ($\beta_{other}$ = -.918, $t$ = -1.841, $p$ = .067) ($\beta_{man}$ = -.073, $t$ = -.54, $p$ = .590) and education ($\beta$ = .06, $t$ = .740, $p$ = .460).

***Appendix H. Results of the full models executed in Study 3***

***Testing for H1a***.

A Type III GLM was performed with signaling personal data usage by the RA (use vs. non-use) as the independent variable, and consumers' intention to adopt the RA as the dependent variable. We also included in the model RA system customizability, gender, education, age, privacy values, whether they experienced a data breach in the past (yes vs no), and whether they come from California (yes vs no). Results revealed a non-significant main effect of personal data usage by the RA on intention to adopt ($F$(1, 372) = 2.489, $p$ = .115, $\eta^2$ = .006), while controlling for RA system customizability ($F$(1, 372) = .258, $p$ = .612, $\eta^2$ = .002), participant's privacy values ($F$ (1, 372) = 0.005, $p$ = .946, $\eta^2$ ≤ .001), participants' age ($F$(1, 372) = 8.032, $p$ = .005, $\eta^2$ = .020), gender, ($F_{\text{other}}$ (1, 372) = .194, $p$ = .66, $\eta^2$ = .002), ($F_{man}$ (1, 372) = 1.803, $p$ = .18, $\eta^2$ = .004), education ($F$ (1, 372) = .464, $p$ = .496, $\eta^2$ ≤ .001), California for state of residency ($F$(1, 372) = .279, $p$ = .598, $\eta^2$ = .001),_and data breach experienced in the past ($F$(1, 372) = 3.5, $p$ = .062, $\eta^2$ = .009).

***Testing for H1b***.

We conducted a binomial logistic regression modeling the probability of being willing to pay (i.e., WTP > $0 (n=303) vs WTP = $0 (n=79)) as the dependent variable and signaling personal data usage by the RA as the independent variable. We also included in the model RA system customizability, gender, education, age, privacy values, the state of California, and data breach. Results revealed a non-significant main effect of personal data usage on the probability of being willing to pay for the RA service ($F(1, 372) = .962$, $p = .327$, $\eta^2 = .004$), while controlling for RA system customizability ($F (1, 372) = 2.063$, $p = .152$, $\eta^2 = .004$), participant's privacy values ($F (1, 372) = 2.757$, $p = .098$, $\eta^2 = .008$), participants' age ($F(1, 372) = .003$, $p = .959$, $\eta^2 \leq .001$), gender, ($F_{\text{other}} (1, 372) = 4.859$, $p = .028$, $\eta^2 = .02$), ($F_{man} (1, 372) = 3.178$, $p = .075$, $\eta^2 = .01$), education ($F (1, 372) = 4.72$, $p = .03$, $\eta^2 = .01$), California for state of residency ($F(1, 372) = .276$, $p = .599$, $\eta^2 = .001$), and data breach experienced in the past ($F(1, 372) = .206$, $p = .65$, $\eta^2 = .001$).

Among those willing to pay for the RA service (n=303), a type III GLM was performed, modeling the actual amount participants were willing to pay (from \$1 to \$100) as the dependent variable, and signaling personal data usage by the RA as the independent variables. We also included in the model RA system customizability, gender, education, age, privacy values, the state of California, and data breach. Results revealed a significant main effect of personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 293) = 6.359$, $p = .012$, $\eta^2 = .03$), while controlling for RA system customizability ($F (1, 293) = 1.194$, $p = .275$, $\eta^2 = .006$), participant's privacy values ($F (1, 293) = 2.536$, $p = .112$, $\eta^2 = .02$), participants' age ($F(1, 293) = .867$, $p = .353$, $\eta^2 \leq .001$), gender, ($F_{\text{other}} (1, 293) = 1.31$, $p = .253$, $\eta^2 = .004$), ($F_{man} (1, 293) = 9.147$, $p = .003$, $\eta^2 = .03$), education ($F (1, 293) = .599$, $p = .44$, $\eta^2 = .005$), California for state of residency ($F(1, 293) = 1.889$, $p = .170$, $\eta^2 = .005$), and data breach experienced in the past ($F(1, 293) = 14.864$, $p \leq .001$, $\eta^2 = .05$).

***Testing for H2a.***

A Type III GLM was conducted with signaling personal data usage by the RA and RA system customizability as the independent variables, and intention to adopt as the dependent variable. We used participants' privacy values, age, gender, education, and whether participants came from California or had experienced a data breach in the past as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' intention to adopt it ($F$ (1, 371) = 7.164, $p$ = .008, $\eta^2$ = 0.02 ), while controlling for participant's privacy values ($F$ (1, 371) = .014, $p$ = .906, $\eta^2 \leq$ .001), participants' age ($F$(1, 371) = 7.910, $p$ = .005, $\eta^2$ = .02), gender, ($F_{\text{other}}$ (1, 371) = .034, $p$ = .854, $\eta^2$ = .002), ($F_{man}$ (1, 371) = 1.339, $p$ = .248, $\eta^2$ = .004), education ($F$ (1, 371) = .512, $p$ = .475, $\eta^2 \leq$ .001), California state ($F$ (1, 371) = .233, $p$ = .629, $\eta^2$ = .001) and data breach ($F$ (1, 371) = 2.91, $p$ = .089, $\eta^2$ = .009).

***Testing for H2b.***

A binomial logistic regression was conducted, modeling the probability of being willing to pay (i.e., WTP > $0 (n=303) vs WTP = $0 (n=79)) as the dependent variable, and signaling personal data usage by the RA and RA system customizability as independent variables. We used participants' privacy values, age, gender, education, and whether participants came from California or had experienced a data breach in the past as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F$(1, 371) = 5.654, $p$ = .018, $\eta^2$ = .01), while controlling for participant's privacy values ($F$ (1, 371) = 2.361, $p$ = .125, $\eta^2$ = .008), participants' age ($F$(1, 371) =

.034, $p = .854$, $\eta^2 \leq .0001$), gender, ($F_{other}$ (1, 371) = 3.919, $p = .049$, $\eta^2 = .02$), ($F_{man}$ (1, 371) = 2.725, $p = .1$, $\eta^2 = .01$) and education ($F$ (1, 371) = 4.887, $p = .028$, $\eta^2 = .01$), California state ($F$ (1, 371) = .218, $p = .641$, $\eta^2 = .001$) and data breach ($F$ (1, 371) = .1, $p = .753$, $\eta^2 = .001$).

A Type III GLM was conducted, modeling the actual amount participants were willing to pay (from $1 to $100) as the dependent variable, and signaling personal data usage by the RA and RA system customizability as the independent variables. We used participants' privacy values, age, gender, education, and whether participants came from California or had experienced a data breach in the past as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F$ (1, 292) = 4.395, $p = .037$, $\eta^2 = .01$), while controlling for participant's privacy values ($F$ (1, 292) = 2.235, $p = .136$, $\eta^2 = .02$), participants' age ($F$(1, 292) = 1.145, $p = .286$, $\eta^2 \leq .001$), gender, ($F_{other}$ (1, 292) = .9, $p = .344$, $\eta^2 = .004$), ($F_{man}$ (1, 292) = 7.535, $p = .006$, $\eta^2 = .04$), education ($F$ (1, 292) = .432, $p = .511$, $\eta^2 = .005$), California state ($F$ (1, 292) = 1.839, $p = .176$, $\eta^2 = .006$) and data breach ($F$ (1, 292) = 14.674, $p \leq .001$, $\eta^2 = .05$).

***Testing for H3-4.***

We tested a moderated mediation model (PROCESS Model 7; Hayes, 2022) with intention to adopt as the dependent variable (vs. WTP), signaling personal data usage by the RA as the independent variable, trust and privacy concerns as mediators, RA system customizability as the moderator and age, privacy values, gender, education, California state and data breach in the past as covariates. Second, we did two other moderated mediations using the same logic, but with (1) the probability of being willing to pay for the RA, and (2) the actual amount they are willing to pay.

Results of a moderated mediation model (PROCESS Model 7; Hayes, 2022) indicate a marginal significant interaction effect between signaling personal data usage by the RA and RA system customizability on trust toward the RA ($\beta$ = .502, $t$ = 1.962, $p$ = .051), while controlling for privacy values ($\beta$ = -.18, $t$= -2.593, $p$ = .01), participants' age ($\beta$= .01, $t$= 1.888, $p$ = .06), gender ($\beta_{other}$ = -.93, $t$ = -1.524, $p$ = .128) ($\beta_{man}$ = .223, $t$ = 1.749, $p$ = .081), education ($\beta$ = .026, $t$ = .305, $p$ = .761), California state residence ($\beta$ = .172, $t$ = .954, $p$ = .341), and prior data breach experience ($\beta$ = .425, $t$ = 3.356, $p \leq .001$).

Results indicated a significant interaction between signaling personal data usage by the RA and RA system customizability on privacy concerns ($\beta$ = –.593, $t$ = –2.266, $p$ = .024), while controlling for privacy values ($\beta$ = .602, $t$ = 8.492, $p \leq .001$), participants' age ($\beta$ = –.016, $t$ = –2.913, $p$ = .004), gender (*other*: $\beta$ = .319, $t$ = .512, $p$ = .609; *man*: $\beta$ = –.051, $t$ = –.392, $p$ = .696), education ($\beta$ = .077, $t$ = .893, $p$ = .372), California state residence ($\beta$ = .068, $t$ = .371, $p$ = .711), and prior data breach experience ($\beta$ = –.261, $t$ = –2.016, $p$ = .045).

*Appendix I. Results of the full models executed in Study 4*

***Testing for H1a.***

A Type III GLM was performed with signaling personal data usage by the RA (use vs. non-use) as the independent variable, and consumers' intention to adopt the RA as the dependent variable. We also included in the model RA system customizability, gender, education, age, privacy values, whether they experienced a data breach in the past (yes vs. no), and whether they come from California (yes vs. no). Results revealed a non-significant main effect of personal data usage by the RA on intention to adopt ($F$(1, 411) = .110, $p$ = .741, $\eta^2 \leq .001$), while controlling for RA system customizability ($F$(1, 411) = .346, $p$ = .557, $\eta^2 \leq .001$), participant's privacy values ($F$ (1, 411) = 0.004, $p$ = .951, $\eta^2 \leq .001$), participants' age ($F$(1, 411) = 9.288, $p$ = .002, $\eta^2 = .020$), gender, ($F_{\text{other}}$ (1, 411) = 16.591, $p \leq .001$, $\eta^2 = .040$), ($F_{man}$ (1, 411) = 4.958, $p$ = .027, $\eta^2 = .010$), education ($F$ (1, 411) = 4.927, $p$ = .027, $\eta^2 \leq .010$), California for state of residency ($F$(1, 411) = .048, $p$ = .827, $\eta^2 \leq .001$), and data breach experienced in the past ($F$(1, 411) = 1.973, $p$ = .161, $\eta^2 = .005$).

***Testing for H1b.***

A binomial logistic regression was conducted, modeling the probability of being willing to pay (i.e., WTP > $0 (n=343) vs WTP = $0 (n=78)) as the dependent variable, and signaling personal data usage by the RA as the independent variable. We also included in the model RA system customizability, gender, education, age, privacy values, the state of California, and data breach. Results revealed a marginal significant main effect of personal data usage on the probability of being willing to pay for the RA service ($F(1, 411) = 3.249$, $p = .072$, $\eta^2 = .010$), while controlling for RA system customizability ($F(1, 411) = .034$, $p = .842$, $\eta^2 \leq .001$), participant's privacy values ($F(1, 411) = 3.591$, $p = .059$, $\eta^2 = 0.010$), participants' age ($F(1, 411) = .103$, $p = .748$, $\eta^2 \leq .001$), gender, ($F_{\text{other}}(1, 411) = 3.962$, $p = .047$, $\eta^2 = .020$), ($F_{man}(1, 411) = .004$, $p = .949$, $\eta^2 \leq .001$), education ($F(1, 411) = .768$, $p = .381$, $\eta^2 = .002$), California for state of residency ($F(1, 411) = .136$, $p = .713$, $\eta^2 \leq .001$), and data breach experienced in the past ($F(1, 411) = .398$, $p = .529$, $\eta^2 = .001$).

Among those willing to pay for the RA service (n=343), a type III GLM was performed, modeling the actual amount participants were willing to pay (from \$1 to \$100) as the dependent variable, and signaling personal data usage by the RA as the independent variable. We also included in the model RA system customizability, gender, education, age, privacy values, the state of California, and data breach. Results revealed a significant main effect of personal data usage by the RA on the amount consumers were willing to pay for the RA service ($F(1, 333) = 7.955$, $p = .005$, $\eta^2 = .030$), while controlling for RA system customizability ($F(1, 333) = 1.312$, $p = .253$, $\eta^2 = .009$), participant's privacy values ($F(1, 333) = 8.446$, $p = .004$, $\eta^2 = .030$), participants' age ($F(1, 333) = 3.360$, $p = .068$, $\eta^2 = .010$), gender, ($F_{\text{other}}(1, 333) = .280$, $p = .597$, $\eta^2 = .002$), ($F_{man}(1, 333) = .030$, $p = .863$, $\eta^2 = .003$), education ($F(1, 333) = 16.380$, $p \leq .001$, $\eta^2 = .040$), California for state of residency ($F(1, 333) = .751$, $p = .387$, $\eta^2 = .002$), and data breach experienced in the past ($F(1, 333) = 6.530$, $p = .011$, $\eta^2 = .020$).

***Testing for H2a.***

A Type III GLM was performed with signaling personal data usage by the RA and RA system customizability as the independent variables, and intention to adopt as the dependent variable. We used participants' privacy values, age, gender, education, and whether participants came from California or experienced a data breach in the past as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' intention to adopt it, $F(1, 410) = 7.775$, $p = .006$, $\eta^2 = .020$, while controlling for participants' privacy values ($F(1, 410) = 0.00$, $p = .997$, $\eta^2 < .001$), participants' age ($F(1, 410) = 9.379$, $p = .002$, $\eta^2 = .030$), gender ($F_{\text{other}}(1, 410) = 16.934$, $p < .001$, $\eta^2 = .040$), ($F_{man}(1, 410) = 4.091$, $p = .044$, $\eta^2 = .010$), education ($F(1, 410) = 5.545$, $p = .019$, $\eta^2 = .010$), California state ($F(1, 410) = 0.00$, $p = .997$, $\eta^2 < .001$), and data breach in the past ($F(1, 410) = 1.977$, $p = .160$, $\eta^2 = .005$).

***Testing for H2b.***

A binomial logistic regression was conducted, modeling the probability of being willing to pay (i.e., WTP > \$0 (n=343) vs WTP = \$0 (n=78)) as the dependent variable, and signaling personal data usage by the RA and RA system customizability as independent variables. We used participants' privacy values, age, gender, education, and whether participants came from California or experienced a data breach in the past as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on consumers' probability of being willing to pay ($F(1, 410) = 3.953$, $p = .048$, $\eta^2 = .009$), while controlling for participants' privacy values ($F(1, 410) = 3.50$, $p = .062$, $\eta^2 = .010$), participants' age ($F(1, 410) = .113$, $p = .737$, $\eta^2 \leq .001$), gender ($F_{\text{other}}(1, 410) = 3.945$, $p = .048$, $\eta^2 = .020$), ($F_{man}(1, 410) = .049$, $p = .825$, $\eta^2 \leq .001$), education ($F(1, 410) = .678$, $p = .411$, $\eta^2 = .002$), California state ($F(1, 410) = .276$, $p = .600$, $\eta^2 \leq .001$), and data breach in the past ($F(1, 410) = .472$, $p = .493$, $\eta^2 = .001$).

A Type III GLM was performed, modeling the actual amount participants were willing to pay (from \$1 to \$100) as the dependent variable, and signaling personal data usage by the RA and RA system customizability as the independent variables. We used participants' privacy values, age, gender, education, and whether participants came from California or had experienced a data breach in the past as control variables. Results indicate a significant interaction effect between personal data usage by the RA and RA system customizability on the actual amount consumers were willing to pay ($F(1, 332) = 7.514$, $p = .007$, $\eta^2 = .020$), while controlling for participants' privacy values ($F(1, 332) = 8.271$, $p = .004$, $\eta^2 = .040$), participants' age ($F(1, 332) = 3.633$, $p = .058$, $\eta^2 = .010$), gender ($F_{\text{other}}(1, 332) = .399$, $p = .528$, $\eta^2 = .002$), ($F_{man}(1, 332) = .003$, $p = .957$, $\eta^2 = .003$), education ($F(1, 332) = 15.268$, $p \leq .001$, $\eta^2 = .040$), California state ($F(1, 332) = 1.135$, $p = .287$, $\eta^2 = .003$), and data breach ($F(1, 332) = 6.690$, $p = .010$, $\eta^2 = 0.020$).

***Testing for H3-4.***

We tested a moderated mediation model (PROCESS Model 7; Hayes, 2022) with intention to adopt as the dependent variable (vs. WTP), signaling personal data usage by the RA as independent variable, trust and privacy concerns as mediators, RA system customizability as the moderator, and age, privacy values, gender, education, California state, and data breach in the past as covariates.

Results indicate a significant interaction effect between signaling personal data usage by the RA and RA system customizability on trust toward the RA ($\beta$ = .526, $t$ = 2.403, $p$ = .017), while controlling for privacy values ($\beta$ = -.129, $t$ = -2.044, $p$ = .042), participants' age ($\beta$ = 0.0130, $t$ = 3.053, $p$ = .002), gender ($\beta_{other}$ = -1.826, $t$ = -4.073, $p$ $\leq$.001) ($\beta_{man}$ = .204, $t$ = 1.895, $p$ = .059), education ($\beta$ = -.1299, $t$ = -1.763, $p$ = .079), California state residence ($\beta$ = -.129, $t$ = -.767, $p$ = .444), and prior data breach experience ($\beta$ = .210, $t$ = 1.957, $p$ = .051).

Results indicated a significant interaction between signaling personal data usage by the RA and RA system customizability on privacy concerns ($\beta$ = –.895, $t$ = –3.258, $p$ = .001), while controlling for privacy values ($\beta$ = .636, $t$ = 8.021, $p \leq$ .001), participants' age ($\beta$ = –.010, $t$ = –1.881, $p$ = .061), gender ($\beta_{other}$ = 1.443, $t$ = 2.568, $p$ = .011; $\beta_{man}$ = –0.009, $t$ = –0.068, $p$ = .946), education ($\beta$ = .155, $t$ = 1.677, $p$ = .094), California state residence ($\beta$ = 0.124, $t$ = .591, $p$ = .555), and prior data breach experience ($\beta$ = –.186, $t$ = –1.386, $p$ = .167).

***Testing for an alternative explanation: privacy fatigue***

We examined the indirect effect of signaling personal data usage by the RA and RA system customizability on consumers' adoption through their level of privacy fatigue, privacy concern, and trust in a PROCESS model (Model 7, 5,000 bootstrap sample; Hayes, 2017). Results suggest a non-significant interaction between signaling personal data usage by the RA and RA system customizability on privacy fatigue ($\beta$ = .232, $t$ =

1.058, $p = .291$), while controlling for privacy values ($\beta = .140$, $t = 2.208$, $p = .028$), whether participants experienced a data breach in the past ($\beta = -.235$, $t = -2.186$, $p = .029$), whether they come from California or not ($\beta = .175$, $t = 1.045$, $p = .297$), participants' age ($\beta = -.019$, $t = -4.563$, $p \leq .001$), gender ($\beta_{other} = .426$, $t = .950$, $p = .343$), ($\beta_{man} = -.187$, $t = -1.735$, $p = .083$), and education ($\beta = .084$, $t = 1.136$, $p = .257$)

HEC MONTRÉAL

Comité d'éthique de la recherche

Le 16 juillet 2025

À l'attention de : Sara-Maude Poirier, (service introuvable), (organisation introuvable)

Cochercheurs : Sara-Maude Poirier; Pierre-Majorique Léger; David Brieugne

**Projet # :** 2023-5067

**Titre du projet :** INFORMATION TRANSPARENCY AND AI RECOMMENDER SYSTEM: A DOUBLE-EDGED SWORD

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Bonjour Sara-Maude Poirier,

Pour donner suite à l'évaluation de votre formulaire F8 - Modification de projet, le CER de HEC Montréal vous informe de sa décision :

Les modifications ont été approuvées et notées au dossier. Le certificat actuel demeure valide jusqu'au prochain renouvellement.

**Date d'approbation du projet :** 26 mai 2022

**Date d'échéance du certificat :** 01 février 2026

En vous remerciant cordialement,

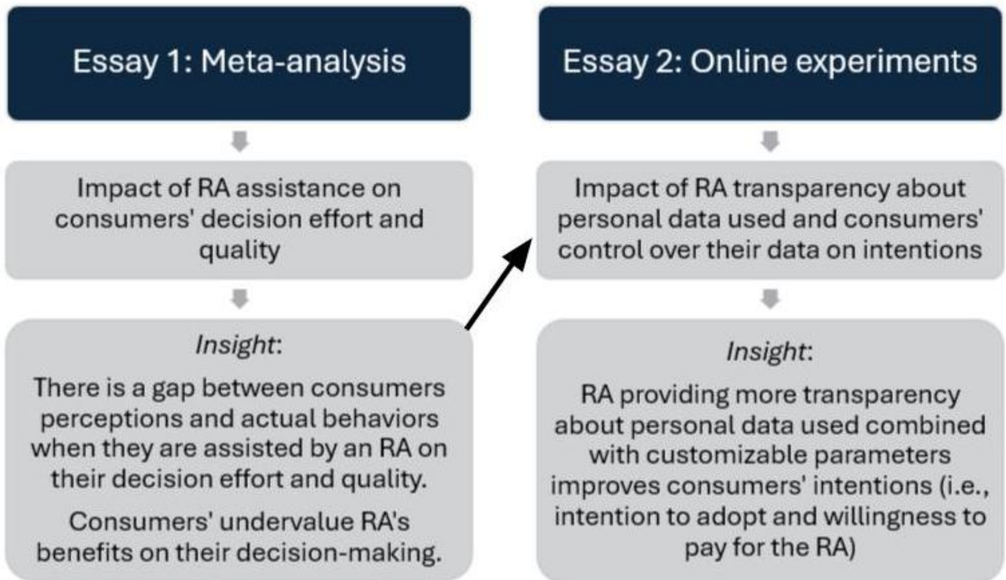
**Le CER de HEC Montréal**

# Conclusion

The premise of this PhD dissertation was that consumers must value RA assistance positively, particularly in terms of decision quality, to provide their personal data more promptly and thereby receive higher personalised recommendations. This is particularly important in a context where privacy legislations around the world (e.g., GDPR in Europe (European Union, 2016), Law 25 in the province of Quebec in Canada (Gouvernement du Québec, 2025) arise to protect individual online privacy. Indeed, more transparency is required from organizations in how they collect, use, and store consumers' personal data. The literature in marketing has shown that transparency can backfire and lead consumers to experience more privacy risk when personal data is used (Bornschein et al., 2020; Lambillotte et al., 2022). Thus, we needed a way to design more responsible and transparent RAs that increase consumers' positive attitude toward these RAs, meaning that they perceived them as of high quality in supporting their decision. Overall, the results of this dissertation combining Essay 1 and Essay 2 allow a comprehension of the state of the art of the impact of RA assistance on perceived and actual decision effort and decision quality, and furnish insights into how to design RA settings that are not only privacy legislation compliant, but also that allow a positive subjective assessment of RA assistance on a retailer website (see Figure 12).

Specifically, to investigate how consumers value RA assistance, we did a meta-analysis in Essay 1 to test the impact of RA assistance (vs. no assistance, vs. human expert/non-expert assistance) on consumers' perceived and actual decision effort and quality. By aggregating 472 effect sizes from 125 studies (embedded into 78 papers)

*Figure 12. Narrative of the PhD dissertation based on the results of Essay 1 and Essay 2*




published from 1999 to 2025, we found that being assisted by an RA (vs. no assistance at all, vs. human assistance) decreases to a greater extent perceived effort compared to actual decision effort and increases to a greater extent actual decision quality compared to perceived decision quality. Thus, consumers tend to undervalue their effort of being assisted by an RA (i.e., perceived that it decreases to a higher extent decision effort than it actually does) and to undervalue the effect of being assisted by an RA on their decision quality (i.e., perceived that it increases to a lesser extent decision quality than it actually does). Results of Essay 1, especially regarding decision quality, were of concern, highlighting the need for retailers to not just invest in the development of a highly accurate system, but also in communicating the beneficial advantages of being assisted by these RAs.

Thus, in Essay 2, we aimed to explore how to enhance consumers' perception of decision quality through an RA by enabling them to act on their data. Specifically, we found that in a context of transparency, where a RA system setting is available to consumers to see which data will be used about them prior to the generation of the recommendation, allowing them to have control over their personal data can positively strengthen how they value the RA assistance, corroborating results from Bornschein et al. (2020). Essay 2 showed that in the presence of customizable parameters, consumers' intentions to adopt the RA and WTP for its service were higher when they agreed to the use of their personal data compared to when they didn't, allowing only the use of their explicit preferences. This effect was explained by a higher level of trust toward the RA in its benevolence, integrity, and competence in processing consumers' personal data. In the absence of customizable parameters, consumers' intentions were higher when the RA only disclosed the use of their task-specific preferences compared to when it combined them with their personal data. In this context, trust did not explain these results, but the activation of privacy concerns was.

A particularity of Essay 2 is that the online experiment manipulation included actual behaviors. In the customizable conditions, participants could select which data they preferred to provide to the RA, leading to their self-assigned participation in the personal data (yes vs. no) condition. While controlling for various selection biases, we examine how actual behaviors influence consumers' perceived quality of the RA system, as measured by the WTP for this service proxy.

Thus, taken together, Essay 1 and Essay 2 provide theoretical contributions on RA assistance and consumers' decision-making. Both essays also provide managerial guidance for operationalizing and designing responsible RAs, while encouraging their adoption and ensuring alignment of interests among firms, consumers, and policymakers (Martin and Palmatier, 2020). Indeed, this PhD dissertation contributes to resolving the mixed findings in the marketing literature regarding how consumers perceive the benefits of using an RA. In turn, we investigate how these perceptions can be enhanced when a transparent RA uses their personal data. In line with past research showing the negative impact of the lack of personal data on RA accuracy and recommendation diversity (Sun et al., 2024), we explore how the highest level of personalisation, achieved through the use of personal data, can be valued by consumers in a service personalised context.

Second, Essay 1 and Essay 2 both contribute to the literature on consumers' perceptual and cognitive biases during decision-making, impacting how they evaluate and respond to RA depending on the available information or contextual elements (e.g., Tsekouras et al., 2022; Xiao & Benbasat, 2018). For instance, the gap found in Essay 1 between consumers' actual decision quality and perceived quality, and also between actual decision effort and perceived decision effort can be strengthened or weakened by other factors, such as the ability by consumers to directly state to the RA their preferences (Ebrahimi et al., 2022), or by the group RA assistance is compared to (Jussupow et al., 2024), whether it is to no assistance at all, or human expert or non-expert assistance. These biases are in line with the Constructive Choice Theory (CCT) (Bettman et al., 1998), suggesting that the shopping context strongly shapes consumers' behaviors and perceptions when interacting with RAs.

In Essay 2, these biases arise especially when customizable parameters for data control purposes are present or absent (Bornschein et al., 2020; Zhang & Sundar, 2019). In line with Signaling Theory (Spence, 1973; 2002), when transparency about personal data used is paired with customizable parameters, it becomes a positive signal for consumers who communicate higher intentions to adopt the RA and WTP for it.

Conversely, when system transparency about personal data used is unaccompanied by customizable parameters, it becomes a negative signal, reducing consumers' intentions to adopt the RA and WTP for it. Control increases consumers' trust in the RA system when it uses their personal data, which in turn explains consumers' positive intentions toward it compared to when it uses only explicit preferences. For its part, when customizable parameters are absent, transparency alone leads consumers to experience more privacy concerns when the RA shows the use of personal data for recommendation generation. For managers, it means that the operationalisation of high-level constructs such as transparency and control should be attentively tested prior to implementation. For policymakers, it also means that they should regulate the implementation of this legislation by providing more guidance, to ensure that retailers do not manipulate consumers into acting in a way that can influence them without their well-informed consent. This is important since the literature on cookie notices has revealed the use of dark patterns from retailers impacting consumers' consent in providing their personal data (Bauer et al., 2021; Burgess, 2020).

This dissertation is not without limitations. First, it mainly focuses on traditional RAs, such as collaborative-filtering RA and content-based RA, with little attention to GenAI agents assisting consumers in their queries. As highlighted in the introduction, interactions between consumers and RAs have shifted significantly with the emergence of GenAI. Moving forward, it will be important to explore not only how consumers value these enhanced RA systems but also how they behave when using them, especially as RAs evolve into personal assistants that operate independently of brands or retailers' websites. For instance, future research should further investigate the notion of trust in RAs, particularly as these systems become increasingly independent actors in online decision-making. Such research should consider contexts beyond retailer-controlled environments, examining how consumers evaluate and interact with autonomous RAs that operate across multiple platforms and are not tied to a single brand or website.

Second, this dissertation considered personal data holistically, focusing on how its use can be perceived as beneficial when it leads to more personalized recommendations. However, such benefits often remain abstract for consumers, making it difficult for them to fully appreciate the value of sharing their data. Future research should therefore investigate how greater transparency regarding the specific use of personal data influences not only the quantity but also the types of data that consumers are willing to share for personalization purposes. Moreover, research should examine how to effectively communicate the distinct benefits of using each data type. For example, highlighting that sharing location data enables the system to recommend products available nearby could help consumers better understand and value the exchange.

Third, this research primarily examines the beneficial effects of RA assistance on consumers' decision-making, focusing on decision effort and accuracy. However, other important outcomes, such as consumers' discovery of new products or retailers through RA use, warrant further exploration. Future studies should also adopt a more collective perspective on RA impact, investigating how these systems can be leveraged to promote sustainable and responsible consumption practices. For example, RAs could be designed to recommend products or services that balance individual consumer preferences with sustainability considerations, thereby encouraging more socially and environmentally conscious decision-making (Satinet et al., 2024).

Finally, this research directly exposed consumers to customizable parameters. In practice, however, some consumers may ignore these settings or experience decision fatigue over time, similar to what has been observed with cookie consent banners. Future research should therefore examine how consumers engage with RA parameters available during navigation (i.e., RA input design) and identify strategies to sustain meaningful interaction. Scholars should explore ways to encourage consumers to actively use these settings, both to increase their awareness of the personal data being collected and to make transparent how RAs influence the content presented to them. This line of inquiry is relevant not only for everyday goods and services but also for high-stakes domains such as news media, financial services, and healthcare, where RA-driven recommendations can significantly shape individuals' choices, knowledge, and behaviors.

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