More Than Meets the Cart

How Online Assortments and the Presence of AI Shape Consumer Wellbeing Across Product Categories

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Submitted

June 4th, 2026

Stockholm School of Economics

Retail Management

Bachelor's Thesis

Abstract

The growth of online retail has exposed consumers to an overwhelming number of options – a condition that may trigger choice overload and its associated psychological costs. This study examines how perceived choice complexity mediates the relationship between choice set size and wellbeing in an online retail context, and tests two proposed mechanisms through which this effect might be strengthened – consumer purchase involvement and AI-assisted recommendations. Using a between-subjects experimental design with six conditions, 593 participants were randomly assigned to evaluate either 24 or 6 product options across two categories: running shoes and t-shirts. The 6-option conditions were presented either with or without AI assistance. Results confirmed that reducing the choice set size from 24 to 6 options significantly lowered perceived choice complexity, and that this reduction fully mediated a positive effect on wellbeing. The effect between choice complexity and wellbeing differed between the two product categories. However, the moderating role of consumer purchase involvement could not be assessed as intended, as respondents did not perceive the two categories as significantly different in involvement. The findings suggest that assortments limiting perceived choice complexity are an effective tool for improving consumer wellbeing in online retail. AI assistance, at least in its current form, offered limited additional benefit, failing to further reduce perceived complexity. Without an incremental reduction in perceived choice complexity, no incremental gain in consumer wellbeing should be expected, with or without AI assistance.

Keywords: wellbeing, choice overload, assortment size, choice complexity, the paradox of choice, online retail, e-commerce, AI assistance

Acknowledgments

We thank our supervisor, *Micael Dahlén*, for his warm kindness and support throughout the writing of this thesis. Emvehå!

We would also like to thank *Magnus Söderlund* for his thoughtfulness and help in conducting this study's experiment. Finally, we would like to express our greatest gratitude to *Henrik Kronberg* and *Henrik Åquist* at *Norstat* for helping us distribute our experiment through their online panel.

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1. Introduction

How does the size of an online assortment shape consumer wellbeing, and can the assistance of artificial intelligence (AI) soften the cognitive burden that variety imposes? This question has become increasingly relevant as e-commerce continues to expand the number of options consumers face, while retailers invest in AI to manage the complexity that comes with it (Wang et al., 2021; Bawack et al., 2022; Davenport et al., 2020). These two trends expose a tension that consumers encounter daily: the same digital shelves that promise unlimited choice may also undermine the experience of choosing.

The structural shift underpinning this tension is well documented. Over the past two decades, online retail has grown rapidly, transforming both the marketplace and consumers' decision-making environments (Xu et al., 2022). A defining feature of that environment is its ability to offer product variety at a scale physically impossible in brick-and-mortar stores. This variety brings value to the consumer in many ways, but it also introduces complexity (Brynjolfsson et al., 2003; Sethuraman et al., 2022). In particular, online environments have been shown to increase choice difficulty and the likelihood that consumers defer a decision altogether (Wang et al., 2021).

The psychological consequences of this abundance are captured by the paradox of choice: the counterintuitive idea that an increased number of options can reduce, rather than improve, post-choice satisfaction. Beyond a certain threshold, choice no longer empowers consumers but burdens them (Schwartz, 2004, pp.1-6). What is at stake, however, may extend beyond the quality of any single decision. Wellbeing – the degree to which individuals experience their lives positively – is genuinely sensitive to everyday consumer experiences, with even occasional commercial stimuli producing measurable shifts in how well people feel (Diener, 1984; Dahlén et al., 2024). When the cognitive burden of choosing from an excessive assortment erodes how people feel, the consequence may no longer merely be a suboptimal choice (Schwartz, 2004 p.124-130; Iyengar & Lepper, 2000), but perhaps also a measurable decline in their overall wellbeing.

In response to the complexity that scale produces, online retailers have increasingly turned to AI-assisted recommendation systems. By inferring consumer interests from behavioral data, these systems filter, rank, and present products tailored to individual preferences, aiming to reduce the complexity of choice (Davenport et al., 2020; Bawack et al., 2022). Kim et al. (2023) find that consumers do not experience the typical negative effects of choice overload when assortments are generated by AI, attributing this to heightened perceptions of accuracy and personal fit. Nevertheless, Rohden and Espartel (2024) state that AI-assisted decisions can in fact be perceived as more uncertain than those made unaided, as consumers feel choices have been made *for* them rather than *by* them. Whether AI assistance meaningfully improves the consumer experience, then, remains an open empirical question.

From a theoretical perspective, choice overload research has developed a nuanced understanding of how assortment size, choice complexity, and individual differences interact to shape decision outcomes (Chernev et al., 2015; Iyengar & Lepper, 2000; Scheibehenne et al., 2010). Yet notable gaps remain. First, although choice overload is typically framed in terms of cognitive burden and post-choice satisfaction, comparatively little research has examined its downstream consequences for the broader construct of wellbeing. Second, while AI-assisted decision-making is rapidly reshaping the online retail environment, empirical evidence on whether it mitigates the psychological costs of large assortments remains limited and conflicting (Kim et al., 2023; Rohden & Espartel, 2024). Third, the role of product category – and its associated level of consumer purchase involvement – in moderating these effects is theoretically grounded (Zaichkowsky, 1994) but rarely tested in the context of online choice overload and wellbeing.

To address these gaps, this study employs a between-subjects 2×3 online experiment in which 593 participants evaluated either a large or reduced set of products across two product categories. Reduced-set conditions were presented either with or without AI assistance. Perceived choice complexity, wellbeing, and related constructs were measured using validated multi-item scales, enabling the study to test the direct effect of assortment size on wellbeing, the mediating role of perceived choice complexity, and the moderating roles of AI assistance and product category. In addition, the study explores how choice set size relates to purchase intention as a commercially relevant outcome, addressing the mixed evidence on whether larger assortments help or hinder consumers' willingness to buy.

The remainder of the thesis is structured as follows. Section 2 integrates prior research on online retail, choice overload, wellbeing, consumer purchase involvement, and AI-assisted decision-making to develop the hypotheses. Section 3 outlines the methodology, including the research approach, pretest, main experiment, measures, and data collection procedure. Section 4 reports the empirical results of the main study. Finally, section 5 discusses the empirical findings in light of the study's purpose, outlines contributions and practical implications, and highlights limitations and directions for future research.

1.1 Purpose

This study examines how choice set size affects wellbeing in an online retail context, and whether perceived choice complexity mediates this relationship. Additionally, the study tests whether product category and AI-assisted recommendations moderate these effects. Through this, the study contributes to existing choice overload literature by expanding the set of outcomes examined beyond cognitive burden to broader consumer wellbeing. As a complementary exploratory aim, the study also examines how choice set size relates to purchase intention as a commercially relevant outcome. The purpose is addressed through an experimental research design.

2. Theory and Hypotheses Development

2.1 The Current State of Online Retail

E-commerce refers to the buying and selling of products and services over the internet. Firms are increasingly engaging in e-commerce in response to growing consumer demand for online services and its potential to generate a competitive advantage (Bawack et al., 2022).

As demonstrated by Xu et al. (2022), the retail landscape has undergone a profound transformation over the past two decades, driven primarily by the rapid expansion of e-commerce as a dominant commercial force. The shift from physical to digital shopping has fundamentally altered the nature of the marketplace and consumers' decision-making environment. The authors further note that, unlike offline shopping where consumers can physically inspect products, online retail requires purchase decisions to be made on the basis of images and text descriptions, creating an inherently different decision-making experience.

A defining feature of the environment of electronic markets is their capacity to offer product variety at a scale physically impossible for brick-and-mortar stores (Brynjolfsson et al., 2003). Brynjolfsson et al. (2003) further demonstrate how the increased online product variety generates consumer welfare gains, an early illustration of just how significant the variety dimension of e-commerce is.

At the same time, the same expansion of variety that creates value for consumers also introduces complexity (Sethuraman et al., 2022). These effects are especially prominent online, where wider choice sets increase consumers' choice difficulty and likelihood of deferring a decision (Wang et al., 2021). As such, the structural advantage of online retail in terms of its virtually unlimited shelf space simultaneously creates conditions that may undermine the quality of the consumers' choice experience (Brynjolfsson et al., 2003; Sethuraman et al., 2022).

2.2 The Paradox of Choice

One well-documented mechanism through which the retail environment undermines consumers' post-choice satisfaction is the paradox of choice. The paradox of choice refers to the counterintuitive idea that an increased number of options can reduce consumers' satisfaction with their decisions, rather than improving their experience of choosing (Schwartz, 2004, pp.1-6). Excessive choice carries emotional costs, including anticipated regret, opportunity cost, and post-choice disappointment. Beyond a certain threshold, choice no longer empowers but burdens the consumer (Schwartz, 2004, p.103).

However, choice overload is not a universal consequence of large assortments but is better understood as context-dependent (Scheibehenne et al., 2010). Chernev et al. (2015) identify choice set complexity as a primary amplifier; when options are difficult to compare, the cognitive burden of evaluation increases. Building on this, the present study operationalizes choice overload through perceived choice complexity of the assortment, rather than by assortment set size alone. Chernev (2003) further supports this, stating that a greater number of options introduces more attributes and trade-offs for the consumer to evaluate. Similarly, Iyengar and Lepper (2000) suggest that the paradox of choice may even decrease consumers' likelihood of making a decision at all.

Schwartz (2004, pp. 80-86) distinguishes between *maximizers*, who invest substantial cognitive and emotional resources in seeking the objectively best option, and *satisficers*, who settle for “good enough”. Despite often making superior choices, maximizers report greater regret, lower satisfaction, and greater vulnerability to the cognitive costs of large assortments relative to satisficers – further supporting the idea that the paradox of choice is personal and context-dependent. Additionally, extensive choice shifts the blame for dissatisfaction inward; poor outcomes become personal failures rather than circumstantial ones, amplifying post-choice regret (Schwartz, 2004, p.88; Nagar & Gandotra, 2016). Furthermore, each choice involves foregoing alternatives, and as the number of alternatives increases, the perceived loss of their benefits becomes more psychologically costly – the attractiveness of what was not chosen actively erodes satisfaction with what was, even when the chosen option is objectively good (Chernev et al., 2015; Schwartz, 2004, p.124; Diehl & Poynor, 2010). Accordingly, the stimuli in this study varied the size of the choice set (24 vs. 6 options), with set sizes selected based on prior research on choice overload (Iyengar & Lepper, 2000). Taken together, this gives rise to the following hypothesis:

H1: *Reducing the choice set size from 24 to 6 products lowers perceived choice complexity.*

2.3 Wellbeing

The preceding sections established that the online retail environment can impose cognitive burden on consumers – but what exactly is at stake when that burden becomes too great? To answer this, we must first define the central outcome variable of the present study: wellbeing.

Wellbeing is understood here through the lens of subjective wellbeing (SWB). SWB is the degree to which people experience their lives positively, encompassing both affective responses and cognitive evaluation of life satisfaction. Critically, SWB is not determined by objective external conditions but by individuals' perceptions of how well their lives are going (Diener, 1984).

This subjective sensitivity is precisely what makes SWB relevant to the consumer context. Dahlén and Thorbjørnsen (2022) demonstrate that wellbeing is a multidimensional construct encompassing happiness, meaning in life, and psychological richness – dimensions that together contribute to individuals' experience of living a good life. Critically, these states are not fixed; Dahlén et al. (2024) demonstrate that even occasional commercial stimuli can produce meaningful shifts in consumers' perceived happiness and wellbeing, establishing that the retail environment is far from emotionally neutral. Guillen-Royo (2019) similarly connects online retail experiences to influencing life satisfaction, indicating that the online retail environment may have effects on broader cognitive wellbeing outcomes. Importantly, these are not isolated reactions but become especially prominent in aggregate effects. While no single consumer decision may drastically alter a person's overall life satisfaction, the accumulated effect of navigating constant, complex decisions introduces a source of cognitive and affective strain. Each instance of choice overload, even if mild, contributes to an incremental reduction in positive effects (Schwartz, 2004, pp. 2-3). Therefore, what appears to be a momentary post-choice response may over time accumulate and negatively affect overall consumer wellbeing.

Taken together, these findings establish that wellbeing is a construct genuinely sensitive to everyday consumer experiences, such as those simulated in this study. When the cognitive burden of choosing from an excessively large assortment erodes positive affect, the consequence is not merely a suboptimal choice (Schwartz, 2004, pp.124-130), but a measurable reduction in how well people feel (Dahlén et al., 2024; Guillen-Royo, 2019). In this study, wellbeing is operationalized along three dimensions: post-choice satisfaction, momentary happiness, and broader life satisfaction (Diener et al., 2018; Dahlén et al., 2025). Together, these measures go beyond immediate post-choice affective responses and capture broader evaluations of consumer wellbeing and life satisfaction. Taken together, we hypothesize that:

H2: *Choice complexity mediates the relationship between choice set size and wellbeing, such that increased perceived complexity lowers wellbeing.*

2.4 Consumer Purchase Involvement

Beyond assortment characteristics such as complexity (Chernev et al., 2015), this study proposes consumer purchase involvement as another influencing factor of post-choice affective states.

Consumer involvement is a product-specific phenomenon that varies across product categories and consumers (Zaichkowsky, 1994). Situational involvement is a temporary state of engagement that arises when a consumer faces a purchase decision (Li et al., 2019;

Michaelidou & Dibb, 2006). The level of situational involvement a consumer experiences is shaped by the characteristics of the product being purchased. Examples of such characteristics include the importance of the product to the consumer, its perceived complexity, price, symbolic value, and the perceived risk associated with making a poor purchase decision (He et al., 2019; Santos & Gonçalves, 2021). Products that score high on these factors are considered high-involvement products; an example of such a category is apparel, due to its degree of personal relevance (Santos & Gonçalves, 2021). Michaelidou and Dibb (2006) further state that involvement varies even within product categories based on price, perceived risk and personal value. In this study, two product categories were selected to represent high- versus low-involvement levels: running shoes and t-shirts respectively. These were chosen as both categories fall within a comparable online retail context, while plausibly differing in perceived involvement (Michaelidou & Dibb, 2006).

The level of product involvement in turn shapes the effort which consumers invest in information search prior to purchase; the more involved a consumer is, the more extensive their pre-purchase search is (Santos & Gonçalves, 2021). Further, when consumers are highly involved, the cognitive costs of navigating a large assortment are amplified by the perceived importance of finding the objectively best option (Schwartz, 2004, pp.90-94). Conversely, Santos and Gonçalves (2021) demonstrate that when faced with a decision in a low-involvement situational context, consumers may navigate even large assortments with relative ease, engaging in limited alternative evaluation. This suggests that the detrimental effects of choice overload on the psychological states of consumers may be more pronounced for high-involvement purchases, thus the following hypotheses are proposed:

H3a: *The effect of choice set size on choice complexity is stronger for high-involvement product categories than for low-involvement product categories.*

H3b: *The effect of perceived choice complexity on wellbeing is stronger for high-involvement product categories than for low-involvement product categories.*

2.5 AI-Assisted Decision-Making in Retail

Recent years have seen rapid development in artificial intelligence (AI) and related technologies, revolutionizing many aspects of our lives, including how consumers interact with their surroundings and make decisions (Kim et al., 2023).

AI refers to machines' capacity to mimic human intelligence through technologies such as machine learning and natural language processing, enabling systems to interpret data, learn, and adapt over time (Huang & Rust, 2018; Kaplan & Haenlein, 2019). Within the customer journey framework proposed by Lemon and Verhoef (2016), AI has become a mechanism through which online retailers aim to shape consumer decision-making – primarily in the pre-purchase stage through personalization and recommendation systems that filter, rank, and present products tailored to individual preferences at scale (Davenport et al., 2020). By inferring consumer interests from behavioral data, these systems aim to guide consumers toward relevant products while reducing the complexity of choice (Bawack et al., 2022).

However, it cannot be assumed that AI assistance reliably benefits consumers, and retailers should approach claims about AI's benefits with caution. While recommendation agents are designed to reduce cognitive effort and simplify complex choices, they have been found to produce a counterintuitive effect: rather than reducing uncertainty, AI-assisted purchase decisions are perceived as more uncertain than those made without technological support (Rohden & Espartel, 2024). This effect is explained by reduced perceptions of control over the decision process – when consumers feel that choices have been made *for* them rather than *by* them, uncertainty increases rather than decreases (Rohden & Espartel, 2024; Davenport et al., 2020). Critically, this heightened uncertainty carries downstream consequences, negatively affecting both choice satisfaction and purchase intentions (Rohden & Espartel, 2024).

Importantly, these effects are not uniform across consumers. Personal characteristics such as risk aversion and maximizing tendencies moderate the extent to which AI assistance increases uncertainty, suggesting that AI is not inherently detrimental but that its effects depend on who is being assisted and under what conditions (Rohden & Espartel, 2024).

Nevertheless, the case for AI assistance remains compelling, given other research showing that consumers are particularly likely to rely on recommendation agents when the number of options exceeds what can be comfortably evaluated (Kim et al., 2023). Tam and Ho (2006) demonstrate that increased personalization functions as a decision aid, whereby exposure to self-relevant recommendations leads consumers to search for less information and reach decisions more efficiently. Kim et al. (2023) extend this further, arguing that consumers do not experience the typical negative effects of choice overload when choice sets are generated by AI, due to increased perceptions of accuracy and personal fit. Critically, this effect appears specific to AI curation – traditional overload patterns re-emerge when the same options are presented by a human – suggesting that AI may produce qualitatively different consumer outcomes beyond what set size alone can explain.

Despite reasons for skepticism, the theoretical case for AI assistance as a mechanism for reducing complexity in an online retail context remains compelling. As such, the present study hypothesizes that:

H4a: *The effect of choice set size reduction on perceived choice complexity is stronger when AI assistance is present.*

H4b: *The effect of perceived choice complexity on wellbeing is stronger when AI assistance is present.*

2.6 Purchase Intention

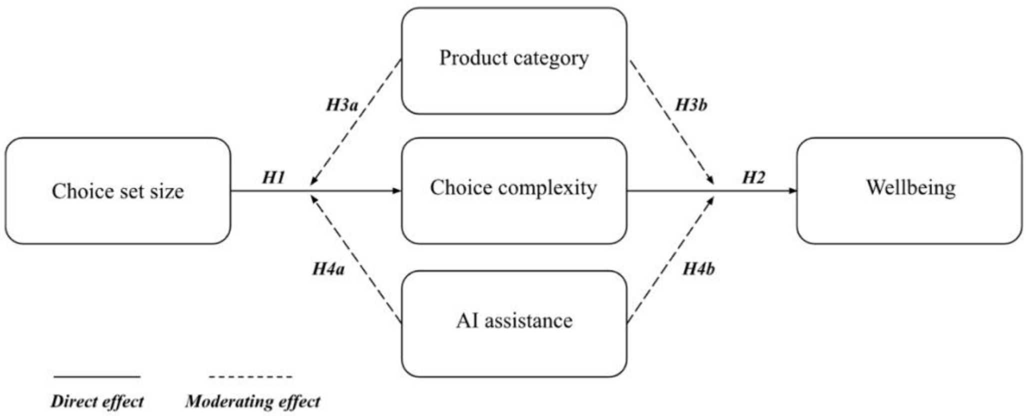
Purchase intention refers to a consumer's self-reported willingness to purchase a product and is used as a predictor of future purchasing behavior (Roudposhti et al., 2018). Factors such as trust, satisfaction, and the quality of product recommendations have been found to significantly influence consumers' intention to purchase in e-commerce contexts (Roudposhti et al., 2018; Ashraf et al., 2019).

Assortment size is one such factor shaping purchase intention. Consistent with Iyengar and Lepper (2000), Long et al. (2025) demonstrate that larger choice sets reduce search probability and purchase intention, as an increased risk of anticipated regret leads consumers to disengage before the decision process begins. However, Scheibehenne et al. (2010) find that assortment size does not consistently lead to choice overload in the absence of moderating factors, and larger assortments have been shown to attract significantly greater initial consumer interest (Chernev & Hamilton, 2009). Taken together, the literature reveals a trade-off: larger assortments may attract greater initial interest while simultaneously increasing choice complexity and cognitive burden, ultimately undermining post-choice satisfaction (Iyengar & Lepper, 2000; Scheibehenne et al., 2010; Long et al., 2025; Chernev & Hamilton, 2009).

The present study includes purchase intention as a complementary outcome variable. Following the literature suggesting that larger assortments may simultaneously increase product attractiveness and choice complexity, we further explore how these competitive forces may affect purchase intention, grounding the findings of this study in commercially relevant terms (see section 4.5).

2.7 Visualization of Hypotheses

Figure 1. Visualization of Hypotheses



3. Methodology

The purpose of this section is to outline the methodological approach adopted in this study. First, the quantitative research approach and between-subjects experiment is outlined. Second, the pretest is outlined. The purpose of the pretest, design and sample profile is described, followed by key results supporting the validity of the core manipulation. Third, the main study is introduced, detailing the experimental procedure, survey design, stimuli and validated measures, followed by a description of the data collection and sampling approach. Finally, the quality of the research design is evaluated through an assessment of validity and reliability.

3.1 Research Approach

To test the hypotheses presented in Figure 1, a cross-sectional online survey was conducted using a between-subjects 2×3 design. This study adopts a deductive, quantitative approach, consistent with prior choice overload research (Iyengar & Lepper, 2000; Long et al., 2025; Kim et al., 2023). As such, our hypotheses are developed based on existing research and tested empirically (Bryman, 2018, p. 49). While qualitative methods may have offered more in-depth insights, a quantitative method was deemed better suited for testing causal relationships and generalizing findings to a broader population (Eliasson, 2018, p. 50; Bryman, 2018, p. 50; Söderlund, 2018, pp. 16-18). Reliability was assessed using Cronbach's alpha, with $\alpha > .70$ serving as the recognized threshold for all multi-item constructs (Söderlund, 2018, p. 136). Statistical significance was set at a conventional threshold of $p < .05$ (Söderlund, 2018, p. 156).

3.2 Pretest

3.2.1 Purpose of Pretest

A separate pretest was conducted prior to the main study with the purpose of validating the core experimental manipulation, namely ensuring that the AI assistance treatment functioned as intended before examining its impact on wellbeing. Conducting the manipulation check in advance was considered advantageous, as it allowed potential issues with the manipulation to be identified and addressed prior to the main study. This helped reduce the risk of incorrect causal inferences and strengthened the study's internal validity by increasing confidence that any observed effect could be attributed to the intended manipulation rather than confounding factors (Perdue & Summers, 1986; Söderlund, 2018, pp. 87-88). Beyond validating the core manipulation, the pretest helped ensure that the experimental stimuli and settings reasonably reflected online shopping choice situations, thereby supporting the ecological validity and behavioral representativeness of the main study.

The stimuli consisted of a reduced set of options, described as tailored to respondents' preferences, collected at the beginning of the questionnaire. The aim was to examine whether participants perceived a difference between a neutral reduced set of options and the set presented as AI-curated and personalized to their preferences.

Accordingly, the pretest aimed to verify that participants in the AI condition would report stronger agreement with statements indicating that (1) the reduced set was curated using AI assistance and (2) that the reduced set reflected their stated preferences.

3.2.2 Pretest Design

The pretest was conducted as an experiment via an online questionnaire, and the data were analyzed quantitatively. Respondents were randomly assigned to one of two conditions: a neutral control condition or an AI-framed treatment condition.

After a brief introduction, participants in the AI-assisted condition were first asked to provide preference inputs before being exposed to the product assortment, introduced with the prompt *"To help you find suitable options, the online store asks a few questions about your preferences".* These inputs concerned non-visual product attributes such as price range, sustainability preferences, frequency of use, and consumption goals rather than aesthetic aspects. This step was included to enable explicit reference to participants' stated preferences in the subsequent AI recommendation. This approach was adopted as personalized AI communication that references clearly stated preferences increases perceived helpfulness and reduces the risk of perceived intrusiveness – a risk that is heightened when personalization lacks clear justification (Zobair et al., 2026). In line with this, Chernev and Hamilton (2009) found that respondents rated product assortments as more attractive when they aligned with the preferences that they had articulated beforehand.

Participants in both conditions were presented with an initial set of 24 running shoes (extensive-choice condition) and were asked to select the option that best matched their preferences. Subsequently, both conditions were shown a reduced set of 6 options (limited-choice condition), either with or without AI.

In the AI condition, the reduced set was presented as having been selected by an AI system based on the participants' stated preferences through the prompt *”You will now be asked to choose a running shoe. You will see a reduced set of options selected for you by an artificial intelligence (AI) system that has optimized the selection based on your stated preferences to best fit your needs”*. In contrast, the control group was shown the same reduced set without any framing of AI.

Following this, all participants were asked to evaluate whether the reduced set appeared to be curated by an AI. The items (e.g., “The reduced set seemed to be selected by an artificial intelligence (AI) system”) were measured on a seven-point Likert scale (1= Strongly disagree to 7 = Strongly agree). Additionally, participants in the AI condition were asked to assess whether the reduced set reflected their stated preferences. These items (e.g., “The reduced set seemed to be based on my stated preferences”) were also measured on a seven-point Likert scale (1= Strongly disagree to 7 = Strongly agree). To ensure high validity (the degree to which a measure appears to capture the intended construct; Söderlund, 2018, pp.135-136), all items referenced directly to the content of the stimuli. These measures were included to verify that both the statement on AI framing and the preference-based recommendations were perceived as intended. An attention check was applied for both groups to ensure data quality.

3.2.3 Pretest Sample

In total, the online survey received 74 raw responses, randomly distributed between the two conditions. Participants were recruited through anonymous links, primarily via students at the Stockholm School of Economics and the authors' personal networks. This corresponds to a non-probability convenience sampling approach (Malhotra, 2020, p. 363). The sample was considered sufficient to provide initial insights and to identify potential issues in the manipulation prior to the main study.

3.2.4 Pretest Results

No respondents were excluded due to incomplete responses. Cases with missing condition assignments (n = 9) were removed prior to analysis. Additionally, participants failing the attention check were excluded (*n* = 7). The final sample comprised 58 participants, with equal allocation to the AI and neutral condition, both (*n* = 29).

Reliability analyses were conducted to verify the internal consistency of the AI perception and preference fit scale. The results indicated satisfactory internal consistency (Cronbach's $\alpha_{\text{AI perception}} = .968$, $\alpha_{\text{Preference fit}} = .909$), supporting the aggregation of the items into one single construct.

An independent-samples t-test was conducted to examine whether participants in the AI assistance condition perceived a greater degree of AI assistance than those in the neutral condition. The results reported a significant difference between the groups with higher perceived AI assistance for participants in the AI condition ($M = 4.38$, $SD = 1.72$) than those in the neutral condition ($M = 3.45$, $SD = 1.63$), $t(56) = 2.12$, $p = .039$. The effect size was moderate (Cohen's $d = 0.56$), indicating a meaningful difference in perceived AI assistance between the conditions.

To assess whether participants in the AI condition perceived the recommendations as matching their stated preferences, a one-sample t-test was conducted against the scale midpoint of 4. The results indicated a perceived preference fit significantly higher than the neutral midpoint ($M = 5.03$, $SD = 1.29$), $t(28) = 4.33$, $p < .001$. The effect size was large (Cohen's $d = 0.80$), suggesting a substantial deviation from the midpoint. The results suggest that participants in the AI condition perceived the reduced product set as matching their preferences (see Table 1). As such, the experimental materials and framing used in the pretest were deemed sufficient for use in the main study.

Table 1. Pretest Results: Perceived AI Assistance & Perceived Preference Fit

Measure	n	M	SD	d	p
Perceived AI assistance				0.56	.039
AI condition	29	4.38	1.72		
Neutral condition	29	3.45	1.63		
Perceived preference fit (AI Condition)	29	5.03	1.29	0.80	<.001

3.3 Main Study

3.3.1 Purpose of Main Study

The purpose of the main study was to test whether reducing the choice set size from 24 to 6 options lowers perceived choice complexity and subsequently improves wellbeing. In addition, it tests whether the relationships between these variables – choice set size, perceived choice complexity, and wellbeing – differ across product categories presumed to vary in involvement, and with the assistance of AI.

3.3.2 Main Study Design

The main study employed a between-subjects 2×3 experimental design, in which choice set size was set as the primary independent variable, perceived choice complexity proposed as a mediating variable, and wellbeing as the dependent variable. Product category and AI assistance were additionally proposed as moderating variables.

Two product categories were tested: running shoes and t-shirts, which were presumed to represent high- and low-involvement purchases respectively. The three choice conditions consisted of: (1) a large assortment of 24 options, (2) a reduced assortment of 6 options, and (3) a reduced assortment of 6 options framed as curated by an AI. In the AI-assisted condition, the manipulated treatment described in section 3.2.2, including preference input and AI framing statement. The resulting six experimental groups and their respective sample sizes are illustrated in Figure 2.

A between-subjects design was chosen to mitigate the risk of carryover effects, sensitization, and demand characteristics that can arise when participants are exposed to multiple experimental conditions. In within-subjects designs, repeated exposure to similar stimuli across conditions may cause participants to become aware of the study's purpose, leading them to form hypotheses about the expected outcomes and adjust their responses accordingly (Charness et al., 2012; Greenwald, 1976). Such sensitization to treatment variations threatens the internal validity of results by introducing systematic bias that cannot be easily distinguished from genuine treatment effects (Greenwald, 1976). This concern was deemed particularly salient in the present study, as identical follow-up questions were asked across conditions, increasing the risk that participants exposed to multiple conditions would use earlier responses as a reference point when answering subsequent ones (Charness et al., 2012). By ensuring that each participant encountered only one choice condition and one product category, this design aimed to minimize the likelihood that such biases would influence the data.

Figure 2. 2×3 Between-Subjects Design

	24 options	6 options	6 options (AI assistance)
Running shoes	***Group 1*** n = 87	***Group 2*** n = 98	***Group 3*** n = 99
T-shirt	***Group 4*** n = 100	***Group 5*** n = 100	***Group 6*** n = 109

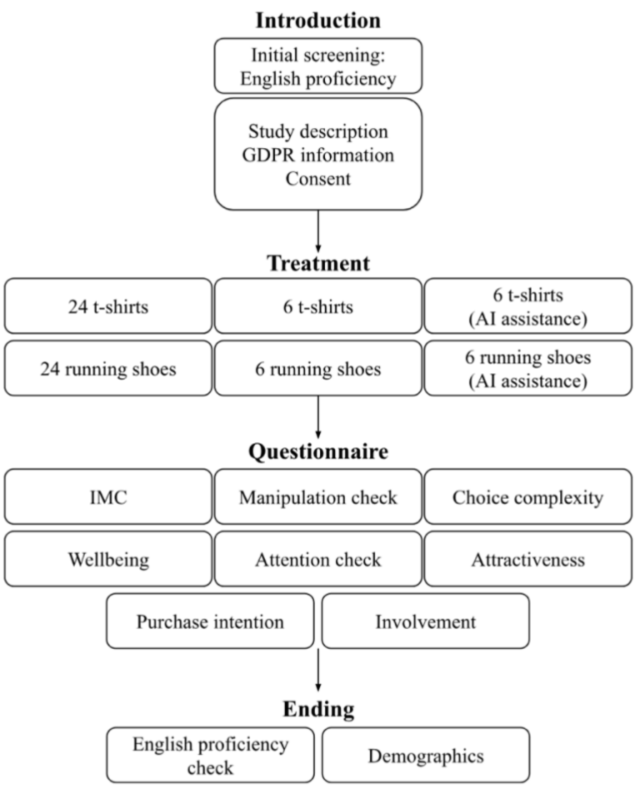
Data were collected through an online questionnaire. To establish an online retail context, respondents were given two framing cues: an introductory statement that *"The purpose of this study is to understand how individuals make decisions in online shopping environments"* and a product scenario stating *"imagine that you are browsing the assortment of an online retailer for a new [product]"*.

Participants first confirmed their ability to complete the survey in English, those unable to do so were screened out and could not continue. Eligible participants then provided consent before being randomly assigned to one of the six experimental conditions. The randomization procedure ensured that each participant had an equal probability of being allocated to any treatment condition. The advantage of randomized allocation is that individual differences are distributed across conditions in a way that allows them to cancel each other out, thereby controlling for inherent differences among participants (Söderlund, 2018, p.34).

Instructional manipulation checks (IMC) were included in all six conditions to verify that participants correctly understood what they were subjected to, including the product category and the size of the choice set (Söderlund, 2018, p.95). A manipulation check was included for the AI-assisted condition, administered after the treatment consistent with Söderlund (2018, p.89).

In terms of the experimental task at hand, participants were asked to select a product by responding to the prompt: *"Choose a [product] that best fit your preferences. Please write the name of your chosen [product]below"*. For the AI treatment groups, the corresponding prompt read: *"You will now be asked to choose a [product]. You will see a reduced set of options selected for you by an artificial intelligence (AI) system that has optimized the selection based on your stated preferences to best fit your needs. Please write the name of your chosen [product] below"*. Following the experimental task, all participants completed an identical set of follow-up questions capturing aspects of the choice experience, including perceived choice complexity, wellbeing, perceived attractiveness of the options, purchase intention, and consumer purchase involvement. An attention check was embedded in this section to ensure data quality. Towards the end of the survey, respondents were asked to complete another English proficiency check by answering three grammar questions (Cambridge English, 2026). Demographic questions were included at the end of the survey. The full survey flow is presented in Figure 3.

Figure 3. Visualization of the Main Study Flow



3.3.3 Stimuli Development

The stimuli were presented in a simulated online shopping environment in which participants were asked to select one product from a set of alternatives displayed in a grid layout. The overall design aimed to resemble a semi-realistic online shopping experience to enhance the realism of the study (see Appendix A). The grids were designed in *Canva*[1] using AI-generated product images (ChatGPT), enabling full control over visual consistency. The experimental manipulation varied the size of the choice set (24 vs. 6 options) and the presence of AI assistance.

To ensure internal validity, all stimuli were controlled across conditions. The products were unbranded and did not display any logos or identifiable brand information, minimizing the influence of prior brand preferences and familiarity on participants' evaluations. This because familiar brand logos have been shown to attract disproportionately more attention and be processed more efficiently than unfamiliar ones (Ou et al., 2025). To further control for potential confounding effects related to price sensitivity and willingness to pay, no price information was displayed (Kurz et al., 2023). Taken together, this ensured that participants evaluated the products under similar conditions and on an equal basis. To ensure that only the manipulated variables differed, the layout, product presentation, and level of detail were kept constant across all conditions.

3.3.4 Measures

A comprehensive list of all measurement items, including their sources, is provided in Table 2. Items were partly adapted from their original sources, and all constructs but involvement were measured using a seven-point Likert scale. Involvement was measured using a seven-point semantic differential scale. Unless otherwise stated, higher values indicate higher levels of the underlying construct.

Choice Complexity. Perceived choice complexity was operationalized through multiple items capturing perceived difficulty and cognitive burden in the decision-making process. This was measured using established items from Scheibehenne et al. (2009), Greifeneder et al. (2010) and Cho et al. (2013). Participants responded to the item "How easy or difficult

[1] Canva: *[https://www.canva.com/]*

was it for you to make a choice?" on a scale ranging from 1 = Very difficult to 7 = Very easy. Additionally, respondents indicated their agreement with the statements "You were overwhelmed by the choice task" and "It was exhausting for you to make the choice" on a scale from 1 = Strongly disagree to 7 = Strongly agree. The first item was reverse-coded prior to analyses so that all items within the construct were directionally consistent.

Wellbeing. To capture not only post-choice affective states but also broader wellbeing and life satisfaction, wellbeing was measured using three items adapted from Dahlén et al. (2025) and Diener et al. (2018). These measures captured post-choice satisfaction, momentary happiness, and broader life satisfaction. Participants were asked, "How happy are you overall right now?" (1 = Extremely unhappy, 7 = Extremely happy) and "How satisfied are you with life right now?" (1 = Very dissatisfied, 7 = Very satisfied). In addition, respondents rated their agreement with the statement "You feel happy after making your choice from the product selection" on a scale from 1 = Strongly disagree to 7 = Strongly agree. Given the subjective nature of wellbeing, self-report scales were used to capture individual perceptions in a reliable and standardized manner (Diener, 1984). The use of multiple items for wellbeing specifically is supported by Diener (1984), who argues that single-item measures are limited in a wellbeing context because variance due to item wording cannot be averaged out, internal consistency cannot be assessed, and such measures fail to capture the full scope of subjective wellbeing. Multi-item scales, by contrast, demonstrate adequate temporal reliability and internal consistency (Diener, 1984).

Perceived Attractiveness. Perceived attractiveness of the choice set was measured to control for potential confounding effects related to product appeal. Participants rated their agreement with the statements "Several good options were available for you to choose between", "You thought the choice selection was good," and "You could find the items you wanted from this product assortment" (Fitzsimons, 2000; Roudposhti et al., 2018). These items were measured on a scale from 1 = Strongly disagree to 7 = Strongly agree.

Purchase Intention. Purchase intention was included to assess the practical relevance of the experimental conditions in an online retail context, as used by Roudposhti et al. (2018). Participants indicated their agreement with the statements "You would buy the items recommended, given the opportunity" and "You predict that you will use this website for your future shopping", using a scale from 1 = Strongly disagree to 7 = Strongly agree.

Consumer Purchase Involvement. Apparel is personally relevant, making consumers more likely to be increasingly involved with it (Michaelidou & Dibb, 2006). The present study tests the moderation of the paths: (1) choice set size to choice complexity and (2) choice complexity to wellbeing, by comparing consumer responses across two product categories within a similar online retail context, running shoes, assumed to be higher-involvement, and t-shirts, assumed to be lower-involvement. Level of involvement was measured using items adapted from Zaichkowsky (1994). The prompt was *"To me [product category] is,"* and the participants evaluated the product category using four semantic differential scales: unexciting–exciting, uninvolving–involving, means nothing–means a lot, and boring–interesting, each on a seven-point scale.

Table 2. Overview of Constructs and Measures

Construct	Item	Source	Reliability measure
Choice Complexity *Perceived difficulty and complexity in making a choice*	How easy/difficult was it for you to make a choice? You were overwhelmed by the choice task. It was exhausting for you to make the choice.	Scheibehenne et al. (2009); Greifeneder, Scheibehenne & Kleber (2010); Cho, Khan, & Dhar (2013)	Cronbach's α = 0.724
Wellbeing *Affective state following the decision*	How happy are you overall right now? How satisfied are you with life right now? You feel happy after making your choice from the product selection.	Dahlén et al. (2025) Diener et al. (2018)	Cronbach's α = 0.684
Perceived Attractiveness *Perceived attractiveness and adequacy of the choice set*	Several good options were available for you to choose between. You thought the choice selection was good. You could find the items you wanted from this product assortment	Fitzsimons (2000); Roudposhti et al. (2018)	Cronbach's α = 0.849
Purchase Intention *Likelihood of purchasing and future usage intentions*	You would buy the items recommended, given the opportunity. You predict that you will use the website for future shopping.	Roudposhti et al. (2018)	Spearman-Brown ρ = 0.783
Consumer Purchase Involvement *Level of personal relevance and interest in the product category*	To me [product category] is... unexciting–exciting uninvolving–involving means nothing–means a lot boring–interesting	Zaichkowsky (1994)	Cronbach's α = 0.936 (running shoes) Cronbach's α = 0.902 (t-shirts)

3.3.5 Sample & Data Collection

Data were collected from 734 respondents recruited through Norstat[2], a leading independent European provider of market research data collection services, ensuring a nationally representative sample.

The target population consisted of individuals aged 18–74, as agreed upon in consultation with Norstat to ensure relevance to the study context. The survey was distributed via Norstat's online panel and data collection took place between April 10th and April 29th, 2026. Participants were randomly assigned to one of the six experimental conditions, with approximately equal distribution across groups.

3.4 Assessment of Reliability & Validity

Reliability refers to the extent to which repeated measurements of the same construct yield consistent results and was assessed using Cronbach's alpha, with $\alpha > .70$ serving as the recognized threshold for all multi-item constructs (Söderlund, 2018, pp. 135-136). As shown in Table 2, most multi-item constructs exceeded this threshold. The wellbeing scale yielded $\alpha = 0.684$, falling marginally below the threshold but deemed acceptable given that the items captured distinct aspects of wellbeing (happiness, life satisfaction, and post-choice affect). Purchase intention was assessed using two items, for which the Spearman-Brown coefficient ρ was computed as the appropriate reliability measure ($\rho = .783$), indicating acceptable consistency (Eisinga et al., 2013).

To ensure content validity, all scales were based on established constructs from peer-reviewed research, with minimal modifications to fit the present study context. In addition, the final questionnaire was reviewed in consultation with experienced researchers at the Stockholm School of Economics and was pre-tested by Norstat prior to final data collection.

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[2] Norstat: *[https://norstat.co/sv]*

4. Results

The purpose of the following section is to present the empirical results of the study. The section begins with preliminary analyses including reliability assessments, followed by data quality checks, a description of the final sample, and descriptive statistics. Hypotheses testing is then presented in the chronological order of the hypotheses, employing a range of statistical methods including independent-samples t-tests, bootstrapped mediation analyses, two-way ANOVAs, and moderated OLS regressions. The section concludes with complementary findings.

Statistical significance was set at a conventional threshold of $p < .05$ (Söderlund, 2018, p. 156). For the bootstrapped mediation analysis, a 95% bootstrap confidence interval was used to evaluate the indirect effect, whereby an indirect effect was considered statistically significant if the confidence interval did not include zero.

4.1 Preliminary Analyses

Reliability. The internal consistency of each multi-item scale was assessed prior to composite score construction. For scales with three or more items, Cronbach's alpha was computed. For two-item scales, the Spearman-Brown coefficient was computed as the appropriate reliability measure. Results are presented in Table 2.

Demographics. The final post-cleaning sample comprised 593 respondents (male: $n = 306$, 52%; female: $n = 282$, 48%; non-binary: $n = 5$, 1%), with a mean age of 43.8 years. To assess whether random assignment produced comparable groups, differences in age and gender across the six experimental conditions were examined. A one-way ANOVA revealed no significant differences in age across conditions ($F(5, 587) = 0.65$, $p = .660$, $\eta^2 = .006$). A chi-square test indicated that the gender distribution differed significantly across conditions ($\chi^2(10) = 27.71$, $p = .002$), with one of the six conditions showing a slightly higher proportion of male participants than the others. However, as gender was not theoretically expected to influence the variables of interest, no further attention was paid to this slight imbalance.

4.2 Data Quality Checks & Final Sample

Attention Check. An attention check was included to ensure data quality. Responses failing this check were excluded from further analysis.

Instructional Manipulation Checks (IMC). Two IMCs were included to verify that participants correctly perceived their condition: "What type of products did you just see?" (shoes/t-shirts/TV/candy) and "How many products were you shown?" (6/24/111). Participants answering either question incorrectly were excluded from further analysis.

English Proficiency Check. Following the initial screening question at the start of the survey, an additional English proficiency check was administered at the end, consisting of three fill-in-the-blank grammar questions (Cambridge English, 2026). Respondents who answered none correctly were excluded.

Manipulation Check. A manipulation check was included to verify that participants in the treatment group correctly perceived the AI manipulation: "Did you receive AI assistance in selecting the product assortment?" (yes/no). This check was used for descriptive inspection only and did not serve as an exclusion criterion. Respondents in the non-AI conditions (Groups 1, 2, 4, and 5) correctly identified the absence of AI assistance at a rate of 97–99%. Respondents in the AI conditions, however, performed considerably worse, with Group 3 (shoes, AI) answering correctly in 50% of the cases and Group 6 (t-shirts, AI) in 61% of the cases. This suggests that the AI manipulation was not consistently perceived by participants as intended, a limitation acknowledged and discussed further in section 5.4.

Final Sample. The cleaning procedure yielded a final sample of 593 respondents (raw n = 734; excluded n = 141). See Figure 2.

4.3 Descriptive Statistics of Main Variables

Prior to hypotheses testing, descriptive statistics and intercorrelations were examined to provide an initial overview of the data and to assess whether the variables behaved in theoretically expected ways. Descriptive statistics of the main variables are reported in Table 3, presenting means and standard deviations. Intercorrelations among all main constructs are also presented in Table 3 and will be further explored in section 4.5.

Table 3. Pearson Correlation Matrix for Main Study Variables

Variable	M	SD	Complexity	Wellbeing	Attractiveness	Purchase Intention	Involvement
Complexity	2.61	1.21	—	−0.18***	−0.09*	−0.07	−0.01
Wellbeing	4.81	1.05	−0.18***	—	0.28***	0.31***	0.25***
Attractiveness	4.50	1.41	−0.09*	0.28***	—	0.67***	0.28***
Purchase Intention	3.54	1.43	−0.07	0.31***	0.67***	—	0.36***
Involvement	3.85	1.37	−0.01	0.25***	0.28***	0.36***	—

Note. $N = 593$. * $p < .05$, ** $p < .01$, *** $p < .001$

4.4 Hypotheses Testing

The following section presents the results of the hypotheses testing. The hypotheses are restated below for reference.

H1: *Reducing the choice set size from 24 to 6 products lowers perceived choice complexity.*
H2: *Choice complexity mediates the relationship between choice set size and wellbeing, such that increased perceived complexity lowers wellbeing.*
H3a: *The effect of choice set size on choice complexity is stronger for high-involvement product categories than for low-involvement product categories.*
H3b: *The effect of perceived choice complexity on wellbeing is stronger for high-involvement product categories than for low-involvement product categories.*
H4a: *The effect of choice set size reduction on perceived choice complexity is stronger when AI assistance is present.*
H4b: *The effect of perceived choice complexity on wellbeing is stronger when AI assistance is present.*

4.4.1 Hypothesis 1

H1 predicted that reducing the choice set size from 24 to 6 products would lower perceived choice complexity. To isolate the pure effect of set size reduction, respondents assigned to the AI-assisted conditions (Groups 3 and 6) were excluded from this analysis, as their exposure to AI assistance constitutes a separate experimental manipulation that could confound the effect of set size alone. An independent samples t-test compared respondents assigned to the 24-option condition ($n = 187$) with those assigned to the 6-option neutral condition ($n = 198$), combining across both product categories. Results revealed that respondents in the 6-option condition reported significantly lower choice complexity ($M = 2.34$, $SD = 1.11$) than those in the 24-option condition ($M = 3.05$, $SD = 1.33$), $t(383) = 5.649$, $p < .001$, $d = 0.575$. H1 is thus supported.

4.4.2 Hypothesis 2

H2 predicted that perceived choice complexity would mediate the relationship between choice set size and wellbeing, such that increased perceived choice complexity would lower wellbeing. To isolate the effect of choice set size, respondents assigned to the AI-assisted conditions were again excluded from the analysis, leaving a sample of 385 respondents across the remaining four groups. A bootstrapped mediation model was estimated using ordinary least squares (OLS) path analysis with 5,000 bootstrap resamples. Choice set size was entered as the independent variable (dummy-coded: 0 = 6-options neutral, 1 = 24-options), perceived choice complexity as the mediator, and wellbeing as the dependent variable. Both product categories were pooled within each set size condition to test the general effect of assortment size on wellbeing, independent of product type. The mediation path is summarized in Table 4 and illustrated in Figure 4.

Path a confirmed that choice set size significantly predicted choice complexity ($b = 0.703$, $SE = 0.124$, $p < .001$), indicating that respondents exposed to the larger assortment experienced greater perceived choice complexity. Path b revealed that complexity significantly and negatively predicted wellbeing when controlling for set size ($b = -0.158$, $SE = 0.043$, $p < .001$), indicating that higher complexity was associated with lower wellbeing. The total effect of set size on wellbeing was non-significant (path c: $b = -0.137$, $SE = 0.107$, $p = .200$), as was the direct effect after controlling for complexity (path c': $b = -0.026$, $SE = 0.109$, $p = .810$). The bootstrapped indirect effect was negative and significant ($a \times b = -0.112$, 95% *CI* [−0.184, −0.051]), with the confidence interval excluding zero, indicating full mediation. These results suggest that choice set size influences wellbeing exclusively through its effect on perceived choice complexity. H2 is thus supported.

Figure 4. Mediated Effect of Choice Set Size on Wellbeing

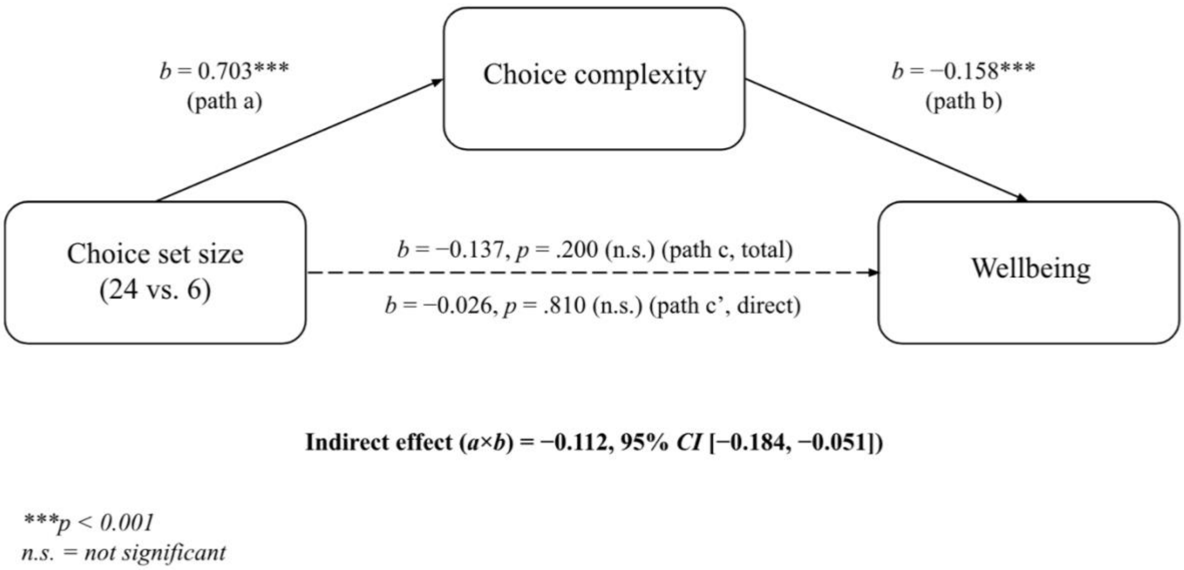

Table 4. H2 Mediation Path Summary

Path	Method	Key statistic	p	Significance	95% CI
Path a — Set size → Choice complexity	Simple linear regression	b = 0.703, SE = 0.124	<.001	Significant	[0.458, 0.948]
Path b — Choice complexity → Wellbeing	Multiple regression	b = -0.158, SE = 0.043	<.001	Significant	[-0.242, -0.073]
Path c — Total effect: Set size → Wellbeing	Simple linear regression	b = -0.137, SE = 0.107	.200	Not significant	[-0.347, 0.073]
Path c' — Direct effect: Set size → Wellbeing	Multiple regression	b = -0.026, SE = 0.109	.810	Not significant	[-0.241, 0.189]
Indirect effect (a×b)		b = -0.112		Significant	[-0.184, -0.051]

4.4.3 Hypotheses 3a & 3b

H3a and H3b both rest on the assumption that the two product categories used in the study (running shoes and t-shirts) differ in consumer purchase involvement, with shoes assumed to represent higher involvement than t-shirts. Before testing the hypotheses, an independent-samples t-test was conducted to verify this assumption. The data revealed no significant difference in perceived consumer purchase involvement between the running shoes (M = 3.86, SD = 1.50) and the t-shirts (M = 3.83, SD = 1.24), $t(591) = 0.262$, $p = .794$, $d = 0.021$. Respondents did not perceive shoes as more involving than t-shirts, indicating that the involvement-based premise underlying H3 was not supported by the data. The hypotheses tests are nevertheless reported below, but with the caveat that observed differences reflect product category rather than involvement.

H3a predicted that the effect of choice set size on perceived choice complexity would be stronger for high-involvement product categories than for low-involvement categories. To isolate the effect of product category, the AI-assisted conditions were excluded from the analysis. To examine whether product category moderated the effect of set size on perceived complexity, a two-way ANOVA was conducted with set size and product category as between-subjects factors and level of perceived choice complexity as the dependent variable. The results showed a significant main effect of set size ($F(1, 381) = 34.24$, $p < .001$, η^2_p = .082), indicating that larger assortments (24-options) were perceived as significantly more complex than smaller assortments ($M_{\text{larger assortments}} = 3.05$, $M_{\text{smaller assortments}} = 2.35$), regardless of product category. Additionally, a significant main effect of product category was found ($F(1, 381) = 14.19$, $p < .001$, $\eta^2_p = .036$), with shoes rated as overall more complex than t-shirts. However, the interaction between set size and product category was non-significant ($F(1, 381) = 0.503$, $p = .479$, $\eta^2_p = .001$), suggesting that the effect of set size on perceived complexity did not differ across product categories. Thus, product category did not moderate the relationship between set size and perceived choice complexity and H3a is not supported.

H3b predicted that the effect of perceived choice complexity on wellbeing would be stronger for high-involvement product categories than for low-involvement product categories. To test this, a moderated ordinary least squares (OLS) regression was conducted. To reduce multicollinearity, complexity was mean-centered prior to analysis. Product category was dummy-coded (0 = t-shirts, 1 = shoes). The model was significant ($F(3, 381) = 7.183$, $p <$ .001), though it explained little variance in wellbeing ($R^2 = .054$, *Adj.* $R^2 = .046$). Neither choice complexity ($b = −0.059$, $t(381) = −1.030$, $p = .304$) nor product category alone ($b = −0.049$, $t(381) = −0.463$, $p = .644$) significantly predicted wellbeing. However, the interaction term indicated that product category significantly moderated the relationship between perceived choice complexity and wellbeing ($b = −0.207$, $t(381) = −2.469$, $p = .014$). Looking at each product category separately revealed that for t-shirts, perceived complexity had no significant effect on wellbeing ($b = −0.059$, $t(381) = −1.030$, $p = .304$). For shoes, choice complexity negatively and significantly predicted wellbeing ($b = −0.266$, $t(381) = −4.372$, $p < .001$). The results suggest that consumers evaluating shoes are more negatively affected by assortment complexity, and that increased perceived choice complexity hurts wellbeing. Again, because the involvement manipulation failed, any moderation by product category cannot be interpreted as involvement-driven moderation, and H3b is therefore not supported *as specified*.

Table 5. Results Hypotheses 3a & 3b

H3a. Two-way ANOVA

Effect on Perceived Complexity	F(1, 381)	p	η^2_p
Set size	34.24	< .001	.082
Product category	14.19	< .001	.036
Set size × Product	0.503	.479	.001

H3b. Moderated OLS Regression

	b	t(381)	p
Complexity (reference: t-shirts)	−0.059	−1.030	.304
Product category	−0.049	−0.463	.644
Complexity × Product	−0.207	−2.469	.014
Simple slope: Shoes	−0.266	−4.372	<.001
Simple slope: t-shirts	−0.059	−1.030	.304

Model fit. $F(3, 381) = 7.183$, $p < .001$, $R^2 = .054$, Adj. $R^2 = .046$
Note. T-shirts served as the reference category (0 = t-shirts, 1 = shoes).

4.4.4 Hypotheses 4a & 4b

Before testing H4a and H4b, initial checks were conducted to verify that reducing the choice set size from 24 to 6 options successfully lowered perceived choice complexity, thereby confirming the validity of the set size manipulation for *both* of the reduced sets. The 24-option condition (M = 3.05, SD = 1.33) reported significantly greater perceived choice complexity than both the 6-option neutral condition (M = 2.34, SD = 1.11), $t(383) = 5.649$, $p < .001$, d = 0.575, and the 6-option AI condition (M = 2.46, SD = 1.08), $t(393) = 4.832$, $p < .001$, d = 0.484.

H4a predicted that the effect of choice set size reduction on perceived choice complexity would be stronger when AI assistance was present. An independent-samples t-test revealed no significant difference in perceived complexity between the 6-option neutral condition (M = 2.34, SD = 1.11) and the 6-option AI condition (M = 2.46, SD = 1.08), $t(404) = -1.071$, $p = .285$, $d = -0.106$. AI assistance did not further reduce perceived choice set complexity beyond what was already achieved by reducing the choice set to 6 options: the AI condition reported a slight, non-significant increase in perceived choice complexity. H4a is therefore not supported.

H4b predicted that the effect of perceived choice complexity on wellbeing would be stronger when AI assistance was present. A moderated OLS regression was conducted to test whether having AI assistance changed the relationship between choice set complexity and wellbeing. Complexity was mean-centered, AI assistance was dummy-coded (0 = neutral, 1 = AI), and an interaction term between the two was included to capture whether the effect of perceived choice complexity on wellbeing differed depending on the presence of AI assistance. The interaction term was non-significant (b = 0.072, $t(402) = 0.768$, $p = .443$), implying that AI did not moderate the effect of perceived choice complexity on wellbeing. The model fit statistics and full regression output are presented in Table 6.

Table 6. Results Hypotheses 4a & 4b

H4a. Independent samples t-test

Choice complexity	M	SD	t(404)	p	d
6-option neutral	2.343	1.110			
6-option AI	2.460	1.082			
Neutral vs. AI			−1.071	.285	−0.106

H4b. Moderated OLS Regression

	b	t(402)	p
Complexity (reference: neutral)	−0.241	−3.651	<.001
AI assistance	−0.231	−2.263	.024
Complexity × AI	0.072	0.768	.443

Model fit. $F(3, 402) = 8.717$, $p < .001$, $R^2 = .061$, Adj. $R^2 = .054$

Table 7. Hypotheses Summary Table

Hypothesis		Results
H1	*Reducing the choice set size from 24 to 6 products lowers perceived choice complexity.*	Supported
H2	*Choice complexity mediates the relationship between choice set size and wellbeing, such that increased perceived complexity lowers wellbeing.*	Supported
H3a	*The effect of choice set size on choice complexity is stronger for high-involvement product categories than for low-involvement product categories.*	Not supported
H3b	*The effect of perceived choice complexity on wellbeing is stronger for high-involvement product categories than for low-involvement product categories.*	Not supported
H4a	*The effect of choice set size reduction on perceived choice complexity is stronger when AI assistance is present.*	Not supported
H4b	*The effect of perceived choice complexity on wellbeing is stronger when AI assistance is present.*	Not supported

4.5 Complementary Findings

Beyond the main hypotheses, a series of complementary analyses were conducted to further explore the roles of assortment attractiveness and purchase intention in relation to set size, perceived choice complexity, and wellbeing.

Two Competing Pathways from Set Size to Wellbeing. While H2 established that choice set size influences wellbeing negatively through increased perceived choice complexity, a parallel mediation analysis revealed a second, opposing pathway operating simultaneously. An independent-samples t-test first confirmed that respondents exposed to the large assortment rated it as significantly more attractive (M = 4.78, SD = 1.38) than those exposed to the reduced assortment (M = 4.39, SD = 1.34), $t(383) = 2.802$, p = .005, d = 0.286. This indicates that larger assortments, despite increasing perceived choice complexity, simultaneously feel more appealing. A bootstrapped parallel mediation analysis (5,000 resamples) then revealed two simultaneous but opposing indirect pathways through which set size influences wellbeing: larger assortments reduced wellbeing indirectly through increased choice complexity (b = −0.080, 95% CI [−0.146, −0.023]), while simultaneously boosting wellbeing indirectly through increased attractiveness (b = 0.090, 95% CI [0.025, 0.169]). Both indirect effects were significant (confidence intervals excluded zero). These two opposing pathways of comparable magnitude effectively cancel each other out: larger assortments were more appealing but also more mentally draining, and these effects were roughly equally strong. This may explain why the total effect of set size on wellbeing was non-significant in H2.

What about Purchase Intention? The correlation matrix (Table 3) revealed that attractiveness was positively associated with wellbeing (r = .28, p < .001) and that wellbeing was in turn positively associated with purchase intention (r = .31, p < .001), suggesting a potential indirect pathway. To formally test this, a bootstrapped mediation analysis (5,000 resamples) was conducted with wellbeing as the mediator between attractiveness and purchase intention. Path a, reflecting the effect of attractiveness on wellbeing, was positive and significant (b = 0.237, 95% CI [0.151, 0.321]), as was path b, reflecting the effect of wellbeing on purchase intention while holding attractiveness constant (b = 0.203, p < .001). The indirect effect was significant (b = 0.048, 95% CI [0.020, 0.081]), confirming that attractiveness drives purchase intention partly through its positive effect on wellbeing.

5. Discussion

The purpose of this section is to interpret the main findings presented in the preceding section. Connecting back to the introduction, the purpose of this study was to examine how choice set size affects wellbeing in an online retail context, and whether perceived choice complexity mediates this relationship. The study further tested the potential moderating effects of product category and AI-assisted recommendations. In addition, the study explored how choice set size relates to purchase intention as a commercially relevant outcome.

5.1 Summary of Main Findings

Our results confirm that reducing the choice set size from 24 to 6 options significantly lowers perceived choice complexity, regardless of product type (H1 supported). Furthermore, reduced choice complexity fully mediated the relationship between choice set size and wellbeing: consumers exposed to larger assortments experienced greater choice complexity, which in turn reduced their state of wellbeing (H2 supported).

Regarding product category involvement, the running shoes did not strengthen the effect of set size reduction on perceived choice complexity relative to t-shirts (H3a not supported). While a significant interaction was found between product category and the choice complexity to wellbeing relationship (H3b), this finding must be interpreted with caution: participants did not rate running shoes as significantly more involving than t-shirts, undermining the theoretical basis of the moderation. As such, H3b is not supported.

Regarding AI assistance, its introduction neither strengthened the effect of choice set size on perceived complexity (H4a not supported) nor the effect of perceived complexity on wellbeing (H4b not supported).

5.2 Interpretation of Main Findings

When AI assistance was introduced alongside the reduced choice set, it failed to further reduce complexity (H4a not supported) and produced no significant boost in wellbeing relative to the neutral 6-option condition (H4b not supported). This pattern is consistent with the mediation structure established by H2, in which the effect of set size operates entirely through perceived choice complexity. Given this, the absence of a wellbeing boost in the AI condition is not surprising. Since AI assistance did not incrementally reduce perceived complexity beyond what set size reduction had already accomplished, the mediation through which wellbeing improvements occur could not increase further; in the absence of further reductions in perceived complexity, no additional gain in wellbeing should be expected, with or without AI assistance.

This pattern suggests that the benefits to consumer wellbeing stem from reductions in complexity, rather than from mere reductions in choice set size or the use of AI assistance alone. This aligns with and extends research by Chernev et al. (2015), who identified choice set complexity as a primary amplifier of the cognitive burden associated with assortments. Additionally, our empirical findings are in line with Scheibehenne et al. (2010) who demonstrate that choice set size has minimal effect on choice overload in the absence of additional influencing factors. The present study builds on the findings from Chernev et al. (2015) and Scheibehenne et al. (2010) by moving beyond cognitive burden alone, demonstrating that perceived complexity carries meaningful consequences for a consumer's broader state of wellbeing and life satisfaction. The findings also contrast prior research suggesting that *how* a choice set is reduced matters as much as *the extent of the reduction* itself, and that AI-generated assortments may mitigate typical choice overload effects (Tam & Ho, 2006; Kim et al., 2023). The present study suggests that the AI condition was perceived as marginally more complex than the neutral reduced condition, with no incremental benefit to wellbeing. As such, wellbeing depends less on *the number of options removed* and more on whether the remaining assortment *feels less complex.* In this sense, *how* the assortment is reduced appears to matter more than *how much* it is reduced, although the findings do not support AI assistance as an effective mechanism for achieving this reduction in perceived complexity.

Finally, the complementary analyses revealed an important tension. Two opposing effects of roughly equal strength were found; while larger assortments increased perceived choice complexity and reduced wellbeing, they simultaneously made the assortment feel more attractive. These findings are consistent with prior research on the trade-offs inherent in large assortments (Iyengar & Lepper, 2000; Chernev & Hamilton, 2009). Larger assortments boosted wellbeing through increased attractiveness, while simultaneously reducing it through increased complexity.

Assortment attractiveness proved a stronger driver of purchase intention than choice set size itself, as attractive assortments fostered positive wellbeing, which in turn predicted stronger purchase intention. This suggests that it may not be the size of the assortment that ultimately matters most to consumers – or takes the greatest toll mentally – but how appealing it feels. The attractiveness of options as a critical variable in terms of consumer wellbeing and ultimately purchase intention extends Chernev and Hamilton's (2009) research which demonstrates that the effect of assortment size on consumer choice can sway depending on its attractiveness.

5.3 Contributions & Practical Implications

This study contributes to existing choice overload literature by expanding the set of outcomes examined beyond cognitive burden to broader consumer wellbeing and life satisfaction. Furthermore, the study explores how AI assistance and product category may influence these effects. In doing so, it offers grounding for practical implications, particularly for online retailers navigating the rise of AI while seeking to balance consumer wellbeing with commercial performance.

First, the findings challenge existing assumptions in literature on AI-assisted consumer decision-making. A growing body of research has suggested that AI-curated assortments can sidestep typical choice overload effects, with consumers responding more favorably to algorithmically reduced choice sets due to perceptions of accuracy, personal fit and reduced search effort (Kim et al., 2023; Tam & Ho, 2006; Davenport et al., 2020). The findings of the present study challenge this optimism. AI assistance failed to further reduce perceived choice complexity beyond what set size reduction alone had already accomplished and worsened state of wellbeing relative to the neutral reduced set condition. These findings are consistent with Rohden and Espartel (2024), who demonstrate that AI-assisted purchase decisions can paradoxically increase rather than decrease perceived uncertainty, and extend their work by demonstrating that this effect also manifests in the affective domain of wellbeing, not just in choice satisfaction or purchase intentions. By showing that AI assistance, in its tested form, offers no incremental benefit to wellbeing, this study positions AI assistance in retail as a tool whose value depends on whether it succeeds in reducing perceived complexity in a way that consumers experience as meaningful.

Second, the study advances prior choice overload literature by extending its consequences beyond simply cognitive burden to the broader domain of consumer wellbeing. Whereas prior research has mainly viewed perceived choice complexity as a cost of decision-making, reflected in decision difficulty, choice avoidance and post-choice regret (Schwartz, 2004; Chernev et al., 2015; Iyengar & Lepper, 2000; Scheibehenne et al., 2010), fewer studies have examined how this complexity translates into broader affective consequences for the consumer. By providing causal evidence that perceived choice complexity fully mediates the relationship between assortment size and consumers' broader state of wellbeing, this study contributes to a more holistic understanding of the psychological consequences of digital choice environments. Our findings reposition perceived choice complexity not as a mere cognitive inconvenience, as previously framed by Chernev et al. (2015), but as a psychologically consequential experience that significantly shapes how consumers feel, not just how hard they think. In doing so, this study bridges choice overload (Schwartz, 2004; Chernev et al., 2015) with wellbeing literature (Diener, 1984; Dahlén & Thorbjørnsen, 2022), showing that everyday consumer experiences in digital environments can meaningfully affect emotional wellbeing.

Taken together, retailers should be cautious about assuming that AI-powered curation tools will automatically benefit consumers or drive purchase intention through improved wellbeing. For online retailers seeking to support consumer wellbeing, assortment reduction alone is not enough. The mechanism through which wellbeing improves is a reduction in perceived choice complexity. If an AI tool fails to deliver that relief, it offers little advantage. In a retail environment increasingly dominated by AI, the strongest driver of choice remains fundamentally human: an attractive assortment. Ultimately, this points to the importance of online retailers focusing on the basics of a positive consumer experience; rather than chasing technological advancements, retailers may be better served by prioritizing assortment attractiveness, which this study found to be a stronger driver of both consumer wellbeing and purchase intention. Retailers who simply reduce their assortment without reducing the felt complexity should not expect a wellbeing benefit, nor the purchase intention benefit that follows from it.

Consequently, when it comes to improving consumer wellbeing in online retail, less is more. Investing in improving the assortment attractiveness and focusing on making consumers happier may ultimately do more for the consumer experience than an AI ever could. The strategic priority should therefore be curating assortments that simultaneously feel cognitively simple and appealing, not merely smaller. In conclusion, simple and attractive assortments make consumers happier, and happier consumers buy more.

5.4 Limitations & Future Research

Several limitations of the present study should be acknowledged, along with questions and perspectives to be considered in future research.

First, the product stimuli were presented in a simulated online retail context, with images generated by ChatGPT. While this approach allowed for controlled and standardized stimuli across conditions, AI-generated images may lack the visual authenticity of real products. Furthermore, the stimuli were presented as images only, stripped of price information, product descriptions, and other attributes that are typically central to the online shopping experience. The absence of such information means the experimental task may bear limited resemblance to how consumers experience choice online, raising questions about the ecological validity of the findings. This was, as stated, an intentional choice to eliminate potential bias. Future research could consider replicating the study using real product listings in authentic online retail environments to assess whether the effects observed here hold under more naturalistic conditions.

Second, the AI manipulation was not genuine, perhaps a reason for the share of sample failing to recognize it, as described in section 4.2. This study employed AI-framing rather than genuine AI-derived product recommendations in the experimental stimuli. This was an intentional choice to ensure comparable conditions across participants. While this strengthens internal validity, it limits external validity, as the findings cannot be directly generalized to real-world AI recommendation systems. Importantly, the effects observed may be attributable to the framing itself rather than to genuine algorithmic personalization. Future research could invest greater efforts in developing and validating AI manipulations that are consistently perceived as such, for instance, through more explicit AI cues like genuine personalized recommendations. Examining whether similar effects would emerge under a more realistic AI-manipulations would better establish the practical relevance of these findings, ensuring that the results reflected a genuine absence of effect rather than a mere consequence of an insufficiently strong manipulation.

Third, the study design did not include a condition combining 24 options with AI assistance, as the AI condition was only introduced at the reduced set level. This was an intentional design choice, reflecting the assumption that AI assistance would only be deployed as a complement to set size reduction rather than as a standalone mechanism. However, this design choice introduced two statistical limitations: testing H4a and testing in a Hayes PROCESS model. Regarding the testing of H4a, it should be noted that the t-test did not formally test AI assistance as a moderator explicitly but rather examines the relationship between set size and choice complexity with AI present through group comparisons. Formal moderation testing was not feasible given the experimental design, making this specific interaction term incomputable. Regarding the Hayes model, the same confound prevented all hypotheses from being tested simultaneously within a single unified Hayes's PROCESS macro (v5.0) in SPSS. Since AI assistance appeared only in the reduced-choice-set condition, set size and AI assistance were perfectly confounded, making them statistically inseparable in a single model. Future research may consider an experimental design that avoids this confound, enabling a more rigorous test of AI assistance as a moderator and a complete mapping of the interplay between choice set size, AI assistance, choice complexity, and wellbeing within a single unified model.

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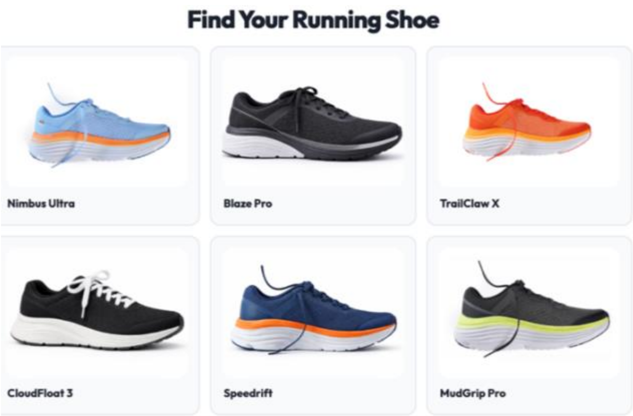
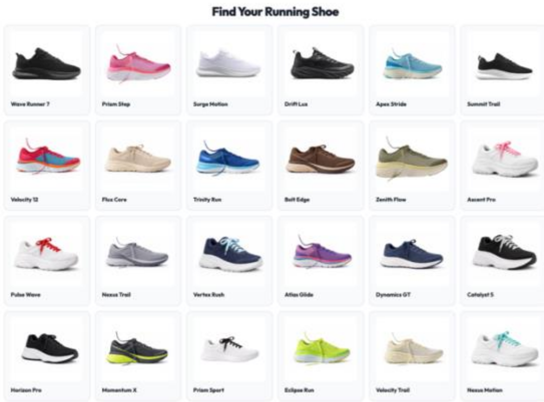
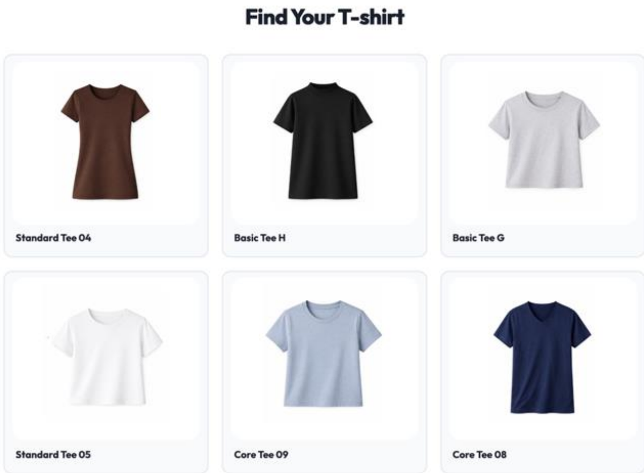
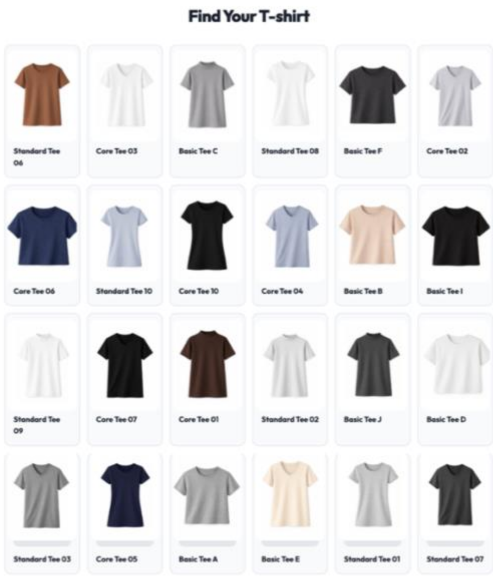
7. Appendix

Appendix A: Experiment Stimuli









Appendix B:

Table 8. Descriptive Statistics M(SD) by Treatment Group

Treatment Group	Complexity	Wellbeing	Attractiveness	Purchase Intention	Involvement
Group 1 *Running shoes, 24 options* *n = 87*	3.25 (1.33)	4.61 (1.06)	4.82 (1.27)	3.59 (1.40)	3.80 (1.54)
Group 2 *Running shoes, 6 options* *n = 98*	2.62 (1.08)	4.99 (1.11)	4.46 (1.33)	3.44 (1.38)	3.79 (1.41)
Group 3 *Running shoes, 6 options + AI* *n = 99*	2.67 (1.08)	4.75 (1.05)	4.49 (1.53)	3.68 (1.59)	3.99 (1.55)
Group 4 *T-shirts, 24 options* *n = 100*	2.87 (1.31)	4.97 (1.02)	4.74 (1.48)	3.42 (1.45)	4.00 (1.20)
Group 5 *T-shirts, 6 options* *n = 100*	2.07 (1.08)	4.90 (0.98)	4.32 (1.35)	3.48 (1.33)	3.65 (1.28)
Group 6 *T-shirts, 6 options + AI* *n = 109*	2.27 (1.05)	4.63 (1.06)	4.21 (1.40)	3.62 (1.42)	3.85 (1.22)

Note. ONE-WAY ANOVAs

Complexity: $F(5, 587) = 12.573$, $p = 0.000$ ***, $\eta^2p = 0.097$
Wellbeing: $F(5, 587) = 2.511$, $p = 0.029$ *, $\eta^2p = 0.021$
Attractiveness: $F(5, 587) = 2.796$, $p = 0.017$ *, $\eta^2p = 0.023$
Purchase Intention.: $F(5, 587) = 0.548$, $p = 0.740$ ns, $\eta^2p = 0.005$
Involvement: $F(5, 587) = 0.933$, $p = 0.459$ ns, $\eta^2p = 0.008$

Involvement was measured using category-specific items: running shoe involvement items for Groups 1-3 and t-shirt involvement items for Groups 4-6.

Appendix C: AI Disclosure

This thesis used two AI tools throughout the process: ChatGPT and Claude. The tools were used for three main purposes: (1) language polishing and grammar refinement to improve readability and flow (2) Python coding, error correction, and output interpretation, and (3) generating product images (for the experimental stimuli). No outputs from AI were included without being reviewed by us (the authors).

Typical prompts focused on readability and clarity include "simplify this sentence," "does this flow well?", "would a reader who doesn't have context to our thesis understand this" and "correct the grammar here". For coding, prompts were directed at understanding and getting help with errors and output interpretation, such as "'what does this error mean and how do I fix it," and "what does this output tell me about the relationship between the variables".

AI helped ensure that the thesis is readable to those unfamiliar with the topic, since our familiarity with the subject matter can otherwise make us overlook this. For coding, AI was good at identifying errors and translating statistical output into concrete, interpretable insights. For the experimental stimuli, AI-generated product images allowed us to present brandless products, avoiding the biases and brand associations that real product images would have introduced.

Two main risks were identified. First, AI tools are unreliable for source retrieval and interpretation as they can hallucinate citations or misrepresent source content to produce a result that sounds plausible. The main risk here is that it often *sounds* really good. To manage this, literature searching, reading, and interpretation were done manually. Second, while AI performs well at executing code, it is less reliable at determining which statistical test is most appropriate for a given hypothesis. It gave ideas however, which then could be further evaluated manually. Therefore, decisions regarding analytical approach and test selection were made by us, using knowledge from previous courses, inspiration from previous research work within similar fields, as well as in consultation with faculty.

What we learned is that AI can be valuable as a support tool for well-defined tasks such as coding and language refinement, and is less reliable when judgment, source interpretation, or methodological reasoning is required. When used critically and within these boundaries, we think that AI meaningfully contributed to the quality of our thesis.