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Course: Managerial Decision Making

Less is More? An Experimental Analysis of the Paradox of Choice in E-Commerce and Its Implications for Customer Experience

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Abstract

This thesis investigates how option numerosity influences decision processes and outcomes in digital choice environments. Although the choice overload literature suggests that larger assortments may impair decision quality, empirical findings remain heterogeneous and often context dependent. To address this issue, the study examines the role of assortment size within a controlled simulated e-commerce environment while holding informational structure and presentation constant.

A quantitative experiment was conducted in which participants interacted with one of two website versions differing only in the number of alternatives presented (reduced vs. expanded sets). The design incorporated three product categories—smartphones, power banks, and phone cases—used as proxies for increasing decision complexity, and compared behavioral responses across three age groups. Behavioral interaction data, task completion, perceived stress, and satisfaction were analyzed using regression models aligned with the factorial structure of the design.

The results indicate that expanded choice environments are associated with lower behavioral interaction intensity, lower task completion, and higher perceived stress, while satisfaction differences are weaker. Product category and, to a lesser extent, age shape how decision time and behavioral persistence respond to option numerosity. Higher-order interaction patterns suggest that the consequences of assortment size vary across specific consumer–product configurations rather than following a uniform structure.

Overall, the findings do not provide a uniform confirmation of the traditional choice overload prediction. Instead, they point to a behavioral disengagement pattern in expanded environments, where larger assortments reduce persistence in completing structured decisions while increasing subjective strain. The study contributes to the literature by showing that the effects of option numerosity depend on the interaction between choice set size, product complexity, and user characteristics within digital decision contexts.

Introduction

Digital marketplaces have dramatically increased the availability of alternatives presented to consumers. Online platforms routinely display dozens or hundreds of options within a single category, promising greater variety, personalization, and freedom of choice. While classical economic reasoning interprets an expanded choice set as unambiguously beneficial, behavioral research has questioned this assumption. The literature on the choice overload paradox proposes that an excessive number of alternatives may complicate evaluation, increase cognitive burden, and ultimately deteriorate decision outcomes.

Despite extensive research, empirical evidence remains inconsistent. Some studies document reduced satisfaction or increased decision deferral in large assortments, whereas others find null or even positive effects. This heterogeneity suggests that option numerosity does not operate as an independent determinant of decision performance but interacts with contextual and individual factors. In particular, digital environments introduce specific characteristics—continuous navigation, attribute comparison interfaces, and self-directed information search—that differ from traditional laboratory tasks and may alter the mechanisms underlying choice overload.

A second unresolved issue concerns decision heterogeneity. The impact of large assortments may depend on who is making the decision and what type of product is being evaluated. Age differences may influence familiarity with digital environments and tolerance toward information-dense interfaces, while product characteristics may shape observable interaction patterns during evaluation. However, these dimensions have rarely been examined jointly within a controlled digital setting that isolates option numerosity from other design interventions such as recommendations or filters.

This thesis addresses these gaps by analyzing decision behavior in a simulated e-commerce environment where informational structure and interface design are held constant and only the number of alternatives varies. The study combines behavioral interaction data with subjective evaluations and examines how assortment size relates to decision processes and outcomes across product categories and age groups. Rather than assuming a uniform effect of large assortments, the research investigates the boundary conditions under which numerosity influences persistence, perceived strain, and engagement during digital decision-making.

By integrating experimental control with a realistic browsing context, the thesis aims to clarify how option numerosity operates within contemporary online shopping environments and to contribute to a more contextualized understanding of the choice overload phenomenon.

1 Literature Review

1.1 Digital Context and Market Transformation

1.1.1 Digital Transformation and the Platform Economy

The digital transformation of the retail sector has redefined the ways in which firms and consumers interact, altering the role of channels, interfaces, and touchpoints along the purchasing process. The evolution of retail reconstructed by Verhoef et al. (2015) can be interpreted as a progression from single-channel to multi-channel, from cross-channel to omni-channel retailing. This trajectory describes the shift from isolated sales systems to increasingly integrated configurations, in which data, information, and processes are coordinated to offer a coherent experience along the entire customer journey.

In the multi-channel model, retailers offer a plurality of channels that remain managed in a parallel and weakly integrated manner: inventories, information systems, and customer relationship management activities are often separated, generating fragmentation in the purchase journey and a management focus on the channel rather than on the customer (Verhoef et al., 2015). Cross-channel retailing introduces a first level of coordination, enabling interactions that connect online and offline contexts (for example, online purchase with in-store pickup or return). The transition to omni-channel retailing represents a qualitative change: channels and touchpoints are integrated within a single architecture oriented toward fluid and coherent journeys, supported by unified processes and shared data (Verhoef et al., 2015).

In this context, channel integration quality becomes salient, understood as the perception of coherence and coordination across channels at both the informational and operational levels. High integration quality allows customers to move across web, app, and physical store without friction, avoiding the need to reconstruct information or repeat search activities at each transition.

This evolution is embedded within the logic of the platform economy, in which value creation is mediated by digital infrastructures capable of coordinating data, actors, and interactions. As highlighted by Verhoef et al. (2015), the integration of back-end systems (logistics, inventory, information systems) represents an essential prerequisite for the creation of coherent experiences. At the same time, integration makes the shopping environment richer in content and accessible options, raising the issue of managing decision-making complexity in digital markets.

1.1.2 Evolution of E-Commerce and Omnichannel Retail

The evolution of e-commerce constitutes one of the main drivers of this transformation. The expansion of digital channels has broadened opportunities for interaction and purchase, but it has also increased the complexity of decision-making paths. Verhoef et al. (2015) show how the growth of e-commerce has generated dynamics of channel conflict and channel synergy: on the one hand, competition among channels; on the other, value creation through the combined use of online and offline channels.

Practices such as showrooming and webrooming highlight how consumers move across digital and physical contexts in a non-linear manner. In response, the evolution toward omni-channel retailing can be interpreted as an attempt to govern this multiplication of paths by coordinating content, information, and services to deliver a coherent customer experience.

Recent bibliometric evidence confirms the growing centrality of omnichannel retailing within e-commerce research. For instance, Judijanto (2025) maps the intellectual structure of the field and identifies dominant and emerging themes such as customer experience, supply chain integration, technological innovation, sustainability, and AI-driven personalization, highlighting the increasing complexity and interdisciplinarity of the omnichannel ecosystem.

1.1.3 Digital Customer Experience

Within this ecosystem, digital customer experience (CX) assumes a central role. Verhoef et al. (2015) conceptualize CX as the set of interactions that customers experience along the entire customer journey, encompassing multiple physical and digital touchpoints. In omni-channel contexts, the quality of channel integration becomes particularly salient, as it affects the continuity of the journey and the coherence of information and services across channels.

Building on this perspective, Mishra et al. (2024) distinguish between cognitive and affective dimensions of customer experience. Cognitive CX relates to perceptions of clarity, efficiency, and ease of comparison, whereas affective CX captures emotional responses such as comfort, pleasure, and reassurance. Both dimensions contribute to perceived value and are shaped by how information is structured, presented, and made comparable throughout the purchase journey.

Research on omni-channel retailing further indicates that customer experience emerges from the interaction between digital and physical attributes of the shopping environment. The integration of online and offline channels—such as the alignment of inventory information, pricing, and availability—reduces friction and uncertainty in decision-making, while failures in integration can generate confusion and increase cognitive effort (Gallino & Moreno, 2014; Rahman et al., 2022). At the same time, digital interfaces introduce high levels of information richness, personalization, and choice availability, which can enhance flexibility and control but also intensify informational demands.

Overall, the digital transformation of retail has rendered the purchase experience more fluid, continuous, and customizable, while simultaneously increasing the cognitive load associated with evaluating and comparing alternatives. This tension between empowerment and complexity provides the conceptual foundation for examining how consumers cope with complex choice environments in e-commerce and omni-channel settings.

1.2 Foundations of Decision Making

1.2.1 Classical Rationality vs. Bounded Rationality

The distinction between classical and bounded rationality represents a fundamental theoretical divide in decision-making theories. Drawing on Simon's foundational work, Egidi and Marengo (2002) argue that classical decision theory assumes that individuals can evaluate all available alternatives and select the globally optimal solution under conditions of perfect information and unlimited cognitive processing.

However, they contend that in complex decision spaces, global optimization becomes computationally intractable, relegating the classical model to a purely normative role. In contrast, bounded rationality (Simon, 1947; 1957) acknowledges cognitive and temporal constraints, leading to a redefinition of the process as procedural rationality (Simon, 1976). This shift focuses on the adequacy of the search procedures rather than the optimality of the outcome.

A cornerstone of this framework is satisficing: agents terminate their search once an alternative meets a predefined aspiration level (Simon, 1957). Egidi and Marengo (2002) extend this by demonstrating that the effectiveness of satisficing is not merely a matter of search costs, but is deeply rooted in problem representation. They show that to manage complexity, agents and institutions employ near-decomposability (Simon, 1965)—breaking down complex problems into quasi-independent sub-problems. While this modularity is a necessary heuristic, it inevitably introduces systematic biases and sub-optimality, as interdependencies between modules are often ignored. Thus, decision-making is less about global calculation and more about the architectural 'framing' and decomposition of the problem space.

1.2.2 Heuristics, Biases, and Decision Difficulties

Under conditions of uncertainty and complexity, decision makers rely on heuristics, that is, cognitive mechanisms that allow the simplification of complex decision problems. Research within the heuristics-and-biases framework, as reviewed by Bottom (2004), shows how such heuristics systematically reduce computational load. Among the main ones are representativeness, availability, and anchoring.

The representativeness heuristic leads individuals to assess probability based on similarity to a prototype, often neglecting statistical information such as base rates. Availability leads to estimates of frequency and probability as a function of ease of recall from memory, making recent or emotionally salient events more prominent. Anchoring produces estimates influenced by an initial value even when it is arbitrary.

The use of heuristics entails systematic biases (e.g., base-rate neglect, overconfidence, framing effects). These distortions represent structural consequences of cognitive functioning in contexts characterized by incomplete information or high complexity.

Schwartz (2004) broadens the perspective by highlighting individual differences in how the decision-making process is managed and experienced. *Maximizers* tend to systematically pursue the best possible option, maintaining high standards and comparing many alternatives; *satisficers* adopt acceptability thresholds and stop searching when they identify an adequate option. The study shows that a maximizing orientation is associated with higher levels of subjective conflict, anticipation of regret, and post-choice rumination, whereas satisficing strategies are more compatible with cognitive constraints and search costs.

1.3 The Choice Overload Paradox

1.3.1 Origins of the Paradox

The choice overload paradox emerges as a theoretical and empirical response to a tension between the expansion of options and the cognitive and motivational limits of human decision makers. While economic tradition interprets an increase in alternatives as an improvement in opportunities, psychological and behavioral literature has shown that an excessive availability of options can produce counterintuitive effects.

The empirical contribution of Iyengar and Lepper (2000) highlights a fundamental tension in consumer motivation: while extensive assortments are more effective at **attracting** initial interest (initial engagement), they significantly undermine the **subsequent motivation** to finalize a choice. Their results showed that while 60% of consumers were drawn to a large display, only 3% completed a purchase, compared to 30% in the limited-choice condition.

The experimental evidence presented in their study, indicates that exposure to very large sets increases initial interest but entails high costs during the evaluation and selection phases. The increase in alternatives raises comparative difficulty and may amplify expectations and post-choice counterfactual comparisons, making the outcome less satisfying relative to the non-chosen alternatives.

Schwartz (2004) broadens the scope of the paradox by integrating a reflection on subjective well-being: an abundance of options not only makes choice more burdensome, but also increases perceived responsibility for the final outcome, amplifying self-criticism and frustration when the outcome is not fully satisfying.

1.3.2 Decision Mechanisms: Conflict, Deferral, and Regret

The literature has explored the mechanisms through which an excess of options can undermine the decision-making process. Dhar (1997) shows that choice deferral becomes more likely when alternatives are close in overall attractiveness, making it difficult for decision makers to form a decisive preference and to commit to a single option. In this account, deferral is consistent with preference uncertainty and the perceived reversibility of small attractiveness differences, and it is not primarily explained by trade-off difficulty or by a purely search-based rationale.

More generally, the presence of a no-choice option can reflect different underlying motivations, including postponement due to the lack of an appealing option (search/avoidance) or postponement driven by difficulty in differentiating among multiple acceptable alternatives. In this sense, abstention may represent a coherent response to highly conflictual or uncertain choice configurations.

While classic deferral literature (Dhar, 1997) focuses on the explicit selection of a 'no-choice' option, this construct can be conceptually extended to digital environments where decision-making is fragmented into multi-step tasks. In this context, the failure to finalize a structured purchase sequence may serve as an observable behavioral proxy for decision abandonment, reflecting the participant's inability to commit to a specific outcome under high-complexity conditions.

Another central mechanism is regret. Schwartz (2004) argues that as the number of available alternatives increases, individuals become more prone to counterfactual thinking and to anticipating regret, because each non-selected option can be construed as a missed opportunity. In high-numerosity contexts, such counterfactual comparison can intensify, reducing satisfaction even when the chosen outcome is objectively positive.

1.3.3 Aggregate Evidence and the Conditional Nature of the Phenomenon

Despite the influence of early experimental evidence, the choice overload paradox does not establish itself as a universal effect. The meta-analysis by Scheibehenne, Greifeneder, and Todd (2010), synthesizing evidence from approximately fifty experiments, reports a near-zero average effect of assortment size alongside substantial heterogeneity, with negative, null, and positive effects coexisting across studies.

This apparent inconsistency has been reinterpreted by subsequent work. In particular, the theory-driven meta-analysis by Alexander Chernev et al. (2015) shows that the null average effect identified by Scheibehenne et al. largely results from aggregating across heterogeneous decision contexts. When theoretically relevant moderators—such as task complexity, preference uncertainty, and decision goals—are explicitly modeled, assortment size exerts a reliable negative effect on decision outcomes.

Taken together, these findings suggest that choice overload is not a general law of consumer behavior, but rather a conditional phenomenon that emerges only under specific configurations of contextual and individual factors.

1.4 Moderators and Boundary Conditions of the Choice Overload Paradox

Building on this aggregate evidence, the literature converges on the view that choice overload arises from the interaction between assortment size and a set of moderating conditions. As clarified by Chernev et al. (2015), numerosity alone is insufficient to generate negative outcomes; instead, overload depends on the structural characteristics of the choice set, the nature of the decision task, and the cognitive and motivational characteristics of the decision-maker.

Process-level evidence further supports this interpretation. The experimental study by Vogrincic-Haselbacher et al. (2021) shows that decision quality in high-information online environments follows an inverse-U pattern: both minimal and exhaustive information processing strategies are associated with poorer outcomes, whereas focused processing of a moderate amount of information leads to superior decisions. These results reinforce the view of choice overload as an emergent, context-dependent phenomenon, rooted not only in the number of options but also in how information is selectively processed.

1.4.1 Characteristics of the Choice Set

A first class of moderators concerns intrinsic properties of the option set and the cognitive demands they impose. Building on the perceptual focus theory (Sela et al., 2009), literature suggests that larger assortments increase decision difficulty, which in turn shifts preferences toward 'virtue' options because they are easier to justify. Radová (2016) extends this mechanism by showing that the introduction of accessible justifications (e.g., through prior altruistic acts, or 'moral licensing') can interact with assortment size to alter this pattern, indicating that numerosity does not exert a uniform effect but interacts with justification processes and post-hoc rationalization.

A second, closely related aspect concerns set architecture, including the availability of explicit exit options. Parker and Schrift (2011) analyze *rejectable choice sets* and show that introducing an explicit no-choice (or “none of the above”) option can change decision processes and outcomes, including increasing decision deferral when conflict is high. This finding underscores that behavioral effects depend not only on the absolute number of alternatives, but also on how the choice set is structurally configured.

In digital environments, these mechanisms are particularly salient because platforms actively shape what users see and in which form. In the e-grocery domain, Scherpinski and Lessmann (2021) argue that short personalized rankings (top-*k*) are often insufficient given large baskets and high preference heterogeneity, and provide field evidence that extending personalization to a long ranking (top-*N*) reduces information overload and search time, with positive downstream effects on business outcomes. More broadly, work using eye-tracking highlights that attention is a central bottleneck in choice: gaze patterns are systematically related to preferences and decisions, and computational models increasingly incorporate attention as part of the choice process (Ting & Gluth, 2024). This supports the general implication that, as complexity increases, the *effective* set of options actually processed by the decision maker may be substantially smaller than the nominal set presented.

1.4.2 Characteristics of the Decision Task

A second set of boundary conditions concerns the nature of the decision task itself. Prior research suggests that the consequences of assortment size depend not only on how many alternatives are available, but also on how the task structures evaluation and comparison. When decision tasks involve high evaluative complexity—such as weak or ill-defined preferences, ambiguous attribute information, or reliance on qualitative inference—increasing the number of available options amplifies uncertainty and comparative difficulty, raising the likelihood of decision deferral and reduced satisfaction (Huffman & Kahn, 1998; Chernev, 2003).

Importantly, the decision task can also moderate the effects of numerosity even in the absence of overt cognitive overload. Diehl and Poynor (2010) show that larger assortments raise consumers' expectations regarding the degree of preference match they believe they can achieve. When these heightened expectations are not fulfilled, negative expectation–disconfirmation emerges, leading to lower post-choice satisfaction even when the chosen option is objectively identical or well-fitting. This mechanism highlights that the task shapes not only processing demands, but also the evaluative standards applied to the outcome of choice.

Taken together, these findings indicate that assortment size does not exert a uniform effect across decision contexts. Rather, the impact of numerosity depends on how the decision task structures preference uncertainty, evaluative difficulty, and expectation formation. Numerosity should therefore be understood as interacting with task characteristics, rather than acting as an isolated determinant of decision outcomes (Chernev, 2012).

1.4.3 Individual Differences

Individual differences constitute another relevant set of moderators. Roets et al. (2012) show that a dispositional tendency toward maximizing is associated with greater regret and lower subjective well-being in societies characterized by high choice availability and a strong cultural emphasis on individual choice. Rather than reflecting a direct effect of assortment size per se, this pattern suggests that maximizing exacerbates the psychological costs of choice in contexts where selecting the "best" option is normatively valued. Decision makers oriented toward maximizing tend to engage in more extensive comparisons and to keep forgone alternatives cognitively salient, thereby increasing the emotional burden of decision making.

Importantly, these effects are not invariant across contexts. The same authors show that in cultural environments characterized by a weaker emphasis on individual autonomy and more constrained choice structures, the relationship between maximizing and well-being is substantially attenuated, despite a persistent association between maximizing and regret. This pattern indicates that individual differences operate in interaction with the societal meaning and consequences of choice, rather than as absolute determinants of decision outcomes.

Converging evidence from hyperchoice research further supports this interactive perspective. Nemmers and Cheng (2020) show that while large assortments systematically increase perceived decision difficulty and reduce satisfaction, these negative experiential effects are significantly weaker among individuals with higher numeracy. Greater competence in processing complex information appears to mitigate some procedural costs of exploration and comparison, without fully eliminating comparison-based regret or expectation-related dissatisfaction. Together, these findings suggest that individual capabilities shape the experience of choice primarily by attenuating—rather than nullifying—the costs associated with large and complex assortments.

1.4.4 Age and Life Cycle

Age represents a particularly relevant moderator in the context of the choice overload paradox. Reed et al. (2008) show that older individuals tend to prefer smaller choice sets than younger adults across multiple decision domains. This age-related preference for reduced choice is interpreted as reflecting a combination of cognitive and motivational factors, including diminished processing resources, greater aversion to decisional conflict, and an increased emphasis on emotional regulation.

These life-cycle differences are especially pronounced in domains characterized by high personal relevance, suggesting that tolerance for extensive assortments decreases with age. Accordingly, the point at which an increase in options is perceived as excessive is likely to vary systematically across the life cycle. This implies that the effects of alternative numerosity cannot be fully understood without accounting for age-related differences in decision preferences and goals.

While these findings concern stated preferences rather than observed choice behavior, they provide a strong theoretical rationale for expecting age-related heterogeneity in the emergence of choice overload.

1.4.5 Theoretical Implications for the Analysis of the Choice Overload Paradox

Overall, the literature indicates that the choice overload paradox emerges from the interaction between the number of options and a plurality of moderators related to the set, the decision task, and the characteristics of the decision maker. This perspective highlights that the effects of assortment expansion are neither uniform nor inevitable, but depend on specific configurations of the decision environment and the decision-maker profile.

Attention to boundary conditions therefore allows choice overload to be interpreted as an emergent and contextual phenomenon, rather than as a universal regularity. This theoretical framing is particularly relevant in e-commerce contexts, in which alternative numerosity coexists with high levels of informational complexity and strong heterogeneity among decision makers. The following section examines how these dynamics manifest specifically in digital purchasing environments.

1.5 The Choice Overload Paradox in E-Commerce Contexts

E-commerce represents a privileged context for the analysis of the choice overload paradox, as it combines high availability of alternatives, informational abundance, and decision-making processes mediated by digital interfaces. Unlike traditional offline contexts, digital platforms make extensive catalogs accessible and allow rapid comparisons, but they also require decision makers to manage multiple alternatives and attributes.

A critical point, consistent with the boundary conditions discussed, is that in digital contexts numerosity is often "governed" by informational architectures, filters, and recommendations. These elements can attenuate or amplify overload, but they also introduce a source of empirical heterogeneity: changes in the structure of choice may mask the effect of numerosity or make it difficult to attribute. For this reason, while acknowledging the role of UI and digital architecture as moderators, the experimental analysis of the present thesis focuses on numerosity while keeping other design components constant.

1.5.1 Navigation and Informational Architectures

Prior research indicates that the effects of assortment size in digital environments are deeply intertwined with the way alternatives are structured, organized, and made accessible through navigation and informational architectures. Rather than being experienced as a raw count of options, numerosity is filtered through menus, categories, rankings, and interaction logic that shape how alternatives are explored and compared.

Evidence from conversion optimization research highlights the importance of these architectural dimensions. Miikkulainen et al. (2018) show that different configurations of interface elements—such as layout, ordering, and visual emphasis—can generate large differences in user behavior even when the underlying content and available options remain constant. Although their contribution is not framed in terms of choice overload, their findings underscore that interface structure can substantially alter the cognitive demands associated with navigating large option spaces.

Relatedly, research on online controlled experiments emphasizes that navigation logic and exposure rules can confound the interpretation of behavioral effects. Liu and Chamberlain (2018) demonstrate that when interaction with interface elements depends on dynamic user behavior, experimental groups may systematically differ in ways that complicate causal attribution. In such settings, changes in navigation or triggering mechanisms can mask or distort the observed impact of other variables, including assortment size.

From a decision-theoretic perspective, Feit and Berman (2019) further show that in many applied e-commerce settings experimentation is conducted under finite traffic and profit constraints, leading firms to prioritize rapid decision-making over precise statistical inference. While their focus is not on choice overload, their analysis illustrates how interface-level variations are often evaluated in ways that blur learning about specific causal mechanisms.

Taken together, these contributions indicate that informational architectures do not merely accompany numerosity but actively shape how it is experienced and measured. As a result, isolating the effect of assortment size requires holding navigation and interface structures constant, particularly in experimental designs aimed at identifying the boundary conditions of the choice overload paradox.

1.5.2 Recommendation Systems

Recommender systems constitute a central mechanism through which digital platforms manage large choice environments. Rather than merely increasing exposure, recommendation algorithms actively structure attention by ranking, filtering, and prioritizing subsets of the available alternatives. As shown by Abhijnan Chakraborty et al. (2019) in the context of non-personalized news recommendation, recommendation strategies necessarily involve trade-offs between relevance, recency, and diversity, and implicitly constrain the set of options that users are likely to process. Even when large catalogs are available, only a fraction of items receives effective attention, while the remaining options remain cognitively latent.

Evidence from AI-driven e-commerce environments further supports this selective-processing view. Jiwang Yin et al. (2025) show that AI-personalized recommendations increase clicking intention primarily by enhancing perceived relevance, inspiration, and immersive experience, rather than by expanding the sheer number of alternatives considered. While personalization can reduce search effort and facilitate engagement, it also reshapes consumers' consideration sets by foregrounding a limited subset of options, thereby altering both perceived complexity and decision dynamics.

Taken together, this literature suggests that recommender systems do not simply alleviate choice overload, but reconfigure it: they can mitigate complexity by guiding attention, yet simultaneously obscure the independent role of alternative numerosity. For this reason, introducing recommendation mechanisms as an experimental manipulation would confound the effects of set size with those of algorithmic prioritization. Accordingly, the present research keeps recommendation systems constant, in order to isolate the impact of numerosity under controlled interface conditions.

1.5.3 UI Design and Digital Choice Architecture

Miikkulainen et al. (2017) show how evolutionary design approaches can identify interface configurations that reduce cognitive load and improve decision performance by optimizing informational density, number of steps, and order of presentation. Liu and Chamberlain (2021) emphasize that such optimizations require experimental validation, as UI effects can be counterintuitive and interact with decision outcomes in non-linear ways. Feit and Berman (2018) further highlight a trade-off between rapid learning and the risk of exposing users to suboptimal configurations during experimentation.

Taken together, these contributions indicate that while UI design governs how choice overload manifests, it does not eliminate the underlying cognitive mechanisms associated with large choice sets. Consequently, isolating the effect of numerosity requires holding the interface constant, so that observed differences can be attributed to set size rather than to variations in presentation architecture.

1.5.4 Synthesis: E-Commerce as a Critical Context and Implications for Experimental Control

Overall, e-commerce accentuates the theoretical conditions of the choice overload paradox: extensive catalogs and informational abundance increase the salience of numerosity. However, the digital environment also includes tools that reorganize and filter choice (informational architectures, recommendations, UI), which can attenuate or amplify overload and contribute to heterogeneity in empirical results. Consequently, analyzing numerosity in a controlled e-commerce context, while keeping informational architecture and presentation modes constant, allows for a more credible isolation of the effect of set size on decision outcomes.

The following section introduces the contribution of neuroscience, focusing on attentional and value-integration limits that make “unobservable” costs plausible even when behavioral outcomes appear unchanged.

1.6 Neuroscience and Cognitive Limits in Choice

The integration of cognitive neuroscience into the study of decision making clarifies the neural mechanisms underlying the limits described by the behavioral literature. Neuroscientific evidence provides a complementary level of analysis, showing how attentional constraints and value-integration costs emerge already in early stages of the decision process. In this sense, neuroscience reinforces the interpretation of the choice overload paradox as a phenomenon rooted in limited cognitive capacities.

1.6.1 Attention, Processing Capacity, and Option Numerosity

Peng et al. (2022) show that increases in information load are associated with greater cognitive conflict and less efficient allocation of attentional resources, as reflected in longer response times and ERP markers of conflict monitoring and value integration. As informational demands increase, only a subset of available information receives deep processing, while remaining elements are processed superficially or ignored.
Although their manipulation concerns information load rather than option numerosity per se, these findings support the interpretation that, in large choice sets, attentional resources are rapidly saturated. Overload thus emerges not as an inability to choose, but as a limitation in the depth and efficiency with which alternatives can be evaluated.

1.6.2 Value Integration and Cognitive Costs

Peng et al. (2021) show that increasing information load in online choice (i.e., presenting a higher number of product attributes) is associated with longer decision times and ERP signatures consistent with greater decision difficulty and higher processing costs (e.g., reduced P3 amplitude). These results suggest that, as the informational demands of evaluation increase, the decision process becomes more resource-intensive, requiring additional time and cognitive effort even when a choice can still be made.

1.6.3 Hidden Overload and Dissociation Between Performance and Experience

Evidence from consumer neuroscience suggests that the absence of observable behavioral differences does not necessarily imply the absence of cognitive costs. For instance, Çakar et al. (2024) demonstrate that financial decisions resulting in similar behavioral outcomes can be supported by distinct patterns of prefrontal activation, reflecting variations in cognitive effort and executive control. This dissociation suggests a 'hidden' dimension of effort that remains unobserved in traditional choice metrics. When integrated with the behavioral framework of the choice overload paradox (Schwartz, 2004), these neuroscientific findings provide a physiological basis for the emergence of subjective costs—such as mental fatigue or reduced post-choice satisfaction—even in the absence of immediate performance decrements

1.6.4 Synthesis: The Neuroscientific Contribution to the Choice Overload Paradox

Overall, neuroscientific evidence reinforces the interpretation of the choice overload paradox as a phenomenon rooted in attentional limits and value-integration costs. This level of analysis supports the conditional nature of the phenomenon and motivates attention not only to behavioral outcomes but also to subjective process costs, as discussed in the following section on gaps in the literature.

1.7 Research Gaps in the Choice Overload Literature

Despite the breadth of the literature on the choice overload paradox, the available evidence presents theoretical and empirical gaps that limit its explanatory power in contemporary applied contexts. As discussed, choice overload emerges as a conditional phenomenon, influenced by factors related to the set, the task, and the decision maker. However, this richness of moderators has contributed to a fragmentation of findings, making a univocal synthesis difficult.

A first gap concerns empirical heterogeneity: meta-analyses and critical reviews indicate that increases in numerosity do not produce uniform effects on satisfaction, likelihood of choice, or decision quality. Many studies focus on single experimental conditions or specific contexts without systematically testing interactions between numerosity and relevant dimensions, resulting in evidence that is weakly cumulative.

A second gap concerns the limited integration between option numerosity and product complexity. Although several contributions acknowledge that not all decisions are equally vulnerable, there is often a lack of direct comparison of how numerosity interacts with the evaluative complexity of the object in determining outcomes.

A further limitation concerns the demographic dimension and the life cycle. Although age is identified as a moderator, many studies consider homogeneous samples or single age groups. Contributions that comparatively analyze how responses to numerosity vary between younger adults and older individuals—particularly in digital contexts—remain relatively rare.

A fourth element concerns the e-commerce context. Many studies rely on laboratory experiments or hypothetical decisions, whereas evidence from real or simulated digital environments remains limited. When present, such studies often introduce multiple design interventions simultaneously (filters, recommendations, interface reorganizations), making it difficult to isolate the specific effect of numerosity.

Another gap concerns the national context of reference. Most available evidence derives from studies conducted in Anglo-Saxon contexts, while experimental contributions focused on Southern European populations, and in particular on the Italian context, are limited. Given generational differences in digital skills and e-commerce usage patterns, the absence of context-specific evidence constrains the understanding of the boundary conditions of the choice overload paradox in these settings.

Finally, the literature often privileges behavioral outcomes, neglecting the cognitive and subjective costs of the process: the absence of differences in final choices does not imply the absence of overload, as suggested by neuroscientific evidence. Few studies integrate measures of subjective experience with controlled manipulations of numerosity in digital contexts.

Overall, these gaps indicate the need for an empirical approach that analyzes the choice overload paradox as a phenomenon emerging from the interaction between option numerosity, object complexity, and decision-maker characteristics, within a controlled e-commerce context.

1.8 Research Objectives, Research Questions, Hypotheses, and Contributions

1.8.1 Research Objectives

Considering the literature analyzed in Sections 1.1–1.7, a multifaceted picture emerges regarding the effects of decision complexity and the choice overload paradox in digital contexts. The evidence shows that increasing the number of options can generate cognitive overload, decision conflict, and deteriorated outcomes, but these effects are not universal and depend on the characteristics of the choice set, task structure, and individual and demographic differences.

In particular, a substantial portion of the literature emphasizes that numerosity does not act in isolation: informational architectures, filters, and presentation modes can attenuate or amplify overload. However, this very interdependence makes it empirically complex to isolate the specific role of numerosity as an autonomous source of overload.

Accordingly, the general objective of this thesis is to empirically analyze the choice overload paradox in the Italian e-commerce context by using option numerosity as the primary controlled experimental lever, while keeping informational structure, choice architecture, and presentation modes constant. This approach allows for a targeted observation of the effects of quantitative complexity on decision outcomes, avoiding the confounding influence of organizational or informational simplification interventions that could reduce the attributability of effects to set size.

The study adopts a comparative perspective that integrates two central dimensions emerging from the literature: (i) demographic differences, with particular reference to decision-maker age, and (ii) the cognitive complexity of the object of choice, distinguishing between functionally related products characterized by increasing levels of informational articulation.

Specifically, the research examines how numerosity influences decision outcomes in simulated digital purchase environments, comparing three product categories (phone cases, power banks, and smartphones) and observing these effects across distinct age groups within the Italian adult population.

1.8.2 Research Questions

Consistent with the experimental design, the research questions focus on the effects of option numerosity—analyzed under constant informational architecture and presentation modes—and on the moderating role of age and object complexity.

RQ1: Does the choice overload paradox systematically emerge in the Italian e-commerce context when option numerosity is manipulated while holding informational architecture and presentation modes constant?

RQ2: How do different age groups (20–35, 35–60, over 60) moderate the relationship between option numerosity and decision outcomes in e-commerce environments?

RQ3: Does the effect of option numerosity vary as a function of the cognitive complexity of the object of choice, even within the same functional category?

RQ4: Is there an interaction between decision-maker age and object complexity in determining the emergence or attenuation of the choice overload paradox in digital purchase contexts?

1.8.3 Research Hypotheses

Based on the available evidence and in coherence with the research questions, the following relationships are translated into testable hypotheses. Numerosity is treated as the primary experimental variable, while age and the cognitive complexity of the object of choice are considered moderating factors.

In the context of the present experimental design, decision completion is operationalized as the successful execution of the structured purchase task assigned to participants. Failure to complete this task is interpreted as a form of behavioral decision abandonment or postponement, consistent with the choice deferral mechanisms discussed in Section 1.3.2. This operationalization allows deferral behavior to be observed within a controlled digital decision environment while maintaining coherence with the theoretical literature on decision avoidance and postponement.

H1: Option numerosity has a systematic effect on decision outcomes in e-commerce simulations when informational architecture and presentation modes are held constant.

H2: Age moderates the relationship between option numerosity and decision quality, with greater sensitivity to decision overload in older age groups.

H3: The effect of option numerosity on decision outcomes is more pronounced for products characterized by high cognitive complexity than for products with low complexity.

H4: The interaction between decision-maker age and object complexity amplifies or attenuates the effects of the choice overload paradox, generating differentiated decision patterns across age groups.

All hypotheses are directly testable through the adopted experimental design.

1.8.4 Theoretical Contributions

From a theoretical perspective, this research contributes to the choice overload literature in several ways. First, it provides empirical evidence from a specific national population, helping to address the gap related to the limited attention given to Italian and European contexts.

Second, the thesis introduces a systematic distinction between objects of choice characterized by differing levels of cognitive complexity, clarifying whether the choice overload paradox should be interpreted as a general property of numerosity or as a phenomenon dependent on the nature of the chosen object.

Third, the joint analysis of age and object complexity contributes to a more precise definition of the phenomenon's boundary conditions, helping to explain part of the heterogeneity observed in empirical findings.

Finally, the study strengthens the dialogue between behavioral literature and applied digital contexts by extending the analysis of the choice overload paradox to realistic and controlled purchase simulations.

1.8.5 Managerial Contributions

From a managerial standpoint, the expected results offer guidance for the design of choice architectures in e-commerce environments. The research suggests that assortment and presentation strategies cannot be considered universally valid, but should instead be calibrated according to the demographic target and the complexity of the offered product.

The comparative analysis across products with different levels of complexity highlights the importance of differentiating choice set design logics, avoiding uniform approaches that may prove ineffective or counterproductive. Attention to generational differences further provides an empirical basis for more informed decisions regarding segmentation, personalization, and testing of digital solutions, anchoring managerial implications to observable evidence.

2 Research Design and Methods

2.1 Research Design

The present research adopts a quantitative experimental approach, with an inferential objective oriented toward testing causal relationships in decision-making processes within digital contexts. Consistent with what was discussed in Chapter 1, the study does not merely describe associations between variables, but aims to observe in a controlled manner how specific manipulations of the choice environment influence users' decision behavior, clarifying the conditions under which such effects emerge, attenuate, or are absent. The adoption of an experimental design therefore responds to the need, highlighted in the literature, to identify the boundary conditions of the choice overload paradox, overcoming the inconsistency of results observed in purely observational studies or those based on abstract tasks.

The research objective is directly anchored to the theoretical and empirical gaps identified in Chapter 1. In particular, recent literature has highlighted that the effects of option numerosity are not universal, but depend on a combination of factors related to the structure of the choice environment, the complexity of the decision object, and the characteristics of decision makers. Moreover, relevant shortages have emerged in experimental studies conducted in realistic digital contexts and focused on specific national populations, as well as limited attention to age differences as a moderator of decision processes. The adopted design intends to operationalize these elements, translating the main theoretical tensions into observable manipulations within a simulated e-commerce environment.

From an operational standpoint, the study is structured as a controlled experiment implemented in the form of an A/B test. Two versions of a simulated e-commerce website are compared, identical in every structural, graphical, and functional aspect, except for the numerosity of alternatives presented for each product category. In one version of the site (reduced-set condition), participants view a limited number of options per page, whereas in the other version (expanded-set condition) the number of available alternatives is significantly larger. In this way, choice set size constitutes the central experimental manipulation, allowing the effect of informational density on experience and decision outcomes to be isolated.

Unlike many previous studies based on single, forced-choice tasks, the adopted design allows participants to freely interact with the digital environment and to make zero, one, or multiple purchases during the experimental session. Participants can explore different product categories, add or remove items from the cart, and autonomously decide whether or not to complete a purchase. This setting more faithfully reflects the typical dynamics of a real e-commerce experience and makes it possible to observe not only the final outcome of choice, but also the decision processes that unfold throughout the interaction.

A second central element of the design concerns product type, used to operationalize different levels of complexity of the decision object. The study includes three product categories: smartphones, power banks, and phone cases. These categories belong to the same technological and functional domain, but differ in the degree of informational articulation and in the cognitive effort typically required in choice. Object complexity is not manipulated through instructions or artificial constraints, but emerges as an intrinsic property of the considered categories, making it possible to observe whether the effect of set size varies across product categories used as proxies for different levels of decision-object complexity.

The demographic dimension is integrated into the design through the segmentation of participants into three predefined age groups: 20–35 years, 35–60 years, and 60 years or older. In line with the evidence discussed in Chapter 1, age is conceptualized as a key moderating variable, potentially influencing the management of complexity and tolerance toward more or less dense choice environments. Treating age as a categorical variable allows systematic differences between groups to be analyzed, without assuming linear trends or developmental models not explicitly supported by the literature.

Overall, the experimental design can be represented as a 2 (set size: reduced vs. expanded) × 3 (product category: smartphone, power bank, phone case) × 3 (age group) factorial structure, enabling the analysis of main effects and interactions among the key dimensions identified by the theoretical framework. This setup makes it possible to test whether and under which conditions choice complexity influences decision behavior, avoiding the a priori assumption of a uniform choice overload effect. The design integrates observational behavioral data with post-task subjective measures, enabling a multi-level interpretation of decision processes. This integration makes it possible to complement the observation of manifest behaviors with an assessment of the experience lived by participants during the choice process. This approach is consistent with the research objective of analyzing decision complexity not only in terms of outcomes, but also in terms of the experience of choosing.

The experimental structure of the study can be visually summarized through the factorial design illustrated in Figure 2.1a. The diagram highlights the hierarchical organization of the experimental manipulation and the observational structure of the data. Participants are randomly assigned to one of two choice set size conditions (between-subject factor). Product categories are observed within each participant, generating repeated observations across products (within-subject factor). Age groups constitute an additional between-subject moderating dimension used to examine heterogeneity in responses to choice set size and product complexity.

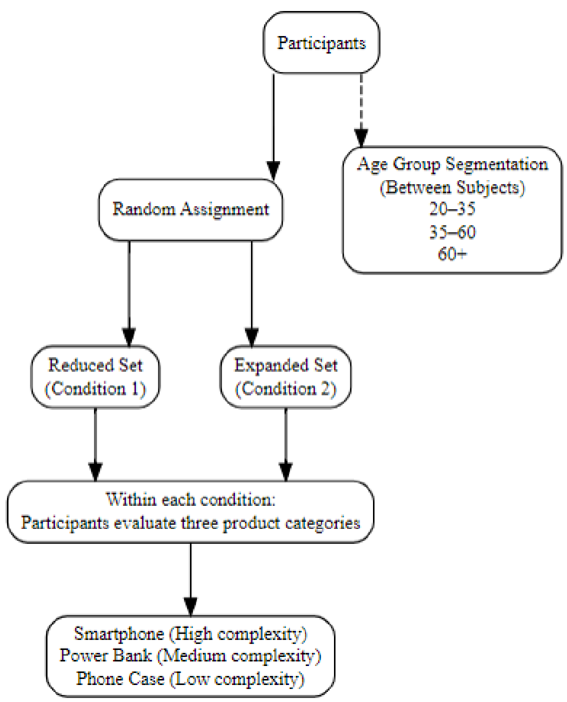

Figure 2.1a Experimental factorial design and participant assignment structure

As shown in Figure 2.1a, the design combines a between-subject manipulation of choice set size with within-subject observations across product categories, while age groups serve as an additional between-subject moderating dimension. This hierarchical structure defines the observational framework used in the empirical analysis and determines the appropriate treatment of repeated observations at the participant level.

This section has defined the research design and the underlying experimental logic. Section 2.2 will describe in detail the experimental context and the stimuli used, illustrating the construction of the simulated e-commerce environment and the product categories. Section 2.3 will instead be dedicated to the sample and the data collection procedure, clarifying the assignment to experimental conditions and the execution of the decision task.

The experimental procedure followed by participants can be summarized through the standardized flow illustrated in Figure 2.1b. The visual implementation of each stage—from the gatekeeping consent page to the final psychometric survey—is documented through platform screenshots in Appendix A (Sections A.2–A.7).

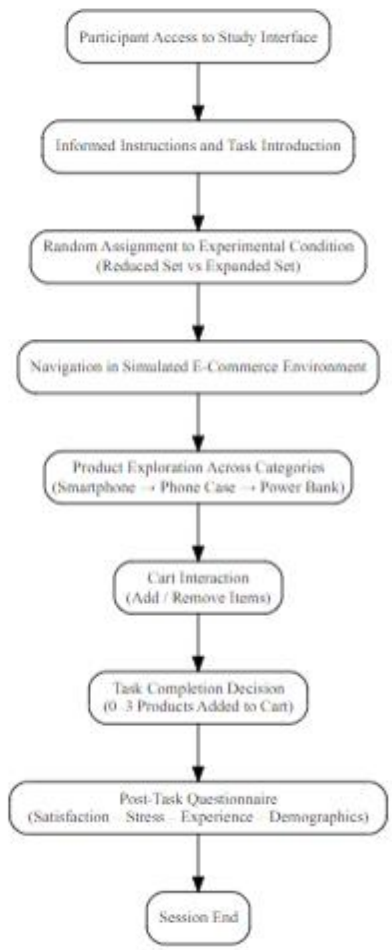

Figure 2.1b – Participant experimental procedure flowchart

2.2 Experimental Context and Stimuli

The experimental context of the research consists of a simulated e-commerce environment, designed to enable the controlled observation of decision-making processes in a realistic digital purchase situation. The experiment reproduces the structure of an e-commerce website, within which participants can navigate across different product categories, explore available alternatives, and freely decide whether to make purchases. The simulated environment is designed to provide a realistic decision context while maintaining the experimental control described in Section 2.1. The objective is not to fully replicate operational e-commerce platforms, but to ensure that participants interact with a coherent and credible digital purchasing interface.

The study includes two versions of the simulated e-commerce website, corresponding to the two main experimental conditions. The two versions are identical in every respect, including layout, navigation structure, graphical interface, product categories, and purchase funnel logic. The only difference between the two conditions concerns the numerosity of alternatives presented within each product page. In one version of the site (reduced-set condition), participants view a limited number of options per category, whereas in the other version (expanded-set condition) a significantly larger number of alternatives is presented. This manipulation makes it possible to directly isolate the effect of informational density and choice set numerosity, avoiding spurious variation. The visual consistency of the 'Reduced' vs. 'Expanded' grid layouts is illustrated in Figure A.4 (Appendix A).

Within each version of the site, participants can explore three product categories: smartphones, power banks, and phone cases. The selection of these categories follows a logic of functional coherence and thematic continuity. All products belong to the same technological domain and are commonly associated with the use of personal electronic devices. Moreover, the categories are functionally connected: the phone case and the power bank represent accessories directly linked to the smartphone, which constitutes the primary device. This choice allows the usage context and the type of need satisfied to be held constant, facilitating comparison across decisions concerning different objects.

While sharing the same functional domain, the three product categories differ in the level of decision complexity typically associated with choice. The smartphone represents a product characterized by high informational articulation, multi-attribute evaluation, and higher perceived purchase risk. The power bank occupies an intermediate position, whereas the phone case represents a relatively simple product requiring more limited attribute comparison and evaluative effort. The smartphone represents a product characterized by high informational articulation. To facilitate this, the interface provided a detailed modal view for technical specifications and social proof, as shown in the experimental interface screenshot in Figure A.5 (Appendix A).

The use of product categories as a proxy for decision complexity is consistent with consumer decision-making research, which shows that product evaluations systematically vary depending on attribute dimensionality, perceived risk, and information processing requirements. Within the present experimental design, complexity is therefore operationalized as a structural characteristic of the decision object rather than as a subjective perception measured ex post. Participants are not explicitly informed about differences in product complexity, allowing complexity to emerge naturally from the evaluation demands associated with each category and enabling observation of spontaneous decision behavior within a controlled digital environment.

Consistent with the experimental logic described in Section 2.1, participants were allowed to freely interact with the available options within each product category and to complete the purchase task without forced-choice constraints. Product categories were presented following a standardized sequence (smartphone, phone case, and power bank), ensuring consistency across participants while preserving freedom of exploration within each category. This structure enables the observation of both decision outcomes and decision processes while maintaining control over task progression.

To ensure the internal validity of the comparison between conditions, all other aspects of the task are held constant. Page structure, option presentation mode, instructions provided to participants, and the task goal remain invariant across set-size conditions and product categories. In this way, any observed differences in behaviors or decision outcomes can be attributed to the manipulation of alternative numerosity and to object complexity, rather than to variations in context or task nature.

Overall, the experimental context and stimuli are designed to balance realism and control, two central requirements for a study oriented toward causal inference in decision research. The simulation of an e-commerce environment allows the experiment to be situated in a context coherent with the themes addressed in Chapter 1, while the targeted manipulation of option numerosity and the selection of product categories enable a parsimonious operationalization of the theoretical dimensions of interest. Section 2.3 will describe the sample and the experimental procedure in detail, illustrating participant recruitment, assignment to conditions, and the operational phases of the study.

2.3 Sample and Procedure

The reference population of the present research consists of adult consumers in the Italian context. The decision to focus on Italy is intentional and directly linked to the gaps identified in the literature reviewed in Chapter 1, which highlights a prevalence of studies conducted in Anglo-Saxon contexts or on samples not clearly located geographically. Focusing on a specific national population allows investigation of whether the decision patterns documented in prior research also emerge in a different socio-cultural context, without assuming a priori full generalizability of results. Consistent with this framing, the sample is not conceived as representative of the entire Italian population, but as functional to the experimental testing of the relationships under study.

A central element of the design concerns the segmentation of participants by age. In line with the research design and with the evidence discussed in Chapter 1, participants are divided into three predefined age groups: 20–35 years, 35–60 years, and 60 years or older. This articulation reflects the theoretical interest in differences in decision processes across the life course and in the role of age as a moderating factor in the management of complexity and option numerosity, particularly in digital contexts. Age is therefore treated as a key moderating variable rather than as a simple control variable.

Participant recruitment took place through procedures consistent with an online experimental study. Participation was voluntary and managed through a gatekeeping interface. The informed consent page and the specific privacy disclosures presented to participants are documented in Appendix A (Section A.2). Nationality was collected to verify adherence to the focus on the Italian context and, where necessary, to enable robustness analyses excluding non-Italian participants. Within the constraints of a controlled experimental design, each participant was assigned to only one version of the simulated e-commerce website, corresponding to one of the two experimental conditions (reduced-set versus expanded-set), and interacted exclusively with that configuration for the entire duration of the session.

From a procedural standpoint, the experiment follows a standardized sequence identical for all participants, except for the manipulation of option numerosity described in Sections 2.1 and 2.2. Participants first access the study through an online interface and receive general instructions. The specific task framing and budget constraints utilized to contextualize the purchase exercise are illustrated in Figure A.3 (Appendix A). They are then introduced to the simulated e-commerce environment, within which they can freely navigate across the available product categories. During this phase, participants may explore alternatives, add or remove products from the cart, and autonomously decide whether to complete one or more purchases.

A relevant feature of the procedure is the absence of constraints on the number of products that may be purchased. Each participant may make zero, one, or multiple purchases during the session, up to a maximum of three, corresponding to the available product categories. This structure allows observation of exploration, partial choice, and abandonment dynamics while maintaining consistency in task progression across participants. Although product categories are presented in a standardized sequence, participants retain full freedom to explore alternatives and manage purchase decisions within each category, consistent with the experimental framework described in Section 2.1.

During interaction with the simulated website, behavioral data related to navigation and participant actions are automatically recorded. At the end of the shopping session, participants complete outcome measures specified by the experimental design, capturing both decision outcomes and the overall experience of the task. A short post-task questionnaire then collects socio-demographic information (age and nationality) and subjective evaluations of the shopping experience. Importantly, these measures are administered only after completion of the decision task, in order to minimize interference with navigation behavior.

The procedural structure also contributes to limiting potential sources of bias. Because each participant interacts with only one version of the website and is not exposed to direct comparisons across conditions, the design reduces the risk of learning effects and contamination between experimental conditions. At the same time, standardized instructions and an identical interface across conditions help contain demand effects, without claiming complete control over all extraneous variables.

With regard to sample size considerations, the final number of observations is determined by the intersection of voluntary participation, assignment to experimental conditions, and the completeness of recorded behavioral data. The achieved sample size is sufficient to support the estimation of main effects and first-order interactions consistent with the factorial structure of the design. Analyses involving higher-order interactions are conducted in an exploratory and interpretive manner, with appropriate caution regarding statistical power. This approach is coherent with the objective of identifying boundary conditions of the choice overload paradox rather than establishing universal effects.

In summary, the sample and procedure are designed to support the analysis of relationships between choice set size, decision-object complexity, and participant age within the specific context of a simulated e-commerce environment. The focus on the Italian context, age segmentation, and freedom of interaction granted to participants directly address gaps identified in the literature and provide a coherent empirical basis for subsequent analysis. Section 2.4 will describe in detail the variables and measures used to operationalize the constructs of interest.

2.4 Variables and Measures

This section describes the variables included in the study and the ways in which they were defined and measured, in coherence with the theoretical framework developed in Chapter 1 and with the experimental design illustrated in Sections 2.1–2.3. The operationalization of variables reflects the causal logic of an experimental approach and prioritizes the use of objective behavioral measures, automatically recorded during participants' interaction with the simulated e-commerce environment. In line with the literature on the choice overload paradox and decision complexity, the study does not aim to directly measure cognitive overload as a latent construct, but to observe behavioral patterns and subjective evaluations compatible with conditions of greater or lesser complexity of the choice environment.

The independent variables of the study include three main dimensions: choice set size, product type, and participant age. Choice set size constitutes the central experimental manipulation and is articulated into two conditions: reduced set and expanded set. In the reduced condition, each product category displayed five alternatives, whereas in the expanded condition twenty alternatives were displayed. The number of options was identical across all three product categories and alternatives were presented simultaneously within the same page layout and navigation structure. Apart from the number of displayed alternatives, all other interface elements (layout, product information, prices, and navigation logic) were held constant across conditions. Participants were randomly assigned to one of the two conditions at the beginning of the session through condition-specific access links, and the researcher did not control individual assignment to conditions. Choice set size is therefore a categorical variable defined a priori by the experimental design and not measured as a subjective perception.

The second independent variable is product type, used to operationalize different levels of decision-object complexity. The study includes three product categories: smartphones, power banks, and phone cases. This variable reflects a structural characteristic of the choice task and serves as a proxy for the decision complexity associated with the object, which emerges from the nature of the product itself and the number and type of attributes generally relevant to evaluation. Complexity is not manipulated through instructions or artificial constraints, but is implicitly embedded in the product category presented to participants.

The third independent variable is age, treated as a categorical variable based on three predefined groups: 20–35 years, 35–60 years, and 60 years or older. Consistent with the research hypotheses and with the demographic gaps identified in Chapter 1, age is conceptualized as a key moderating variable, potentially influencing how participants cope with choice environments characterized by different option numerosity and different object complexity.

The dependent variables of the study include behavioral process measures, behavioral outcome measures, and post-task subjective measures, collected during or at the end of the interaction with the simulated environment. Process measures include time spent on individual product pages and total time required to complete the shopping session. These temporal variables are used behavioral indicators of interaction intensity during evaluation, insofar as the reflect how long participants remain engaged with the available alternatives within the interface. Time is interpreted cautiously as a behavioral indicator of evaluation activity, without being equated with a direct measure of cognitive overload.

Alongside temporal measures, the study records indicators of interaction with the interface, such as viewing product details, navigating across pages, and adding or removing products from the cart. These behavioral signals are not analyzed individually, but are jointly integrated into a composite behavioral index capturing overall decision effort during the task.

The composite effort index is constructed using principal component analysis (PCA). The detailed statistical procedure for component extraction, including the assessment of common variance and factor loadings, is provided in Appendix B (Section B.2).PCA is employed to reduce dimensionality and capture the common variance underlying multiple correlated engagement measures. The resulting index represents a standardized summary indicator of overall behavioral interaction intensity during the decision process. Detailed information regarding variable selection, standardization procedures, component extraction criteria, and robustness checks is provided in Appendix B.

Behavioral outcome measures include whether or not the purchase is completed within the simulated task, treated as a dichotomous variable. In the present experimental context, completion is operationally defined as completion of the experimental purchase task, corresponding to the successful addition of all three target products—smartphone, phone case, and power bank—to the shopping cart during the session. The variable is therefore coded as a binary indicator equal to one when participants add all three product categories to the cart, and zero otherwise.

Importantly, this measure captures task completion within the experimental framework and should not be interpreted as equivalent to real purchase conversion in commercial settings. Rather, completion represents a behavioral proxy for decision persistence versus decision deferral or abandonment, consistent with the theoretical mechanisms discussed in the choice overload literature. This distinction allows the study to observe how variations in choice architecture influence the likelihood that participants carry the decision process through all required stages of the experimental task.

At the end of the decision task, post-task subjective measures are collected. The visual layout and phrasing of the Satisfaction and Stress scales are shown in the final survey screenshot in Figure A.7 (Appendix A). The measures are relating to: (i) overall satisfaction with the shopping experience, and (ii) perceived stress or confusion during the decision process. These measures make it possible to integrate observation of manifest behaviors with a subjective evaluation of decision experience, consistent with the research focus on choice complexity in digital contexts. In this case as well, measures are not intended as direct indicators of cognitive overload, but as perceptual outcomes associated with conditions of greater or lesser complexity of the choice environment.

A self-reported measure of familiarity with e-commerce interfaces is included as a control variable (see Figure A.2, Appendix A, for the demographic data form).This variable captures heterogeneity in prior exposure to online shopping environments and is introduced to account for baseline differences in navigation efficiency and decision confidence unrelated to the experimental manipulation.

With regard to control variables, no additional covariates are included at the analytic level. Control of alternative explanations is pursued primarily through the experimental design, particularly through standardization of context, interface, and procedure, as described in Sections 2.1–2.3. Nationality is collected in order to verify the coherence of the sample with the focus on the Italian context, which constitutes one of the central elements of the empirical gap addressed by the research. Specifically, collecting this information makes it possible to identify any non-Italian participants and to assess their impact on overall results. If necessary, nationality is used to conduct robustness analyses by comparing results obtained on the full sample with those observed on a subsample consisting exclusively of Italian participants.

Overall, the definition of variables and measures reflects close alignment between the theoretical framework, experimental design, and empirical operationalization. The integration of behavioral measures and post-task subjective measures makes it possible to address the choice overload paradox from a dynamic and multi-level perspective, observing how the complexity of the choice environment manifests not only in final outcomes, but also in processes and in participants' decision experience. Section 2.5 will describe the data analysis techniques used to systematically examine these variables and to test the research hypotheses formulated in Section 1.8.

To improve transparency and replicability of the empirical analysis, Table 2.4 summarizes all variables included in the study, providing their conceptual role, operational definition, measurement scale, and data source. Detailed technical construction procedures for composite indicators and data transformations are documented in Appendix B.

VARIABLE	ROLE	OPERATIONAL DEFINITION	SCALE / CODING	DATA SOURCE
CONDITION	Independent variable	Experimental manipulation of choice set size (reduced vs expanded assortment)	Binary categorical	Experimental assignment
PRODUCT CATEGORY	Independent / Within-subject factor	Product type used as proxy for decision-object complexity (smartphone, power bank, phone case)	Categorical	Website interaction logs
AGE GROUP	Moderating variable	Participant age category (20–35, 35–60, 60+)	Categorical	Post-task questionnaire
COMPLETION	Behavioral outcome	Successful addition of all three target products to cart during session	Binary (1 = completed task, 0 = otherwise)	Interaction logs
EFFORT INDEX	Process measure	Composite behavioral indicator capturing interaction intensity during decision process	Standardized continuous index	Interaction logs (see Appendix B)
TIME ALLOCATION	Process measure	Time spent evaluating each product category	Continuous (log-transformed time +1)	Interaction logs
PERCEIVED STRESS	Subjective outcome	Self-reported stress/confusion during decision process	Likert scale (1–7)	Post-task questionnaire
SATISFACTION	Subjective outcome	Overall evaluation of shopping experience	Likert scale (1–7)	Post-task questionnaire
EXPERIENCE	Control variable	Self-reported familiarity with e-commerce interfaces	Likert scale (1–5)	Post-task questionnaire

Table 2.4 – Summary of Variables and Operational Definitions

2.5 Data Analysis Techniques

The analysis of the data collected in this study is aimed at systematically examining decision behavior within the simulated e-commerce environment, in coherence with the research questions and hypotheses formulated in Section 1.8. In line with the adopted experimental design, the analytical strategy distinguishes clearly between decision-process measures and decision-outcome measures, allowing both the dynamics of choice and the final outcomes to be examined within a unified empirical framework. This approach reflects the need, emphasized in the literature, to move beyond a perspective focused exclusively on outcomes and to consider how decision complexity manifests throughout the choice process.

As a preliminary step, descriptive analyses are conducted to characterize the final analysis sample and to verify balance across experimental conditions and age groups. These analyses include the distribution of participants by condition and age category, as well as summary statistics for the main behavioral and subjective variables. This phase serves to assess data quality and to provide an overall descriptive picture of observed behaviors prior to inferential analysis. The sequential filtering process from raw sessions to the final analytical sample (N=205) and the specific criteria for outlier removal are detailed in Appendix B.1.

Decision-process measures are analyzed primarily through time-based behavioral indicators and a composite effort index. Time spent on individual product pages and overall interaction time are treated as continuous variables and interpreted as behavioral proxies of decision effort and task difficulty. To capture overall effort while avoiding multiple testing on highly correlated indicators, several interaction-related measures (including navigation activity and cart-related actions) are jointly summarized into a standardized effort index constructed using principal component analysis. The statistical results of the PCA, including component loadings and variance explained, are provided in Appendix B.2.This index reflects overall engagement and processing intensity during the task and is analyzed as a continuous outcome variable. Time-based measures of decision effort exhibit a right-skewed distribution, as a small number of sessions are characterized by substantially longer interaction times. To account for this distributional asymmetry and to reduce the influence of extreme values, decision time at the product level is transformed using a logarithmic specification of the form log(time + 1). The visual justification and the econometric properties of this transformation are documented in Appendix B.3. The addition of a constant ensures that zero-valued observations are retained in the analysis. This transformation stabilizes variance and improves the interpretability of regression estimates. Coefficients associated with log-transformed time outcomes are interpreted as approximate relative differences in decision time, rather than absolute changes measured in seconds, allowing a more meaningful comparison of decision effort across experimental conditions and product categories. Accordingly, coefficients estimated in models using log-transformed time outcomes should be interpreted as relative differences in decision time allocation across conditions and product categories, rather than as absolute changes measured in seconds.

Inferential analysis of process measures is conducted using linear regression models consistent with the factorial structure of the experimental design. These models estimate the effect of choice set size on decision effort, while accounting for participant experience and, where relevant, interactions with age group and product category. Standard errors are computed using heteroskedasticity-robust or cluster-robust estimators to ensure reliable statistical inference. In models exploiting within-participant variation across product categories, observations are no longer independent; therefore, standard errors are clustered at the session level to account for intra-session correlation, as specified in the econometric robustness protocols in Appendix B.4. This approach ensures that statistical inference remains valid in the presence of repeated observations generated by the same participant, consistent with best practices in panel-style behavioral data analysis. All estimations were performed using the R statistical environment, utilizing the specific packages for robust estimation listed in Appendix B.5.

Decision-outcome measures focus on purchase completion, treated as a dichotomous variable capturing choice deferral versus completion within the simulated task. This outcome constitutes a core dependent variable in the empirical analysis and is examined using regression models appropriate for binary data. These models assess whether and under which conditions choice set size influences the likelihood of completing a purchase, considering both direct effects and moderation by participant age.

Alongside behavioral indicators, post-task subjective measures are analyzed to complement the interpretation of observed decision patterns. In particular, perceived stress or confusion during the decision process and overall satisfaction with the shopping experience are examined as continuous outcomes measured on Likert scales. These variables are analyzed using linear models analogous to those applied to behavioral measures, allowing consistency in interpretation and comparison across outcomes.

A central element of the analytical strategy concerns the examination of interaction effects among the main experimental dimensions. In accordance with the theoretical framework, particular attention is devoted to interactions between choice set size and product category, between choice set size and age group, and to higher-order configurations capturing how object complexity and individual characteristics jointly condition the effects of option numerosity. The objective of these analyses is not to identify universal effects of choice overload, but to clarify the boundary conditions under which differences in decision behavior and experience emerge.

With regard to evaluation criteria, interpretation of results relies on standard inferential benchmarks, complemented by an assessment of the substantive relevance and coherence of observed effects with the theoretical framework. A clear distinction is maintained between statistical significance and theoretical interpretation, and results are discussed with caution, particularly in the presence of higher-order interactions. Where relevant, robustness checks are conducted to verify the stability of findings with respect to sample composition.

Overall, the adopted analytical strategy is designed to leverage the richness of the collected behavioral and experiential data while maintaining a high level of methodological rigor. By integrating process measures, outcome measures, and subjective evaluations within a coherent modeling framework, the analysis allows the choice overload paradox to be examined as a context-dependent phenomenon, consistent with the objectives and hypotheses of the study. Section 2.6 will discuss the main validity considerations and methodological limitations arising from the adopted design and analytical choices.

2.6 Validity, Reliability, and Methodological Limitations

Assessing validity, reliability, and methodological limitations is essential for the correct interpretation of the empirical results and for positioning the study’s contribution within the theoretical framework outlined in Chapter 1. Consistent with an experimental approach oriented toward causal inference, this section discusses the main dimensions of validity supported by the adopted design, while also clarifying the limits that constrain interpretation and generalizability.

From the perspective of internal validity, the study presents several strengths. The central independent variable—choice set size—is manipulated directly through two versions of a simulated e-commerce environment that are identical in all respects except for the number of alternatives presented. This controlled manipulation allows observed differences in decision behavior and experience to be attributed to option numerosity, reducing the risk that results are driven by confounding variations in interface design, task structure, or instructions. Moreover, each participant is exposed to only one experimental condition, limiting potential learning or comparison effects and strengthening causal interpretation.

Internal validity is further supported by the use of objective behavioral measures automatically recorded during interaction with the digital environment. The integrity of these measures is ensured by the automated data processing pipeline described in Appendix B.1, which minimizes manual coding errors. Process indicators based on time allocation and composite measures of behavioral effort reduce reliance on self-reported data and limit biases related to recall or social desirability. Although such indicators do not allow direct observation of underlying cognitive states, they provide consistent and replicable proxies of observable decision processes, in line with established practices in experimental decision research.

The integration of behavioral indicators with post-task subjective evaluations—specifically perceived stress and overall satisfaction—contributes to interpretive coherence. The joint consideration of process measures and experiential outcomes allows behavioral patterns to be interpreted in relation to participants' reported experience of the task, reducing the risk of purely mechanical interpretations of interaction data.

The ecological validity of the study derives from the simulated e-commerce environment described in Sections 2.1 and 2.2, which allows participants to interact with a realistic purchasing interface while preserving experimental control. The present section focuses on evaluating the implications of this design choice for the interpretation and generalizability of the results rather than reintroducing the design logic itself.

External validity must nevertheless be evaluated with caution. The empirical focus on the Italian context responds to a specific gap identified in the literature, but limits direct generalization to other national or cultural settings. Accordingly, results should be interpreted as evidence of context-dependent decision patterns rather than as universally applicable effects. This limitation is consistent with the study's objective of clarifying the boundary conditions of the choice overload phenomenon rather than establishing invariant behavioral laws.

In terms of reliability, the automated recording of behavioral data and the standardized experimental procedure support consistency and replicability. The unambiguous definition of variables and the transparent documentation of data transformation procedures in Appendix B allow the experimental setup to be reproduced in analogous contexts.

Alongside these strengths, several methodological limitations should be acknowledged. First, although the simulated environment captures key features of digital shopping, it does not incorporate real economic consequences, such as actual financial expenditure or long-term consumption outcomes. As a result, observed behaviors may differ in magnitude from those exhibited in real market situations. Second, behavioral proxies of decision effort and complexity remain indirect measures and should not be interpreted as direct indicators of cognitive overload.

A further limitation concerns the analysis of higher-order interactions. While the experimental design allows interactions between choice set size, product type, and age to be examined, statistical power to detect complex interaction effects may be limited within specific subgroups. Consequently, results involving interaction terms should be interpreted prudently and viewed as indicative of systematic patterns rather than definitive causal estimates.

Overall, these limitations do not undermine the validity of the study, but delineate the scope within which the findings should be interpreted. Explicit recognition of these constraints contributes to a balanced evaluation of results and provides a foundation for future research aimed at extending the analysis to other populations, contexts, or complementary experimental designs. This section concludes Chapter 2 by establishing a clear methodological framework for the empirical analyses presented in Chapter 3.

3 Empirical Findings

3.1 Overview of the Empirical Strategy

This chapter presents the empirical analyses conducted to examine the relationships between choice set size, decision-object complexity, and individual characteristics within a controlled e-commerce simulation. The empirical strategy is designed to test the research questions formulated in Section 1.8, building directly on the experimental design and the operationalization of variables described in Chapter 2. Throughout the chapter, the analysis is organized around clearly defined research questions (RQ1–RQ4), with each question addressed through a coherent set of models aligned with the nature of the dependent variables and the structure of the data. The purpose of this section is to outline the logic of the empirical approach, clarify how the different analytical components fit together, and prepare the reader for the presentation of results in the subsequent sections, without anticipating or discussing empirical findings.

The empirical setting consists of a controlled experiment in which participants interact with a simulated e-commerce environment under one of two alternative informational architectures: a reduced choice set or an expanded choice set. Assignment to experimental conditions is exogenous and mutually exclusive, and all other elements of the interface, procedure, and task structure are held constant across conditions. This design allows observed differences in decision behavior to be attributed to variation in choice set size rather than to confounding factors related to layout, content, or task framing. As such, the comparison between reduced and expanded conditions provides the basis for causal inference within the limits inherent to an experimental simulation. The empirical strategy does not aim to estimate universal or context-independent effects of option numerosity, but rather to identify systematic patterns and sources of heterogeneity consistent with the theoretical framework developed in Chapter 1.

The analysis is structured around four research questions. RQ1 focuses on the main effect of choice set size on decision processes and outcomes, comparing behavior and subjective evaluations between reduced and expanded conditions. RQ2 examines whether this relationship is moderated by participant age, thereby assessing heterogeneity in responses to choice complexity across different stages of the life course. RQ3 shifts the focus to the characteristics of the decision object, investigating whether the effect of choice set size varies across product categories that differ in cognitive complexity. This question exploits within-participant variation, as each individual is observed across multiple product categories within the same experimental session. Finally, RQ4 explores the joint role of choice set size, age, and product category by analyzing higher-order interaction patterns. This last research question is explicitly exploratory in nature and is intended to provide a nuanced picture of how multiple dimensions of complexity may interact, rather than to establish definitive causal claims.

A central organizing principle of the empirical strategy is the analytical separation between decision process measures and decision outcome measures. Process measures capture how decisions unfold over time and how participants interact with the task during the decision process. These measures include a composite effort index derived from multiple behavioral indicators, as well as time allocation across product categories. They are interpreted as behavioral indicators of decision process intensity and interaction activity within the interface, not as direct measures of cognitive load. Outcome measures, by contrast, capture the results and subjective consequences of the decision process. These include completion of the purchasing task, perceived stress during decision-making, and overall satisfaction with the shopping experience. Maintaining a clear distinction between process and outcome measures allows the analysis to address different dimensions of the choice overload phenomenon without conflating how decisions are made with what decisions ultimately result.

The unit of analysis varies across research questions, reflecting the structure of the experimental design and the nature of the dependent variables under examination. For RQ1 and RQ2, the analysis is conducted at the session level, with each observation corresponding to a single participant's interaction with the simulated e-commerce environment. In these analyses, behavioral outcomes, subjective evaluations, and composite effort measures are aggregated at the individual session level.

By contrast, RQ3 and RQ4 exploit within-session variation across product categories. In these cases, the unit of analysis is the product within the session, such that each participant contributes multiple observations corresponding to the different product categories evaluated during the same experimental interaction. This structure allows the analysis to examine how variation in decision process intensity, proxied by time allocation, varies across products of different complexity while holding individual-level characteristics constant.

Standard errors in product-level analyses are adjusted accordingly to account for the non-independence of observations within the same session.

The empirical analysis proceeds by estimating separate regression models for each research question, ensuring coherence between the research objective, the dependent variable under consideration, and the statistical specification. For outcome variables defined on a continuous scale, linear regression models are employed, while binary outcomes are analyzed using models appropriate for dichotomous dependent variables. Interaction terms are introduced selectively and only where required by the corresponding research question, in order to examine moderation effects without imposing unnecessary complexity on baseline specifications. Across all models, the analytical focus remains on patterns of association consistent with the experimental manipulation and the hypothesized sources of heterogeneity, rather than on the identification of isolated coefficients.

All empirical models include a measure of self-reported familiarity with e-commerce interfaces as a covariate. This variable captures heterogeneity in prior exposure to online shopping environments and is included to account for baseline differences in navigation efficiency and decision confidence that are not attributable to the experimental manipulation. Its role is strictly that of a control variable, introduced to improve comparability across participants and to reduce residual variance, rather than to test substantive hypotheses.

Given the factorial structure of the design and the presence of interaction effects, the presentation of results combines regression tables with graphical representations based on predicted values. Tables are used to report the estimated models in a compact and standardized format, while figures are employed to illustrate interaction patterns and to facilitate interpretation of heterogeneous effects across conditions, age groups, and product categories. This dual presentation strategy reflects the objective of emphasizing substantive patterns over isolated numerical estimates and supports a clear and transparent reading of the empirical evidence.

Overall, the empirical strategy adopted in this chapter is deliberately structured, modular, and closely aligned with the experimental design. By organizing the analysis around distinct research questions, maintaining a clear separation between process and outcome measures, and matching model specifications to the nature of the data, the chapter aims to provide a rigorous and coherent assessment of how choice set size operates under different conditions. The sections that follow present the empirical results corresponding to each research question in turn, building cumulatively toward an integrated interpretation of the choice overload phenomenon in a simulated digital context.

3.2 Descriptive Statistics and Sample Balance

This section presents the descriptive characteristics of the final analytical sample used in the empirical analyses. Its purpose is threefold: (i) to document the composition of the sample retained after data cleaning, (ii) to provide a transparent overview of the distribution of observations across the experimental conditions and age groups, and (iii) to offer an initial descriptive orientation regarding the main process and outcome variables examined in subsequent models.

No inferential claims are made in this section, and no statistical tests of differences are reported.

3.2.1 Sample Composition

The final sample used in the empirical analyses consists of 205 observations, corresponding to individual experimental sessions with complete information on all variables required for model estimation. Observations with missing values on any of the core variables were excluded in a listwise manner, resulting in a single, consistent dataset used across all analyses in Chapter 3.

The initial dataset consisted of 232 experimental sessions. Data cleaning was conducted following predefined behavioral validity criteria in order to remove sessions unlikely to reflect actual task engagement. First, sessions with extremely short duration (below 30 seconds) were removed, as these were interpreted as immediate exits from the interface without meaningful interaction. Second, sessions exceeding one hour of total duration were excluded, as they likely corresponded to inactive or abandoned browser sessions rather than continuous decision-making activity. Third, extreme values in session duration were addressed by trimming observations above the 95th percentile of the session time distribution in order to reduce the influence of anomalous behavioral logs while preserving the large majority of observations. After applying these criteria, the dataset was reduced to 207 observations. Finally, two additional observations with missing information on key variables required for model estimation were excluded through listwise deletion, resulting in a final analytical sample of 205 sessions.The same cleaned dataset was used consistently across all empirical models presented in Chapter 3.

The experimental design allocated participants to two conditions differing in the size of the choice set. Of the 205 observations, 104 sessions were assigned to the reduced condition, while 101 sessions were assigned to the expanded condition. This allocation results in a near-even distribution of observations across experimental conditions.

The sample is further distributed across three age groups. The 20–35 age group accounts for 62 observations, the 35–60 age group for 66 observations, and the 60+ age group for 77 observations. Each age group is represented in both experimental conditions, allowing for descriptive inspection of age-related heterogeneity without implying statistical balance or imbalance.

Overall, the joint distribution of observations by condition and age group reflects a broadly comparable representation across cells, with no single category dominating the sample. A detailed breakdown of frequencies and percentages is reported in Table 3.2a and b, which summarizes the sample composition by experimental condition and age group.

condition	n	pct
reduced	104	50.73171
expanded	101	49.26829

Table 3.2a Sample composition by condition

age_group	n	pct
20-35	62	30.24390
35-60	66	32.19512
60+	77	37.56098

Table 3.2b Sample composition by age group

3.2.2 Descriptive Patterns of Key Variables

This subsection reports descriptive statistics for the main variables of interest, computed separately for the reduced and expanded conditions. The objective is to provide contextual information on the levels of key process and outcome measures prior to the presentation of multivariate models.

For each experimental condition, means and standard deviations are reported for the effort index, perceived stress, and satisfaction. The completion rate is reported as the proportion of sessions in which all required items were successfully completed, reflecting the binary nature of this variable. No interactions or subgroup breakdowns are considered at this stage.

The effort index summarizes multiple behavioral indicators of decision-making activity into a single standardized measure. Perceived stress and satisfaction capture subjective evaluations collected through post-task survey items. The completion rate provides a descriptive indicator of task accomplishment under each condition. These measures are reported exclusively in a descriptive manner and are not interpreted as evidence of causal effects or condition differences.

The statistics presented in this subsection are intended solely to orient the reader and to provide baseline context for the regression analyses that follow. All descriptive statistics by condition are reported in Table 3.2c.

condition	N	effort_mean	effort_sd	stress_mean	stress_sd	satisfaction_mean	satisfaction_sd	completion_rate
reduced	104	0.1226504	0.6867486	3.076923	1.836482	4.932692	1.352914	0.7500000
expanded	101	-0.1262934	1.2338855	3.712871	1.888580	4.544554	1.539641	0.5940594

Table 3.2c Descriptive statistics by condition

3.3 Main Effects of Choice Set Size (RQ1)

This section addresses Research Question 1 (RQ1), which investigates the main effect of choice set size on decision-making processes and outcomes in an online shopping environment. Specifically, the analysis compares participants exposed to a reduced versus an expanded choice set, focusing on average differences between experimental conditions.

All models are estimated on the same analysis sample and include a control for prior familiarity with e-commerce interfaces, measured on a five-point Likert scale, in order to account for baseline heterogeneity in navigation efficiency and decision confidence unrelated to the experimental manipulation. The results are presented separately for each dependent variable, distinguishing between process measures and outcome measures, in line with the conceptual structure of the study.

The section is organized as follows. Section 3.3.1 examines the effect of choice set size on decision effort. Section 3.3.2 focuses on task completion. Sections 3.3.3 and 3.3.4 analyze perceived stress and satisfaction, respectively.

3.3.1 Effects on Decision Effort

Decision effort is analyzed using an Ordinary Least Squares (OLS) regression model specified as follows:

$$effort_{i} = \beta_0 + \beta_1 \cdot condition_{i} + \beta_2 \cdot experience_{i} + \varepsilon_{i}$$

The effort index serves as a composite process measure capturing the intensity of behavioral engagement. The estimated coefficient for the expanded condition is negative and statistically significant at the 10% level ($\beta = -0.256$, $p < 0.1$), indicating lower average decision effort relative to the reduced condition. This suggests that participants exposed to a larger assortment may have reduced their engagement after controlling for prior experience. The experience control variable is not statistically significant in this specification. Results are reported in Table 3.3a.

	RQ1a: Effort (OLS)
Expanded (vs reduced)	-0.256+
	(0.145)
Experience	-0.033
	(0.054)
Num.Obs.	205
R2	0.018
Std.Errors	vcovHC(x, type = "HC3")

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors (HC3) in parentheses.

Table 3.3a Effect of condition on decision effort (effort index)

3.3.2 Effects on Purchase Completion

Task completion is examined using a logistic regression model, where the dependent variable is a binary indicator of successful task fulfillment. The model estimates the log-odds of completion as:

$$\ln\left(\frac{P(completion_i = 1)}{(1 - P(completion_i = 1))}\right) = \beta^0 + \beta^1 \cdot \text{condition}_i + \beta^2 \cdot \text{experience}_i$$

where:

$$logit(p) = ln(\, p \,/\, (1 - p)\,)$$

The coefficient on the expanded condition is negative and statistically significant at the 5% level ($\beta = -0.689$, $p < 0.05$), indicating a significantly lower likelihood of completing the task under the expanded choice set. The experience control variable exhibits a positive but non-significant coefficient. Estimated coefficients are presented in Table 3.3b.

	RQ1b: Completion (Logit)
Expanded (vs reduced)	-0.689*
	(0.311)
Experience	0.167
	(0.117)
Num.Obs.	205
R2	0.031
Std.Errors	VcovHC(x, type = “HC3”)

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors (HC3) in parentheses.

Table 3.3b Effect of condition on task completion

3.3.3 Effects on Perceived Stress

Perceived stress is modeled using OLS regression:

$$stress_i = \beta_0 + \beta_1 \cdot condition_i + \beta_2 \cdot experience_i + \varepsilon_i$$

The estimated coefficient for the expanded condition is positive and statistically significant at the 5% level ($\beta = 0.647$, $p < 0.05$), indicating higher average perceived stress among participants in the expanded group. This confirms that increasing assortment size is associated with a higher subjective psychological load. Experience does not show a systematic relationship with stress in this model. Regression results are reported in Table 3.3c, with mean stress levels visualized in Figure 3.3a.

	RQ1c: Stress (OLS)
Expanded (vs reduced)	0.647*
	(0.264)
Experience	0.050
	(0.102)
Num.Obs.	205
R2	0.030
Std.Errors	vcovHC(x, type = "HC3")

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors (HC3) in parentheses.

Table 3.3c Effect of condition on perceived stress

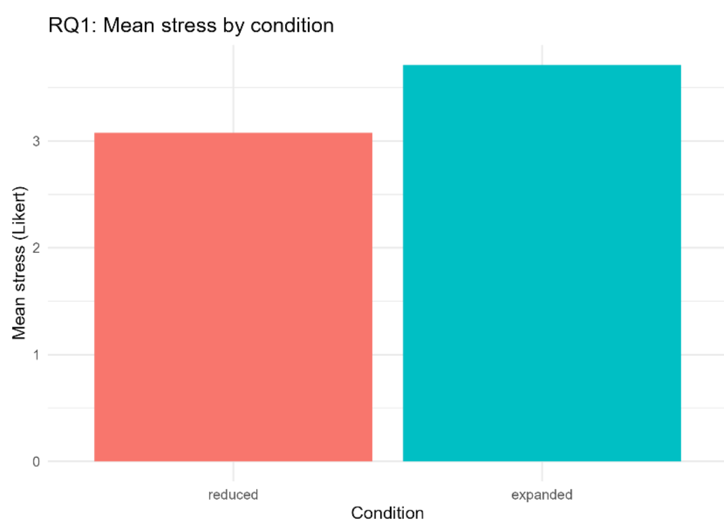

Figure 3.3a Mean stress by condition

3.3.4 Effects on Satisfaction (RQ1d)

Satisfaction is examined using an OLS regression model analogous to the stress specification:

$$satisfaction_i = \beta_0 + \beta_1 \cdot condition_i + \beta_2 \cdot experience_i + \varepsilon_i$$

The coefficient for the expanded condition is negative and significant at the 10% level ($\beta = -0.345$, $p < 0.1$), indicating lower satisfaction under the expanded choice set. Notably, the experience control variable exhibits a positive and statistically significant association with satisfaction ($\beta = 0.191$, $p < 0.05$), suggesting that digital familiarity mitigates part of the negative evaluative impact of the task. Full results are presented in Table 3.3d and Figure 3.3b.

	RQ1d: Satisfaction (OLS)
Expanded (vs reduced)	-0.345+
	(0.202)
Experience	0.191*
	(0.081)
Num.Obs.	205
R2	0.050
Std.Errors	vcovHC(x, type = "HC3")

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors (HC3) in parentheses.

Table 3.3c Effect of condition on satisfaction

Figure 3.3b Mean satisfaction by condition

3.4 Age as a Moderating Factor (RQ2)

Research Question 2 (RQ2) investigates whether the effect of choice set size on decision processes and outcomes varies across age groups. While the analysis presented in Section 3.3 focused on average effects across the full sample, the present section explicitly introduces age as a moderating factor in order to capture potential heterogeneity in individual responses to option numerosity. From a behavioral perspective, age may proxy differences in cognitive resources, accumulated decision experience, and familiarity with complex choice environments, which can plausibly shape how individuals react to variations in assortment size.

Empirically, moderation is examined by augmenting the baseline specifications with interaction terms between the experimental condition (reduced vs. expanded choice set) and categorical age groups. The analysis remains focused on identifying differential patterns across age cohorts rather than establishing universal or normative effects. All models include the same control variables as in Section 3.3, and results are reported separately for each outcome of interest.

3.4.1 Moderation of Completion by Age

To assess whether the impact of choice set size on task completion differs across age groups, a logistic regression model is estimated with purchase completion as the dependent variable. Completion is defined as a binary indicator equal to one if the participant successfully completed the full purchase task (three out of three products), and zero otherwise. The model includes the experimental condition, age group indicators, their interaction terms, and self-reported experience with e-commerce interfaces as a control variable:

$$\text{completion} = \beta_0 + \beta_1\text{condition} + \beta_2\text{age\_group} + \beta_3(\text{condition} \times \text{age\_group}) + \beta_4\text{experience}$$

The interaction terms allow the association between choice set size and completion to vary across age cohorts, relative to the baseline group (20–35). Results from this specification are reported in Table 3.4a. Coefficients are interpreted in terms of differences in log-odds across conditions and age groups, with particular attention to whether the direction and magnitude of the condition effect differ across cohorts. The focus remains on heterogeneity in completion patterns rather than on identifying a single age group for which the expanded or reduced condition performs best.

	Completion (Logit)
Expanded (vs reduced)	-0.816
	(0.706)
Experience	0.141
	(0.118)
Age: 35–60 (vs 20–35)	-0.583
	(0.701)
Age: 60+ (vs 20–35)	-1.204+
	(0.659)
Expanded × Age 35–60	-0.270
	(0.906)
Expanded × Age 60+	0.376
	(0.854)
Num.Obs.	205
R2	0.060
Std.Errors	vcovHC(x, type = "HC3")

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors (HC3) in parentheses.

Table 3.4a Moderation of completion by age group

3.4.2 Moderation of Stress by Age

A parallel moderation analysis is conducted for perceived stress, which captures the subjective psychological load experienced during the decision task. Stress is measured on a Likert scale and modeled using ordinary least squares (OLS). As in the completion analysis, the specification includes the experimental condition, age group indicators, their interactions, and the experience control:

$$\text{stress} = \beta_0 + \beta_1\text{condition} + \beta_2\text{age\_group} + \beta_3(\text{condition} \times \text{age\_group}) + \beta_4\text{experience} + \varepsilon$$

This specification allows the stress response to an expanded versus reduced choice set to differ across age groups. Results are presented in Table 3.4b. The interaction coefficients provide information on whether the stress differential associated with choice set size is amplified, attenuated, or reversed for older cohorts relative to younger participants.

To facilitate interpretation of these interaction patterns, predicted stress values by condition and age group are visualized in Figure 3.4a. The figure is intended to provide an intuitive representation of the estimated relationships, without implying causal or normative interpretations.

	Stress (OLS)
Expanded (vs reduced)	1.235*
	(0.477)
Experience	0.048
	(0.106)
Age: 35–60 (vs 20–35)	0.585
	(0.483)
Age: 60+ (vs 20–35)	-0.012
	(0.438)
Expanded × Age 35–60	-0.727
	(0.672)
Expanded × Age 60+	-0.889
	(0.645)
Num.Obs.	205
R2	0.065
Std.Errors	vcovHC(x, type = "HC3")

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Robust standard errors (HC3) in parentheses.

Table 3.4b Moderation of perceived stress by age group

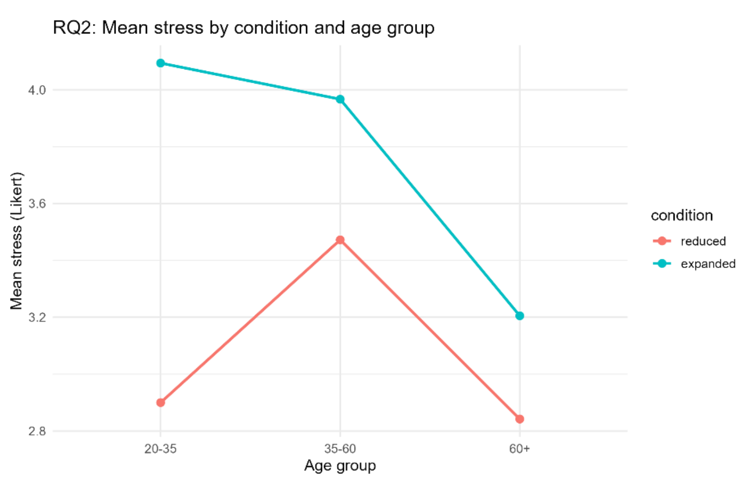

Figure 3.4a Mean stress by condition and age group

3.5 Product Complexity and Process Measures (RQ3)

This section examines how product complexity interacts with choice set size in shaping decision processes within the simulated e-commerce environment. In line with Research Question 3 (RQ3), the analysis focuses on whether the effect of option numerosity varies across product categories that differ in cognitive and informational complexity. The emphasis is placed exclusively on process measures, specifically the time allocated to decision-making, rather than on decision outcomes or subjective evaluations.

Product complexity is a central dimension in the choice overload framework, as products differ substantially in the amount of information available for evaluation, the perceived risk associated with the decision, and the observable interaction required to compare alternatives. Even when the interface and presentation modes are held constant, navigating a set of smartphones is inherently more demanding than selecting a phone cover, with intermediate levels of complexity typically associated with power banks. This section builds on this conceptual distinction by analyzing how decision time is allocated across product categories under reduced and expanded choice conditions.

Methodologically, the analysis exploits within-participant variation by restructuring the data in long format, such that each participant contributes multiple observations—one for each product category—within a single experimental session. As a result, the unit of analysis is the product within the session, allowing the comparison of time allocation patterns across products while holding individual-specific characteristics constant.

3.5.1 Time Allocation Across Product Categories

To assess how product complexity moderates the relationship between choice set size and the decision process, time spent on each product category is analyzed as a process measure. Decision time captures how participants distribute their interaction across alternatives during the choice process and is therefore interpreted as a process measure rather than an outcome in itself.

The dependent variable is the time spent on each product category, transformed using a logarithmic transformation of the form log(time + 1) to account for right-skewness in the distribution of raw time measures and to reduce the influence of extreme values. The empirical specification is given by:

$$\text{log\_time}_{ip} = \beta_0 + \beta_1 \text{condition}_i + \beta_2 \text{product}_p + \beta_3 \left(\text{condition}_i \times \text{product}_p\right) + \beta_4 \text{experience}_i + \varepsilon_{ip},$$

where i indexes participants and p indexes product categories. The variable *condition* distinguishes between reduced and expanded choice sets, *product* identifies the product category, and *experience* captures self-reported familiarity with e-commerce interfaces. Phone covers are treated as the reference category, such that all product coefficients and interaction terms are interpreted relative to this baseline.

Because each participant contributes multiple observations—one per product category—standard errors are clustered at the session level to account for intra-subject dependence in decision times across products. This approach ensures that statistical inference reflects the repeated-measures structure of the data.

The results of this model are reported in Table 3.5a, which presents coefficient estimates for the main effects of condition and product category, as well as their interaction terms. To facilitate interpretation of the interaction between choice set size and product complexity, predicted values derived from the estimated model are visualized in Figure 3.5a, displaying average log-transformed decision time by product category and experimental condition.

	Log time (OLS)
Expanded (vs reduced)	0.226
	(0.143)
Powerbank (vs cover)	0.280***
	(0.079)
Smartphone (vs cover)	0.949***
	(0.094)
Experience	0.072+
	(0.040)
Expanded × Powerbank	-0.264*
	(0.128)
Expanded × Smartphone	0.235
	(0.147)
Num.Obs.	615
R2	0.192
Std.Errors	by: session_id

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors clustered at the session level in parentheses.

Table 3.5a Moderation by product complexity

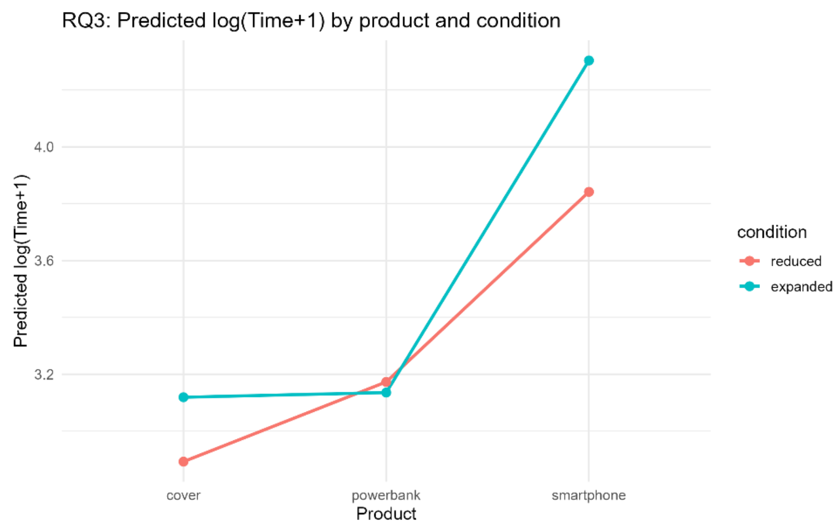

Figure 3.5a Predicted log(time+1) by product and condition

3.5.2 Interpretation in Terms of Decision Complexity

The patterns observed in the estimated model can be interpreted in light of differences in decision complexity across product categories. Relative to phone covers, which serve as the baseline category, both power banks and smartphones are associated with higher levels of decision time, consistent with higher informational requirements and greater interaction activity associated with these products. Smartphones occupy the upper end of the complexity spectrum, given their higher prices and richer attribute spaces.

The interaction terms between choice set size and product category indicate that the relationship between option numerosity and decision time is not uniform across products. Instead, the magnitude and direction of the association vary depending on the underlying complexity of the decision object. This heterogeneity highlights that choice set expansion does not simply scale decision effort proportionally across all products, but interacts with product-specific cognitive demands.

Importantly, these results should be read as descriptive patterns within the experimental setting rather than as universal or context-independent effects. The analysis does not introduce additional covariates or higher-order interactions and does not seek to establish causal hierarchies between product types. Rather, it provides a structured account of how decision effort, as proxied by time allocation, differs across products of varying complexity when participants are exposed to reduced versus expanded choice environments.

Together, the findings reported in this section complement the earlier analysis of aggregate decision effort by demonstrating that the process-level implications of choice set size depend critically on the nature of the product being evaluated. The next section extends this logic further by examining how product complexity and choice set size jointly interact with individual characteristics.

3.6 Joint Moderation by Age and Product Complexity (RQ4)

This section explores the joint moderating role of age group and product complexity in shaping the relationship between choice set size and decision processes. Building on the heterogeneity patterns documented in RQ2 and the product-level dynamics highlighted in RQ3, Research Question 4 (RQ4) examines whether these dimensions interact simultaneously when individuals allocate decision time across products of different complexity under alternative choice set sizes.

From a theoretical perspective, a three-way interaction between choice set size, age, and product complexity is potentially informative, as it allows the coexistence of cognitive heterogeneity and task-related difficulty to be considered within a unified framework. At the same time, such specifications are empirically demanding and sensitive to sample size and noise. For this reason, the analysis is explicitly exploratory in nature. The results are presented as descriptive patterns rather than as generalizable effects, and they are interpreted with caution.

3.6.1 Three-Way Interaction Results

To examine the joint moderation structure, a regression model including a three-way interaction between condition, age group, and product category is estimated. The dependent variable is the logarithm of time spent on each product category, treated as a process measure of decision effort. The model specification is as follows:

$$\begin{aligned}\text{log\_time}_{ips} = {} & \beta_0 + \beta_1 \text{condition}_s + \beta_2 \text{age\_group}_i + \beta_3 \text{product}_p + \beta_4 (\text{condition}_s \times \text{age\_group}_i) \\ & + \beta_5 \left(\text{condition}_s \times \text{product}_p\right) + \beta_6 \left(\text{age\_group}_i \times \text{product}_p\right) \\ & + \beta_7 \left(\text{condition}_s \times \text{age\_group}_i \times \text{product}_p\right) + \gamma \text{experience}_i + \varepsilon_{ips}\end{aligned}$$

where $i$indexes individuals, $p$products, and $s$sessions. Standard errors are clustered at the session level to account for within-subject dependence across product observations.

Given the complexity of the specification and the large number of interaction terms, individual coefficients are not emphasized in isolation. The full set of estimated coefficients is reported in Appendix B (Table B.1) for completeness. The interpretation instead focuses on how combinations of age group, product category, and choice set size are associated with different time allocation patterns, as summarized through predicted values.

3.6.2 Visual Interpretation of Predicted Patterns

To support the interpretation of the three-way interaction, Figure 3.6a presents predicted values of log-transformed decision time by product category and choice set size, separately for each age group. The figure is organized into panels by age group, allowing a direct visual comparison of how patterns differ across demographic segments.

For younger participants (20–35), the predicted profiles suggest relatively pronounced differences in time allocation across product categories, with higher time spent on more complex products. The distinction between reduced and expanded choice sets appears primarily in the relative steepness of these profiles rather than in uniform shifts.

Among middle-aged participants (35–60), the predicted patterns display a more compressed structure, with smaller differences across product categories and less pronounced divergence between choice set sizes. This configuration is consistent with a more homogeneous allocation of attention across tasks.

For older participants (60+), the visual patterns indicate greater variability across product categories, particularly for higher-complexity products. Differences between reduced and expanded choice sets emerge mainly in specific product categories rather than uniformly across the decision environment.

Across all panels, the figures are intended to illustrate directional and configurational differences, not to substitute for formal inference. They serve to highlight how age and product complexity jointly shape the way decision time is distributed under alternative choice architectures, complementing the coefficient-based results reported in the appendix.

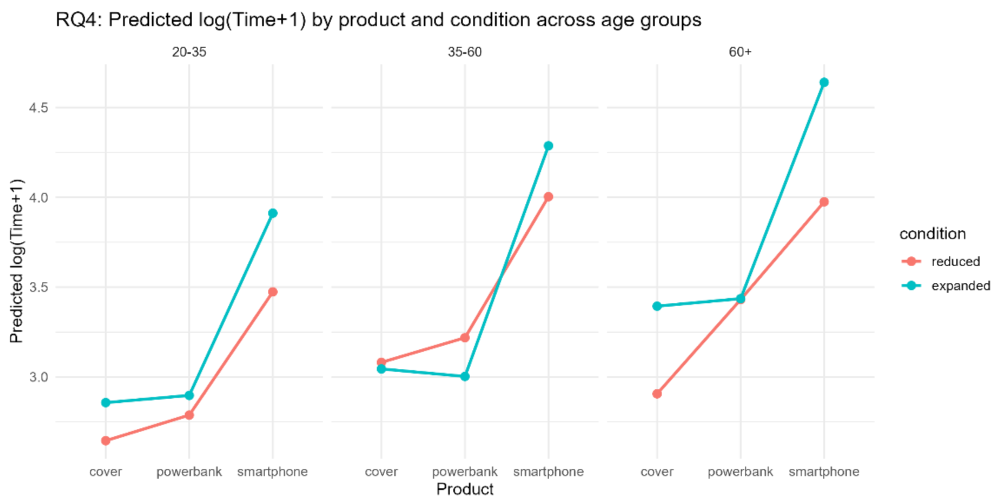

Figure 3.6a Predicted log(time+1) by product and condition across age group

4 Managerial Implications and Research Limitations

4.1 Discussion of Empirical Findings

This chapter integrates the empirical results presented in Chapter 3 and positions them within the broader literature on choice overload and digital consumer decision-making. While Chapter 3 reported statistical patterns across process, behavioral, and psychological outcomes, the present section aims to provide an interpretative synthesis of these findings. Rather than evaluating performance or prescribing optimal decision environments, the discussion focuses on identifying how the effects of choice set size emerge across heterogeneous decision contexts.

The discussion is structured progressively. It begins by revisiting the main effect of option numerosity, then moves toward the heterogeneous patterns revealed by age differences and product complexity, and finally reflects on the theoretical implications of decision effort and outcome divergence.

4.1.1 From Average Effects to Heterogeneous Decision Patterns

The results associated with RQ1 document that option numerosity exerts a measurable but partial effect on decision processes and outcomes. The transition from reduced to expanded choice sets is associated with systematic variations in several observed variables, including decision effort, perceived stress, and behavioral completion rates. However, these average effects do not appear uniform across decision contexts.

The analyses conducted for RQ2 and RQ3 demonstrate that the impact of choice set size varies across consumer characteristics and product categories. Age differences reveal that individuals belonging to different age groups respond differently to variations in option numerosity, particularly in terms of behavioral completion and perceived cognitive strain. Similarly, product-level analyses show that time allocation across alternatives varies significantly depending on the complexity of the product category under consideration.

The exploratory analysis conducted in RQ4 further suggests that these two sources of heterogeneity do not operate independently. Instead, age and product complexity appear to combine into contingent decision patterns that vary across specific consumer–product configurations. Although the evidence associated with three-way interactions remains exploratory and should be interpreted cautiously, it indicates that the relationship between choice set size and decision behavior is unlikely to follow a uniform structure across individuals and product types.

Taken together, these findings move beyond simplified interpretations of the choice overload phenomenon. Rather than suggesting that increased option numerosity systematically deteriorates decision outcomes, the evidence supports a more nuanced perspective in which the consequences of expanded choice environments depend on both who is making the decision and what is being evaluated.

4.1.2 Decision Effort as Engagement Rather Than Friction

One of the central contributions emerging from the empirical analysis concerns the interpretation of decision effort. In traditional choice overload frameworks, increased cognitive effort is often conceptualized primarily as a cost that reduces decision quality and user satisfaction. However, the empirical evidence observed in the present study suggests a more complex interpretation.

The results indicate that reduced choice environments are associated with higher levels of measured decision effort, as captured by the composite effort index. Importantly, this increase in effort is not accompanied by a consistent deterioration in behavioral outcomes such as task completion, nor by systematic reductions in satisfaction levels. This pattern suggests that decision effort does not necessarily function exclusively as cognitive friction.

Instead, the findings are consistent with an interpretation of effort as engagement-oriented effort, characterized by focused cognitive investment within a constrained decision environment. When the number of available options is reduced, decision-makers may allocate greater attention to each alternative, increasing the depth of evaluation rather than reducing cognitive involvement altogether. In this sense, effort does not disappear when the choice environment is simplified; rather, it appears to be re-oriented toward more concentrated exploration of individual alternatives.

This interpretation aligns with emerging strands of research suggesting that cognitive investment can reflect meaningful engagement with the decision task rather than purely reflecting decision difficulty. While the present study does not directly measure engagement or attention allocation, the observed behavioral patterns are consistent with a model in which simplified choice environments may promote more focused decision processing.

4.1.3 Divergence Between Psychological and Behavioral Outcomes

Another important pattern emerging from the empirical findings concerns the divergence between psychological and behavioral outcomes. The analyses show that completion behavior, perceived stress, and satisfaction do not consistently move in parallel across experimental conditions.

In particular, reductions in choice set size are associated with shifts in stress levels without corresponding changes in satisfaction or task completion across all contexts. This divergence suggests that decision quality and emotional comfort represent distinct dimensions of the decision-making experience rather than interchangeable indicators of decision performance.

The observed separation between psychological and behavioral responses contributes to the literature by challenging the implicit assumption that reduced cognitive strain necessarily translates into higher satisfaction or improved behavioral outcomes. Instead, the results indicate that decision-makers may successfully complete decision tasks even in environments associated with higher perceived cognitive demands, and conversely may report favorable satisfaction levels without experiencing reduced stress.

By highlighting these distinctions, the findings support a multidimensional view of decision outcomes in digital choice environments, where behavioral effectiveness, subjective satisfaction, and psychological experience represent complementary but non-equivalent components of the decision process.

4.1.4 Integrating Product Complexity Into the Choice Overload Framework

The analyses related to product-level decision processes provide further insight into the mechanisms through which option numerosity influences consumer behavior. The results show that time allocation differs systematically across product categories, with higher-complexity products associated with longer decision times and stronger interactions with choice set size.

Product complexity appears to structure how consumers explore alternatives and distribute cognitive resources during decision-making. Categories requiring more elaborate evaluation processes tend to amplify differences in time allocation across experimental conditions, suggesting that the cognitive demands associated with product evaluation play a central role in shaping the impact of option numerosity.

Importantly, the evidence does not suggest a hierarchical ranking of product categories in terms of importance or value. Rather, it indicates that product characteristics influence the structure of decision processing and may condition the extent to which expanded choice environments affect consumer behavior.

By integrating product complexity into the analysis, the findings contribute to the broader choice overload framework by emphasizing that decision difficulty arises not only from the number of available options but also from the informational and evaluative demands associated with the alternatives themselves. This perspective supports a more contextualized understanding of digital choice environments, in which the effects of option numerosity are shaped by the interaction between structural features of the choice set and characteristics of the decision task.

4.2 Managerial Implications

The empirical findings of this study offer several managerial implications for the design of digital choice environments. These implications derive from the observed decision patterns within a controlled e-commerce simulation and should therefore be interpreted as context-dependent rather than universally generalizable. The objective of the following discussion is not to prescribe optimal interface configurations, but to highlight how the structuring of choice environments may support user decision processes. In line with the experimental nature of the study, the implications are framed as design considerations aimed at improving user interaction quality rather than strategies to directly maximize conversion outcomes or spending behavior.

4.2.1 Choice Architecture as a Tool for Engagement, Not Simplification

The results indicate that reducing the number of available options does not necessarily diminish user involvement in the decision process. Instead, reduced choice environments were associated with higher levels of decision effort, interpreted in this study as engagement-oriented effort rather than purely cognitive friction. This pattern suggests that the managerial role of choice architecture extends beyond simplifying decision tasks and may involve structuring user attention toward more focused evaluation of available alternatives.

From a design perspective, this finding supports the use of curated assortments, where a subset of options is presented as an initial exploration layer without restricting access to the full assortment. Similarly, progressive disclosure mechanisms—such as expandable option lists, filtered search results, or tiered navigation structures—may allow platforms to present manageable choice sets while preserving perceived variety. Such approaches can structure exploration by gradually increasing information exposure as users actively seek additional alternatives.

In this sense, choice architecture may function as a mechanism for guiding attention and supporting evaluation rather than constraining decision autonomy. The results suggest that users may allocate cognitive resources more intensively when the informational environment reduces dispersion across alternatives, thereby potentially enhancing the depth of evaluation for each option presented.

4.2.2 Segment-Sensitive Design Without Hard Personalization

The moderation analysis revealed heterogeneous decision patterns across age groups, indicating that users may process choice environments differently depending on demographic characteristics. However, these differences do not support deterministic segmentation or rigid personalization strategies. Instead, the findings suggest the potential relevance of flexible interface designs that accommodate varying levels of cognitive engagement without explicitly targeting individual user profiles.

Adaptive complexity represents one possible design implication. Digital interfaces may provide multiple layers of information depth, allowing users to determine the level of detail they wish to access during product evaluation. For instance, summary information panels, expandable technical specifications, and comparison tools that users can activate voluntarily may allow decision environments to accommodate heterogeneous evaluation styles.

Layered information structures may further support this approach by organizing product attributes hierarchically, enabling users to navigate progressively from general information to more detailed comparisons. Importantly, such designs preserve user agency by maintaining control over information access and navigation pathways. The results therefore suggest that interface design may adapt to decision processes rather than relying on predefined assumptions about user preferences or behavioral tendencies.

4.2.3 Product-Specific Choice Strategies

The findings related to product complexity highlight that decision processes vary systematically across product categories. Time allocation patterns differed between smartphone, power bank, and phone cover categories, suggesting that product-specific characteristics shape how users interact with choice sets. These results imply that uniform choice architectures across heterogeneous product categories may not fully support user decision processes.

For products characterized by higher decision complexity, broader assortments may facilitate exploratory comparison and deliberation. In such contexts, users may benefit from structured comparison tools, attribute-based filtering systems, and visualization interfaces that support multi-criteria evaluation. Conversely, for products associated with lower decision complexity, streamlined assortments and simplified navigation pathways may support efficient decision completion without reducing perceived choice adequacy.

Importantly, these implications do not suggest that increasing product variety systematically improves decision outcomes. Rather, the results indicate that the relationship between assortment size and user interaction depends on how effectively the choice environment structures perceived trade-offs and supports comparison across relevant product attributes. Product-specific design strategies may therefore facilitate exploration while maintaining clarity in the evaluation process.

Overall, the findings suggest that effective digital choice environments may emerge from the alignment between assortment structure, product complexity, and user-driven exploration patterns. Within this framework, managerial decisions regarding assortment presentation should prioritize supporting deliberation and structuring information accessibility, while maintaining flexibility for diverse decision pathways.

4.3 Limitations and Directions for Future Research

Every empirical investigation is necessarily shaped by methodological and contextual constraints. Recognizing such constraints does not undermine the relevance of the results presented in this study but rather defines their appropriate interpretative scope. The findings documented in this thesis contribute to the understanding of choice overload in digital environments under controlled experimental conditions. However, several limitations related to the experimental setting, measurement choices, and modeling strategy should be acknowledged in order to contextualize the conclusions and identify promising avenues for future research.

4.3.1 Experimental Setting and External Validity

A first limitation concerns the experimental nature of the research design. The empirical analyses are based on a simulated e-commerce environment in which participants interacted with a controlled interface presenting alternative choice architectures. While this approach allows the isolation of informational structure as the primary source of variation, it also introduces constraints regarding the external validity of the findings.

Simulated environments necessarily differ from real-world online marketplaces in several respects. In particular, participants operated within a decision context characterized by limited or absent economic incentives, which may influence the intensity and strategic nature of product evaluation. Real purchasing situations typically involve monetary consequences, brand familiarity, and repeated interactions with platforms, all of which may shape decision behavior in ways that cannot be fully reproduced in a laboratory-style setting.

Furthermore, the experiment captures decision behavior within a single interaction session. Real-world digital consumption, by contrast, often unfolds through repeated exposures, dynamic search processes, and cumulative learning across multiple visits. As a result, the observed behavioral patterns should be interpreted as representations of immediate decision processes rather than long-term consumer adaptation.

At the same time, the controlled experimental setting represents a methodological strength insofar as it allows the systematic manipulation of choice set size while holding interface design and information presentation constant. This design enhances internal validity by isolating decision mechanisms that might otherwise be confounded by platform-specific design features or marketing interventions. Future research could complement the present findings by replicating similar analyses in field settings or by incorporating real purchase incentives to evaluate whether the observed patterns persist under economically consequential decision conditions.

4.3.2 Measurement and Modeling Choices

A second set of limitations relates to the operationalization of key constructs and the statistical modeling strategy adopted in the empirical analysis. The effort index used in this study represents a composite behavioral proxy derived from time allocation, navigation intensity, and interaction frequency. While this measure captures observable engagement during the decision process, it does not directly measure cognitive load or subjective mental effort. Behavioral engagement may reflect multiple underlying psychological processes, including attention allocation, curiosity-driven exploration, or decision uncertainty. Consequently, the interpretation of effort as engagement-oriented cognitive investment should be considered an indirect inference rather than a direct psychological measurement.

Similarly, the analysis relies on self-reported measures to capture perceived stress and satisfaction. Although these constructs are widely used in consumer research, self-reported indicators are inherently subject to individual interpretation, response styles, and retrospective evaluation biases. The inclusion of these measures nonetheless provides valuable insight into subjective decision experiences but does not fully capture emotional dynamics that may evolve throughout the decision process.

From a modeling perspective, the use of linear and logistic regression models provides a tractable and interpretable framework for examining relationships between choice architecture and decision outcomes. However, complex behavioral phenomena such as decision effort and emotional responses may involve nonlinear dynamics and unobserved heterogeneity that cannot be fully captured through parametric regression approaches. The modeling strategy adopted in this study is consistent with established empirical practices in the literature and aligns with the exploratory objective of identifying systematic patterns rather than estimating fully structural behavioral models. Future research may benefit from integrating alternative modeling frameworks, such as hierarchical models or process-tracing methodologies, to provide a more granular representation of individual decision trajectories.

4.3.3 Exploratory Nature of Higher-Order Interactions

A final limitation concerns the interpretation of higher-order interaction effects analyzed in RQ4. The three-way interaction between choice set size, age group, and product category was introduced to explore whether heterogeneous patterns identified in earlier analyses coexisted across multiple dimensions of decision complexity. The three-way interaction was introduced to explore whether previously observed patterns coexisted, rather than to establish stable laws of behavior.

Although the results highlight potentially meaningful configuration patterns, the statistical complexity of higher-order interactions increases sensitivity to sample composition and reduces the precision with which subgroup-specific behavioral regularities can be estimated. The available sample size, while adequate for primary analyses, limits the possibility of drawing definitive conclusions regarding fine-grained behavioral heterogeneity across combined demographic and product dimensions.

The exploratory nature of these findings suggests several directions for future research. Larger-scale experimental studies could provide more robust estimates of higher-order interactions and allow for more detailed segmentation of decision processes. In addition, extending the analysis to alternative product categories characterized by different levels of decision complexity would help evaluate the generalizability of the observed patterns. Longitudinal designs or field experiments conducted in real commercial environments may further clarify how repeated exposure to digital choice architectures influences decision behavior over time.

Overall, the limitations identified in this section do not diminish the empirical contribution of the study but delineate its interpretative boundaries. By explicitly acknowledging measurement constraints, contextual limitations, and exploratory analytical components, the study aims to provide a transparent foundation upon which future research can build more comprehensive models of consumer decision-making in digital choice environments.

4.4 Concluding Remarks

This study set out to examine the role of option numerosity in shaping decision processes and outcomes within simulated e-commerce environments. By combining a controlled experimental design with quantitative behavioral and self-reported measures, the research aimed to isolate the mechanisms through which choice set size influences decision-making. The empirical analyses contribute to clarifying how variations in assortment size affect not only observable outcomes but also the underlying cognitive processes guiding user interaction with digital choice environments. More broadly, the study integrates individual characteristics, contextual decision structures, and product-specific features into a unified analytical framework, thereby providing a more nuanced understanding of how consumers navigate complex digital marketplaces.

The findings collectively suggest that the implications of option numerosity cannot be interpreted through a linear or universally applicable lens. Rather, the relevance and impact of assortment size appear to depend on who is making the decision, what type of product is being evaluated, and the contextual features of the decision environment. These results indicate that the cognitive and behavioral consequences of choice architecture emerge from the interaction between individual decision-makers, the structure of available information, and the inherent complexity of the decision object. Such a perspective encourages a shift away from simplified interpretations of assortment effects toward a more contextual and process-oriented understanding of consumer decision behavior.

Within the broader academic discourse on choice overload, this study does not aim to provide a definitive resolution to existing theoretical debates. Instead, it contributes to refining the conceptual framing of the phenomenon by highlighting the importance of interaction effects across decision-related dimensions. Rather than resolving the choice overload debate, this study contributes to reframing it as a question of interaction between individuals, choice environments, and decision objects. By emphasizing this multidimensional perspective, the research supports the view that the consequences of assortment design are contingent and context-dependent, thereby encouraging future investigations to further explore the dynamic interplay between cognitive processes, product characteristics, and digital decision environments.

Appendix A — Experimental Interface and Stimuli

A.1 Introduction to the Experimental Platform

The study was conducted through a custom-developed web application designed to simulate a modern e-commerce environment. The platform was engineered to collect high-granularity behavioral data (clickstream and dwell time) while maintaining a realistic shopping experience. The experiment followed a linear flow: Consent → Demographics → Instructions →Shopping Task → Final Survey.

A.2 Informed Consent and Privacy

The landing page presented the research objectives and legal information.

- **Content:** Identification of the researcher, data treatment (GDPR compliance), and the voluntary nature of the study.
- **Gatekeeping:** The application logic prevented any further progress until the participant interacted with the consentCheck and clicked the "Accetto e continuo" button.

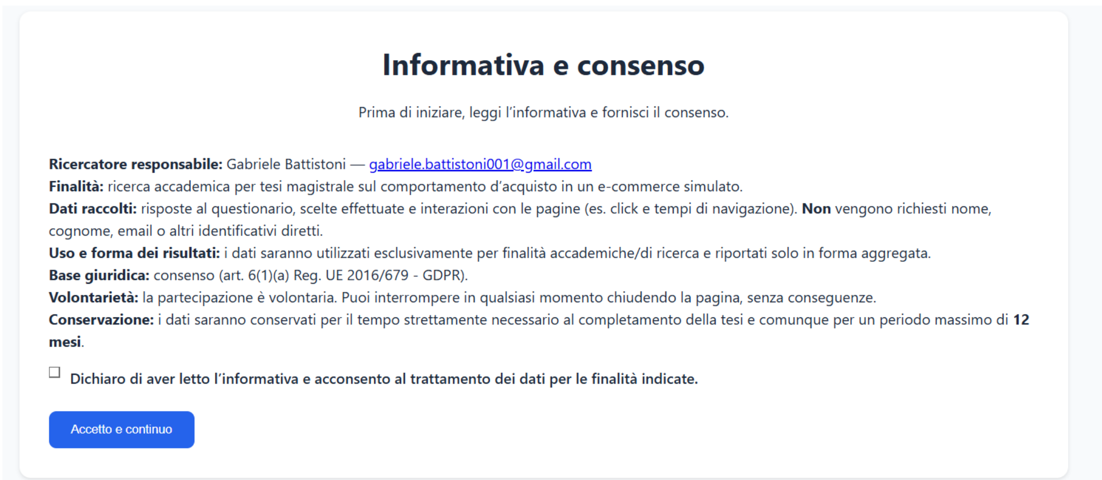

Figure A.1: Screenshot of the Informed Consent Page

A.3 Demographic Data and Digital Experience

Participants were required to provide three key pieces of information used as moderators in the statistical analysis:

1. **Age:** (Numeric input).
2. **Gender:** (Selection: Male, Female, Other).

3. **Digital Experience:** A self-reported 5-point Likert scale (from 1 to 5) measuring familiarity with e-commerce platforms.

Figure A.2: Screenshot of the Demographic Data Form

A.4 Task Framing and Instructions

Before entering the shop, participants received specific instructions to contextualize the task as a **constrained choice exercise**.

- **Objective:** Select one smartphone, one cover, and one power bank.
- **Budgets:** Explicit limits were set to induce trade-off reasoning:
  - **Smartphone:** €250.
  - **Cover:** €15.
  - **Power Bank:** €30.
- **Rules:** Participants were informed they could navigate back and forth, remove items from the cart, or even choose not to purchase if unsatisfied.

Figure A.3: Screenshot of the Instructions Page

A.5 The Shopping Environment: Interface and Information Search

The shopping interface was designed to minimize aesthetic distractions, focusing the participant's attention on product attributes and price.

Product Display and Layout As shown in **Figure A.4**, products were presented in a grid layout. Each card included:

- A high-resolution product image.
- The product name and price.
- A brief introductory description.
- Call-to-action buttons for "Aggiungi al carrello" (Add to Cart) and "Dettagli" (Details). The budget constraint for the specific category was persistently displayed at the top of the grid to ensure constant goal-salience.

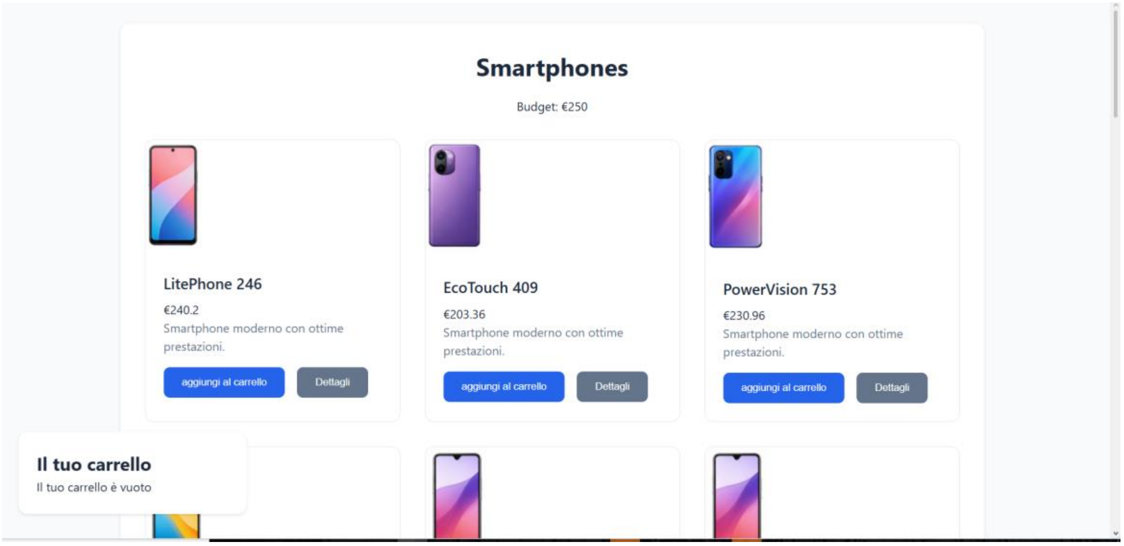

Figure A.4: Main shopping interface for the Smartphone category (Budget: €250).

Information Depth (Modal View) By clicking "Dettagli", participants accessed a modal window (see **Figure A.5**). This view provided the technical specifications and social proof necessary for high-involvement decisions:

- **Specifications:** Detailed list (e.g., Camera, RAM, Memory) as defined in the specs object of the code.
- **Reviews:** A "Social Proof" section with star ratings and qualitative user feedback to simulate a realistic e-commerce environment. The collection of view_details events during this phase was used as an indicator of information-search activity (detail views).

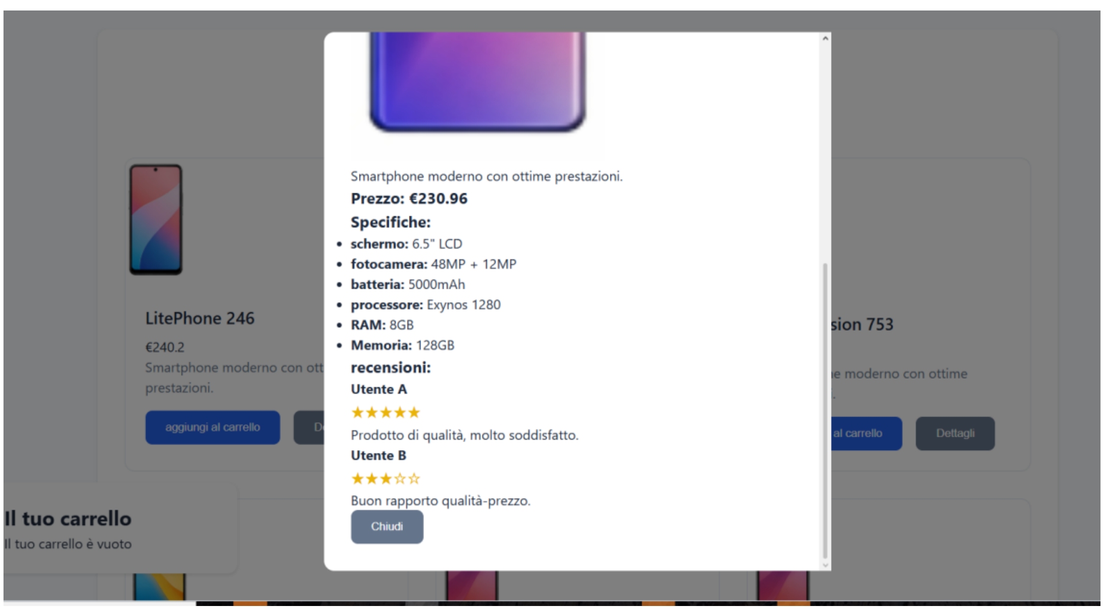

Figure A.5: Detailed product modal with technical specifications and user reviews.

Navigation and Continuity Participants moved between categories using the "Avanti" and "Indietro" buttons (see **Figure A.6**). This allowed for iterative decision-making, where users could reconsider previous choices based on the remaining total budget.

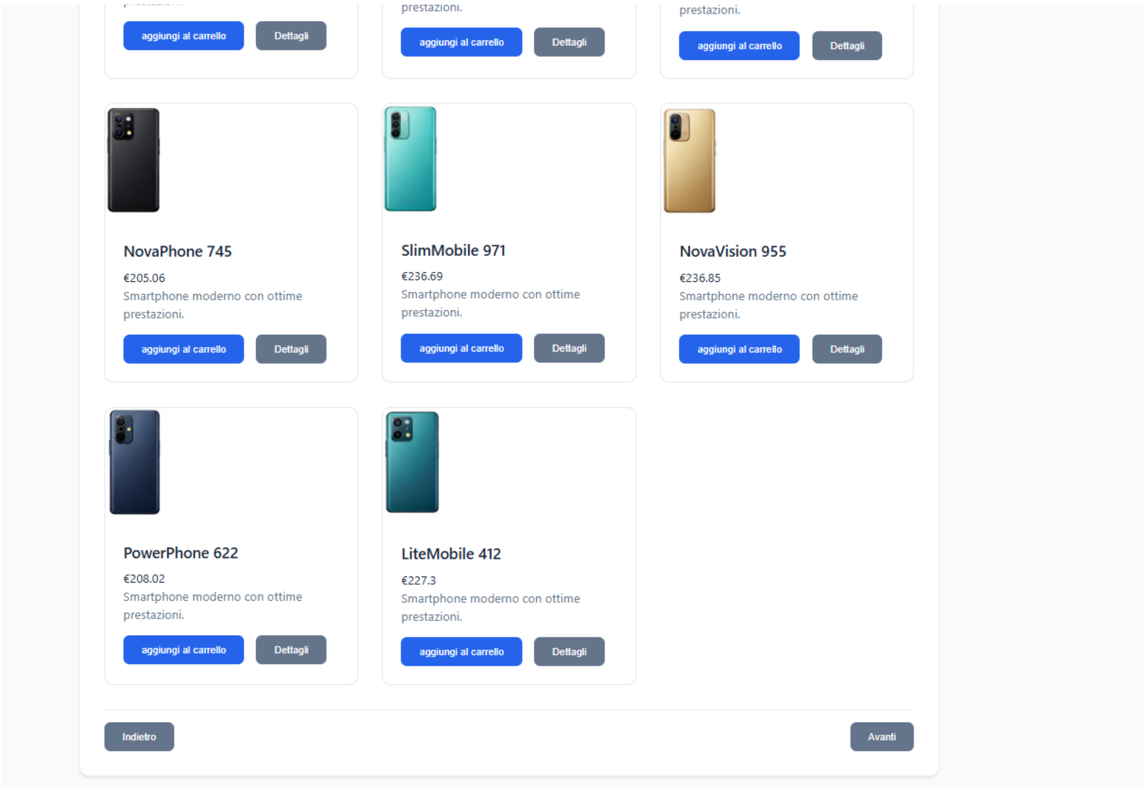

Figure A.6: Navigation controls at the bottom of the product listing page.

A.6 Navigation and Real-time Feedback (Cart Logic)

The shopping experience was non-linear, allowing participants to manage their choices dynamically.

- **The Float-Cart:** As shown in **Figure A.4**, a persistent UI element ("Il tuo carrello") provided immediate feedback on the selection status. This ensured that participants could track their progress without leaving the product grid.
- **Budget Enforcement:** The interface displayed the specific budget for each category (e.g., "Budget: €250" in **Figure A.4**). The visible budget information encouraged participants to consider trade-offs between attributes and price during evaluation.
- **Navigation Flow:** The "Avanti" and "Indietro" buttons (see **Figure A.6**) allowed users to revisit previous categories. This was essential for participants who, after selecting a cover or power bank, realized they needed to change their smartphone choice to stay within a perceived total expenditure.

A.7 Post-Task Evaluation and Qualitative Feedback

The experimental session concluded with a mandatory survey. This phase was designed to collect subjective data to complement the behavioral metrics (Time and Clicks) recorded during the shopping task.

Psychometric Measurement (7-point Likert Scales): As shown in **Figure A.7**, participants evaluated their experience across three key dimensions:

1. **Shopping Satisfaction:** To assess the hedonic outcome of the choice process.
2. **Decision Stress:** To measure perceived confusion or frustration, providing a subjective counterpart to the objective *Effort Index*.
3. **Purchase Intent (Ecological Validity):** A realism check to determine how likely the participant would be to make the same choices in a non-experimental setting.

Qualitative Insights: Two open-ended text fields allowed participants to provide granular feedback on:

- **Choice Drivers:** What factors (price, specs, reviews) most influenced their final decision.
- **Usability Suggestions:** Feedback on the website interface, ensuring that any recorded "effort" was due to the choice set size and not to technical friction or bugs.

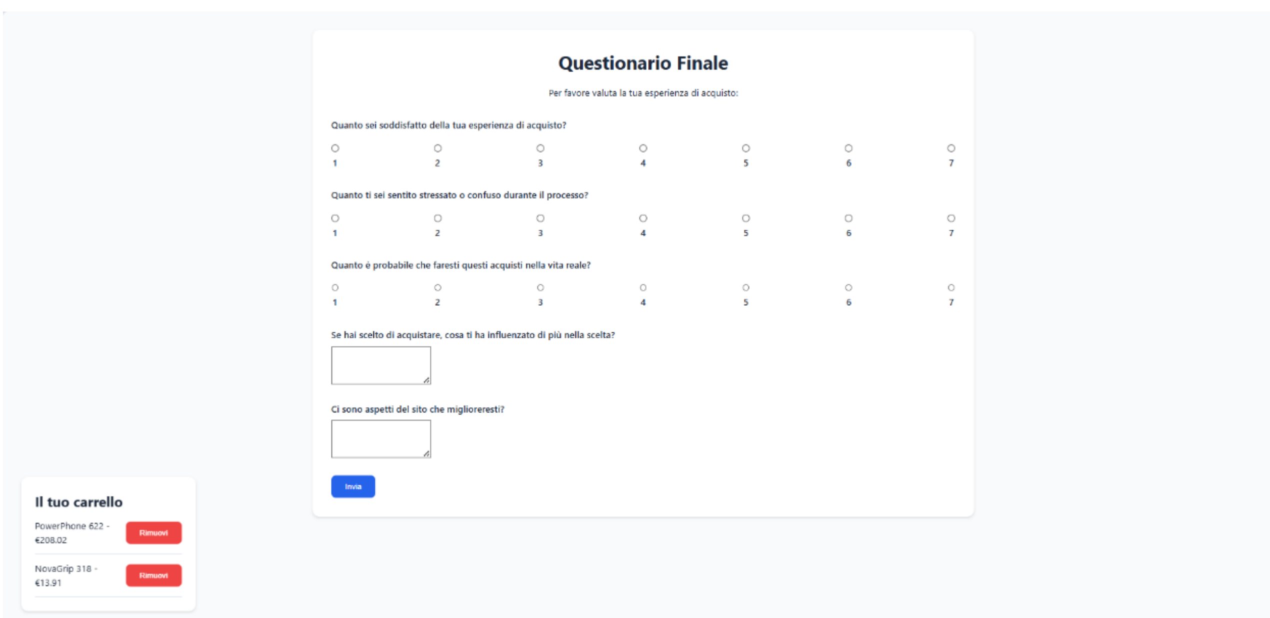

Figure A.7: The Final Survey interface showing Likert scales and qualitative feedback fields.

Appendix B — Variable Construction and Data Processing

B.1 Data Cleaning and Sample Selection Flow

To ensure the integrity of the behavioral analysis, the raw dataset underwent a sequential filtering process. This stage was critical to exclude sessions unlikely to reflect meaningful task engagement.

1. **Raw Data Collection:** The initial pool consisted of **N=232** recorded sessions.
2. **Engagement & Outlier Filtering: * Under-engagement:** Participants with a total session time of less than 30 seconds were excluded (fast-clickers).
    - **Abandonment:** Sessions exceeding 60 minutes were removed to avoid noise from inactive browser tabs.
    - **Statistical Trimming:** The top 5% of the time distribution (**95th Percentile**) was removed to mitigate the impact of extreme outliers on the variance of OLS residuals.
    - After these filters, the sample was reduced to **N=207**.
3. **Missing Values (NA) Removal:** A final listwise deletion was performed on participants with incomplete survey data or broken navigation logs, resulting in the **final analytical sample of N=205**.

B.2 Dimensionality Reduction: The Effort Index

To capture the multidimensional nature of decision effort without incurring in multicollinearity issues, we performed a **Principal Component Analysis (PCA)** on four behavioral metrics:

- **Total Interaction Time** (Seconds)
- **Product Detail Views** (Count of view_details)
- **Page Transitions** (Navigation events)
- **Cart Interactions** (Add/Remove actions)

Statistical Results:

- **Standardization:** All indicators were standardized to have mean $\mu = 0$ and standard deviation $\sigma = 1$ prior to PCA.
- **Variance Explained:** The first principal component (PC1) explains **42.1%** of the total variance, indicating a strong common underlying factor.
- **Component Loadings:** The index is primarily defined by *Total Time* (-0.598) and *Product Views* (-0.586).

- *Note on Polarity:* For the regression analysis, the PC1 scores were mathematically inverted to ensure that higher values of the **Effort Index** represent higher levels of behavioral engagement.

B.3 Logarithmic Transformation

Due to the characteristic positive skewness of the temporal data (confirmed by visual inspection of the density plots), category-level decision time was log-transformed:

$$\text{LogTime}_{i,p} = \ln(T_{i,p} + 1)$$

This procedure reduces right-skewness and helps stabilize variance in the regression residuals. Coefficients from log(time + 1) models should be interpreted as approximate relative differences in decision time rather than absolute changes in seconds.

B.4 Econometric Robustness

- **Standard Errors:** In models involving repeated observations per user (RQ3 and RQ4), standard errors were **clustered at the session ID level** (N=205).
- **HC3 Covariance:** For session-level models (RQ1, RQ2), we utilized **HC3 robust standard errors** to protect the inference against heteroscedasticity.

B.5 Software Environment

All empirical analyses were conducted using the R statistical environment. Estimation procedures relied on the fixest package for regression modeling and sandwich for heteroskedasticity-consistent covariance estimation.

B.6 Additional Regression Results (Interaction Models)

This section reports the complete set of coefficient estimates for the three-way interaction model associated with Research Question 4 (RQ4). The purpose of this appendix is to ensure transparency of the estimation procedure and allow verification of the graphical interpretations presented in Section 3.6 of Chapter 3.

The model analyzes decision time at the product level, measured as the logarithm of time spent evaluating each product category during the experimental session. The specification includes the experimental condition (reduced vs. expanded choice set), categorical age groups, product category indicators, all corresponding two-way interactions, and the three-way interaction between condition, age group, and product category. Self-reported familiarity with e-commerce interfaces is included as a control variable.

The reduced condition, the 20–35 age group, and the phone-case category serve as the reference categories. Consequently, all reported coefficients are interpreted relative to this baseline configuration.

Observations correspond to product-level decisions nested within participant sessions. Because each participant contributes multiple observations, standard errors are clustered at the session level to account for intra-subject dependence across product evaluations.

Due to the relatively small number of observations within some subgroup cells, higher-order interaction terms should be interpreted cautiously. Consistent with the approach adopted in Chapter 3, the three-way interaction model is treated as exploratory, and the graphical patterns discussed in Section 3.6 are intended to illustrate potential configuration differences rather than to provide confirmatory evidence of systematic behavioral heterogeneity.

	Log time (OLS)
(Intercept)	2.380***
	(0.219)
conditionexpanded	0.212
	(0.249)
age_group35-60	0.436*
	(0.204)
age_group60+	0.261
	(0.225)
productpowerbank	0.143
	(0.108)
productsmartphone	0.828***
	(0.134)
experience	0.082*
	(0.041)
conditionexpanded × age_group35-60	-0.249
	(0.334)
conditionexpanded × age_group60+	0.276
	(0.353)
conditionexpanded × productpowerbank	-0.103
	(0.154)
conditionexpanded × productsmartphone	0.226
	(0.171)

	Log time (OLS)
age_group35-60 × productpowerbank	-0.006
	(0.143)
age_group60+ × productpowerbank	0.382+
	(0.205)
age_group35-60 × productsmartphone	0.094
	(0.171)
age_group60+ × productsmartphone	0.240
	(0.253)
conditionexpanded × age_group35-60 × productpowerbank	-0.076
	(0.277)
conditionexpanded × age_group60+ × productpowerbank	-0.380
	(0.297)
conditionexpanded × age_group35-60 × productsmartphone	0.094
	(0.282)
conditionexpanded × age_group60+ × productsmartphone	-0.049
	(0.361)
Num.Obs.	615
R2	0.237
Std.Errors	by: session_id

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Standard errors clustered at the session level in parentheses.

Table B.6 — Full regression results for the three-way interaction model (RQ4)

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