Human Technology

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 22(1), May 2026, 5-20

CLICKING ON IMPULSE OR THINKING TWICE? EYE-TRACKING REVEALS THE HIDDEN DRIVERS OF ONLINE CONSUMER DECISIONS

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Abstract: This study examines how different information processing tendencies are associated with economic decision-making in consumer contexts. Using eye-tracking technology, we analyze the relationship between visual attention patterns and task-specific decision accuracy in simulated online purchasing tasks. Participants (N = 100) evaluated mobile phone plans. Cluster analysis revealed two visual-attentional profiles: perfectionists and impulsive decision-makers. Results show that detailed attention, self-control, and systematic information processing are associated with higher decision accuracy. Age and conscientiousness positively correlate with deeper information processing and more accurate task performance. Rather than treating eye-tracking as a direct measure of decision quality, the study interprets gaze behavior as an indicator of how consumers inspect, compare, and revisit information in a digitally structured choice environment. The findings offer implications for consumer research, digital marketing, and interface design.

Keywords: *eye-tracking, consumer behavior, decision-making, dual-process theory, information processing, online shopping*

DOI: https://doi.org/10.14254/1795-6889.2026.22-1.1

INTRODUCTION

Decision-making is a critical cognitive process that significantly shapes human behavior across personal, professional, and societal domains. In consumer behavior, decisions vary from routine, low-involvement choices to complex, high-stakes purchases requiring careful deliberation. The study of how individuals process information and arrive at decisions has been a longstanding focus of research in psychology and behavioral economics. Among the various cognitive frameworks that attempt to explain decision-making, dual-process theory stands out for its widespread empirical support. This theory proposes two distinct systems of thought: intuitive (System 1) and analytical (System 2) processing (Kahneman, 2011; Evans & Stanovich, 2013).

System 1, or intuitive processing, is characterized by its speed, automaticity, and emotional underpinnings. It operates with minimal cognitive effort, often in familiar or time-pressured contexts. In contrast, System 2 involves slower, more deliberate, and effortful thinking, activated in novel or complex scenarios requiring logic, reasoning, and self-control. Although these systems are theoretically distinct, they frequently interact and influence one another. Rather than being treated as rigidly separate or directly observable systems, recent perspectives suggest that in real-world contexts decision-making may emerge from a dynamic interplay between intuitive tendencies, reflective monitoring, situational demands, and contextual affordances (Evans & Stanovich, 2013; Fabio & Caprì, 2019, 2023; Moriuchi & Moriyoshi, 2024).

In consumer behavior, the interplay between these two systems is particularly evident. Consumers may rely on heuristics, brand familiarity, or emotional appeals (System 1) or engage in more detailed comparisons, cost-benefit analyses, and long-term evaluations (System 2) (Bettman et al., 1998; Chandon & Wansink, 2007; Shigemune et al., 2024). The increasing complexity of online shopping environments, characterized by information overload and multitasking, heightens the need to understand how consumers allocate attention and engage cognitive resources during decision-making processes. Importantly, in online contexts, decision-making is not only an internal cognitive process, but also an interaction with a technologically structured environment that shapes what information becomes salient, comparable, and behaviorally actionable.

Advancements in technology, particularly eye-tracking, have provided novel ways to explore the cognitive mechanisms underlying consumer decisions. Eye-tracking technology measures where, how long, and how frequently individuals fixate their gaze on elements of a visual display, offering real-time indicators of attention allocation (Cherubino et al., 2019; Chen, 2024). Unlike self-report measures, which can suffer from bias and retrospective inaccuracies, eye-tracking provides objective data on how consumers process information and make decisions in real time. At the same time, eye-tracking should not be interpreted as providing direct access to reasoning quality or decision quality in themselves. Rather, it offers an indirect but informative window into how visual attention is allocated during the unfolding of a choice.

Recent research in neuroscience and psychology has shown that attentional focus is not merely a byproduct of cognitive engagement but a central component of decision-making. Attention determines which information is processed and integrated into final choices, influencing both the efficiency and quality of decisions (Kool et al., 2010; Bendall &

Thompson, 2015; Luo et al., 2024). However, gaze behavior alone cannot fully capture the broader cognitive, emotional, and interpretive processes involved in decision-making. For this reason, eye-tracking data are best understood in the present study as indicators of information inspection and attentional engagement, rather than as direct measures of good or poor decision-making. By integrating eye-tracking with consumer decision-making, researchers have gained valuable insights into how visual attention and cognitive processes interact to shape behavior.

The Role of Information Processing in Decision-Making

The role of information processing in consumer decision-making is crucial, particularly as e-commerce continues to evolve. The rapid development of online platforms has revolutionized how product-related information is generated, accessed, and distributed. While this has made information more accessible, faster, and cheaper, it has also led to information overload, which can hinder rational decision-making (Lee & Lee, 2004; Lee & Cho, 2005). The sheer volume of information, often presented in rapid succession and from multiple sources, makes it more difficult for consumers to evaluate alternatives effectively.

In this context, managing the flow of information becomes a critical task for both consumers and businesses. Companies provide extensive product details to influence consumer behavior and achieve their economic objectives (Ben-Shahar & Schneider, 2014). However, consumers must navigate this information overload, which can lead to suboptimal decisions unless they can efficiently process and filter the information available to them.

Psychologically, it is hypothesized that consumers can navigate large volumes of information and make informed choices, but this ability varies across individuals (Delaney et al., 2024; Mittal, 2017; Fabio & Caprì, 2023). Consumers' cognitive styles and information processing abilities play a significant role in how they approach, acquire, and organize information during decision-making.

This study seeks to identify and analyze the different information processing styles associated with decision accuracy in an online shopping task. Unlike previous studies that relied on self-reports and inferred behaviors (Delaney et al., 2024; Mittal, 2017), the present research employs eye-tracking technology to capture real-time patterns of visual attention and information inspection during decision-making. In this way, the study provides an objective and time-sensitive indication of how participants inspect, compare, and revisit information while making choices, without assuming that these measures directly reveal the overall quality of the underlying reasoning process.

Information Processing Styles

Building on dual-process theory, this study examines how different patterns of information processing are associated with decision accuracy in an online shopping task. Previous research has identified various consumer decision-making styles, often classifying them based on how extensively they engage with information. For instance, Sproles and Kendall (1986) proposed a typology of consumers that includes perfectionists, quality seekers, brand-loyal buyers, and impulsive consumers. Mittal (2017) further refined this classification into four groups: (1) "extensive optimizers," who thoroughly process information to select the best option; (2) "balanced and diligent consumers," who review information but avoid additional searches; (3)

“confused buyers,” who struggle with information processing despite attempts; and (4) “reckless decision-makers,” who make snap decisions with minimal effort.

This study adopts these classifications to explore how visual attention and cognitive control manifest in distinct decision-making styles, focusing on two major types: perfectionists, who engage in careful, methodical analysis, and impulsive decision-makers, who make rapid, heuristic-driven choices. In the revised framing, however, these profiles are treated as empirical visual-attentional tendencies emerging from the data, rather than as fixed psychological essences or direct one-to-one expressions of two isolated cognitive systems. The goal is to understand how these visual-attentional tendencies are associated with decision accuracy in a simulated online shopping context.

Information Processing Styles and Decision Quality

Information processing plays an important role in decision-making, but its relation to decision outcomes is not always linear or univocal. Poor decision-making often results from insufficient processing of available information, a phenomenon that has been extensively studied (Tversky & Kahneman, 1974; Kahneman & Frederick, 2005; Kim & Kim, 2024). However, some studies have argued that less precise decision-making can still lead to successful outcomes (Simon, 1992; Gigerenzer, 1996; Gigerenzer & Brighton, 2009; Göktaş et al., 2024). For instance, decision-making models suggest an inverted U-shaped relationship between the effort invested in processing information and decision quality, where optimal decisions occur at moderate levels of cognitive effort, neither too high nor too low. This suggests that more information processing should not automatically be equated with better decision-making, but needs to be interpreted in relation to task demands, context, and the criteria used to define decision success.

Moreover, research suggests that consumers confronted with overwhelming amounts of information may resort to familiar options or simple heuristics (Sasaki et al., 2011). While these approaches reduce cognitive load, they may also diminish decision satisfaction, particularly among those who invest considerable effort into decision-making (Carmon et al., 2003). Previous studies have assumed that consumers rely on heuristics due to cognitive limitations, but the present research examines how different patterns of visual attention and information inspection are associated with task-specific decision accuracy in real time, using eye-tracking as an indirect indicator of attentional engagement rather than as a direct measure of cognitive quality.

Despite extensive research on decision-making, few studies have examined the direct relationship between real-time information processing and decision quality (Vogrincic-Haselbacher et al., 2021). Rather than claiming to assess decision quality directly through eye movements, the current study addresses this gap by examining how eye-tracking indicators of visual attention are associated with decision accuracy in an online shopping task, while explicitly recognizing that such indicators do not exhaustively capture decision quality as a whole. In this sense, the study focuses more specifically on the relationship between visual-attentional behavior and performance within a defined digital choice environment.

Research Gap and Contribution

While much of the existing literature has explored the cognitive mechanisms behind consumer decision-making, there remains a significant gap in understanding how real-time attention allocation, as captured by eye-tracking, is associated with decision outcomes. Previous studies have either focused on self-reported behaviors or used indirect measures of attention, which may not fully capture the dynamics of information processing during decision-making. At the same time, attention allocation should not be assumed to correspond directly or exhaustively to decision quality, since gaze patterns represent only one component of a broader cognitive and affective decision process.

This study offers a novel contribution by combining dual-process theory with objective, real-time eye-tracking data to examine how visual attention and cognitive control may be reflected in different patterns of information inspection during consumer decision-making. Rather than treating dual-process theory as a rigid explanatory template, the present study adopts it as a heuristic framework for interpreting broad tendencies in how participants engage with online choice environments. It extends the literature by providing empirical evidence on how distinct information processing styles - perfectionists and impulsive decision-makers - can be identified as visual-attentional profiles in a simulated online shopping context.

More specifically, the study contributes by examining how these profiles emerge through the interaction between individual tendencies and the informational structure of a digitally mediated interface. In this sense, the study not only addresses consumer decision-making, but also contributes to a better understanding of how technological environments shape attentional pathways and decision behavior.

To this end, the research addresses the following questions and hypotheses:

RQ1: What distinct visual-attentional profiles can be identified through eye-tracking behavior in a simulated online shopping task?

RQ2: How do these processing styles relate to decision accuracy, operationalized in relation to expert-defined task criteria?

H1: Participants who exhibit higher levels of visual attention, systematic search, and self-control will demonstrate greater decision accuracy.

H2: Participants with more impulsive, fast-paced processing patterns will exhibit lower decision accuracy.

H3: Age and conscientiousness will be positively associated with systematic processing and higher decision accuracy.

These hypotheses are intended to capture broad associations between attentional behavior and task performance, rather than to imply a one-to-one correspondence between gaze patterns and the full quality of the underlying decision process.

METHODS

Participants

The study involved 100 participants (43 males and 57 females), aged between 18 and 42 years ($M = 31.4$, $SD = 9.23$), all of whom had normal or corrected-to-normal vision. Participants were recruited through university mailing lists and social media advertisements. Because purchasing decisions (particularly for rate plans) involve the general population, participants from diverse socioeconomic backgrounds were recruited. Inclusion criteria required participants to have basic familiarity with online shopping and to engage in it at least once per month. All participants gave informed consent in accordance with institutional ethical guidelines (Ethical Committee of the Local University: 001145/B of the 3/5/23). The sample size was determined a priori based on methodological recommendations for multivariate analyses. Specifically, a minimum of 90 participants was required to satisfy the assumptions of exploratory factor analysis (based on 6 eye-tracking indicators), cluster analysis, and within-subject ANOVAs with medium expected effects ($\eta^2 \approx .06$), 95% confidence, and 80% power. The final sample of 100 participants thus provided sufficient statistical power while accounting for potential data loss due to calibration issues or eye-tracking artifacts.

Design and Procedure

The study employed a within-subjects experimental design in which each participant completed a simulated online shopping task aimed at selecting a mobile phone plan. This design allowed each individual to serve as their own control, reducing between-subject variability and increasing statistical power. Figure 1 shows the different phases of the design.

The experimental scenario was structured to closely replicate real-life decision-making conditions, presenting participants with multiple mobile phone options varying in features such as monthly cost, data allowance, number of call minutes, number of text messages, and provider reputation. In some conditions, additional detailed annotations were included for selected plans to test their influence on visual attention and decision-making behavior (see Figure 2).

Prior to beginning the task, participants completed a demographic and psychological questionnaire. This included items on their age, gender, education level, and occupation, as well as measures of online habits, interest in technology and mobile phone plans, and relevant personality traits (e.g., conscientiousness, impulsivity). These variables were collected to account for potential individual differences in consumer decision-making styles.

Following the questionnaire, participants underwent a 9-point eye-tracker calibration procedure using a Tobii Pro Fusion system to ensure high-quality gaze data acquisition. The eye-tracking equipment was integrated into a 15-inch LCD monitor with a Matrix video board, equipped with a high-speed infrared-sensitive camera. The camera included a built-in LED that emitted low-intensity infrared light directed at the participant's retina. Eye movement tracking was conducted using the Pupil Center/Corneal Reflection method, which reliably estimates the direction of gaze based on corneal light reflections and pupil positioning.

During the experimental task, participants interacted with a web-based interface developed to resemble a commercial e-commerce platform. They were asked to choose a mobile plan that best suited their preferences, with the instructions to behave as if they were making a real purchase. No time constraints were imposed, allowing for natural decision-making. Participants were informed that their choices would be evaluated post hoc against predefined expert-based criteria regarding the efficiency and suitability of their selections. Importantly, among the full set of 48 mobile phone plans displayed, three were identified a priori as the most efficient in terms of quality-to-price ratio, based on an expert evaluation. These three plans were consistently positioned across participants and used to define specific Areas of Interest (AOIs) for focused analysis.

The eye-tracking system recorded participants' visual responses throughout the task. Specifically, it captured gaze fixations, fixation durations, and scan paths, offering insights into the allocation of visual attention and the sequence of information processing. Eye-movement data were analyzed using Passive Gaze Tracing software (LC Technologies, Inc., São Paulo, Brazil), which generated eye-found flags, pupil location, gaze point coordinates, and pupil diameter during the visual exploration phase.

At the conclusion of each task, participants completed a short debriefing questionnaire assessing their perceived decision-making confidence and task difficulty. This subjective evaluation was intended to complement the objective measures derived from the eye-tracking data and behavioral outcomes.

The Tobii Pro Fusion eye-tracking system enabled the precise collection of oculomotor data during participants' interaction with the experimental interface. The analysis focused in particular on fixation parameters, defined as moments during which the participant's gaze remained relatively stable on a specific point of the screen for a sufficient duration to allow for cognitive processing of the stimulus.

Fixations were identified using the I-VT (Identification by Velocity Threshold) classification algorithm implemented in the Tobii analysis software, which distinguishes fixations from saccadic movements based on angular velocity thresholds. For each fixation, the system recorded its duration (in milliseconds), the spatial coordinates (X,Y) of the gaze point on the screen, and the total number of fixations associated with each visual stimulus.

These fixation data were used to compute key indicators of visual attention, including the average fixation duration per Area of Interest (AOI), the total number of fixations per tariff plan, and the temporal distribution of gaze behavior throughout the decision-making process. Such parameters provided an indirect, yet reliable measure of cognitive load and the perceived relevance attributed to each informational element presented on the screen. These metrics served as the foundation for several key dependent variables used in subsequent analyses.

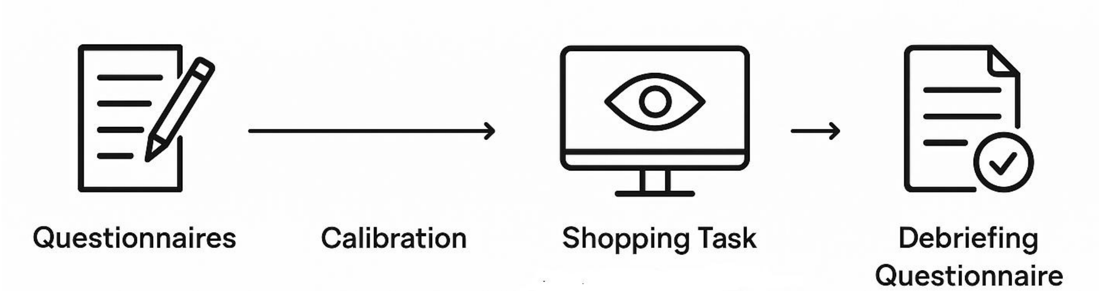

Figure 1. Overview of the experimental procedure. The study consisted of four phases: (1) completion of preliminary questionnaires, (2) eye-tracking calibration, (3) execution of a shopping task simulating a real-life decision-making scenario, and (4) completion of a debriefing questionnaire.

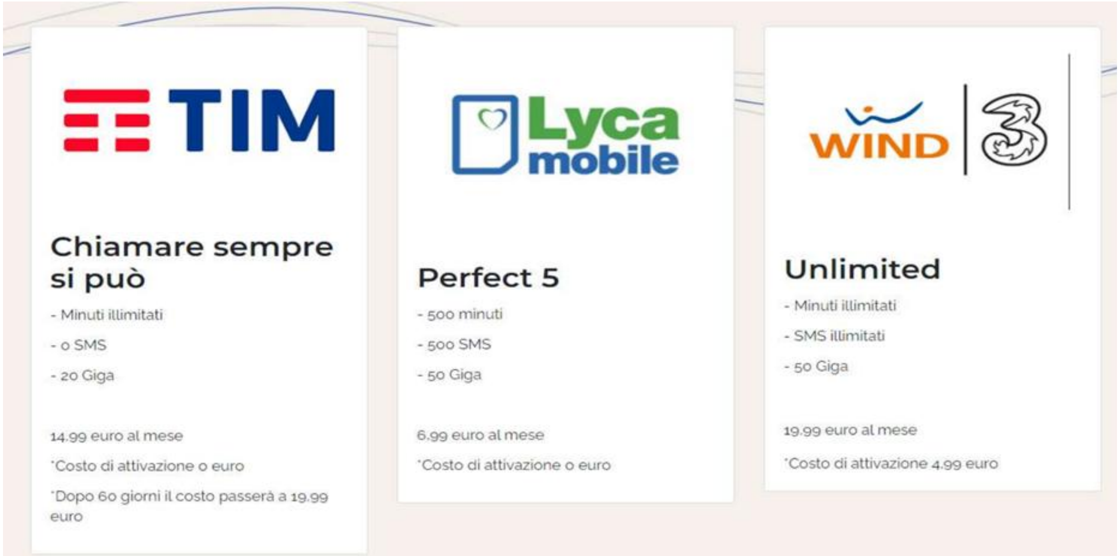

Figure 2. Example of mobile phone plan options presented to participants during the experimental task. The providers offered plans that differed in terms of call minutes, SMS, data allowance, monthly cost, and activation fees. These variations were used to simulate realistic consumer decision-making scenarios.

Measures

The primary dependent variables were a set of eye-tracking indicators that captured participants' attentional dynamics and decision strategies. These included: 1) total decision time (i.e., the number of seconds from the beginning of the task to end of the selection task), 2) focused evaluation time on the three top-rated alternatives (number of seconds the participant spent looking at the three best-rated alternatives) and 3) the alternation index, reflecting the number of gaze shifts between these top plans. Additional indices were calculated to assess 4) the orderliness of visual exploration, assessed via path analysis, indicating whether participants adopted a systematic (serial) or disorganized (random or erratic) viewing strategy, 5) attention to detail (operationalized as time and fixations on fine print and technical specifications), and 6) self-control, measured through the frequency of revisiting previously inspected options.

The independent variables were a set of individual characteristics that captured participants' demographic and personality traits. These included: 1) age (participant's chronological age in years), 2) gender (categorized as male, female, or non-binary), 3) daily internet usage (mean number of hours spent online each day), 4) interest in mobile plans and clothing (self-reported level of interest rated on a 1–10 scale), 5) impulsivity (assessed via a brief self-report screener measuring tendencies toward impulsive behavior, as outlined by Stanton, Forbes, & Zimmerman, 2018), and 6) conscientiousness (measured using the BFI-10, which assesses traits like responsibility, organization, and self-discipline, as described by Rammstedt & John, 2007).

Each task included three objectively optimal choices based on expert consumer guidelines. Choices were coded as correct (1) if they were among the three optimal options, or incorrect (0) if they belonged to one of the remaining 45 suboptimal alternatives.

Statistical Analysis

Data were analyzed using IBM SPSS Statistics (Version 30). First, descriptive statistics were calculated for all variables. To reduce the dimensionality of the eye-tracking indicators, an exploratory factor analysis (EFA) with Varimax rotation was conducted. The resulting factor scores were used in a two-step cluster analysis to categorize participants based on processing styles.

Cluster validity was assessed via silhouette coefficients and visually through cluster dendrograms. A discriminant function analysis was performed to cross-validate the cluster solution.

To examine associations between information processing behavior and decision performance, Spearman's rho correlations were computed. One-way ANOVAs were conducted to test for significant differences in decision accuracy, attention measures, and psychological traits between identified consumer groups.

Chi-square tests assessed differences in accuracy distributions across clusters. Finally, all statistical tests adhered to a significance threshold of $p < .05$, with effect sizes reported as eta-squared (η^2) or correlation coefficients as appropriate.

RESULTS

Preliminary Analyses

Descriptive statistics for all eye-tracking indicators are presented in Table 1. Total decision time ranged from 62 to 517 seconds ($M = 214.07$, $SD = 114.94$), and participants spent an average of 22.01 seconds ($SD = 12.80$) evaluating the top three alternatives. The average alternation index was 1.29 ($SD = 0.64$), reflecting modest comparative behavior between options.

Table 1. Descriptive Statistics for Main Eye-Tracking Variables.

Variable	M	SD
Total decision time	214.07	114.94
Focused time (top 3)	22.01	12.80
Alternation index	1.29	0.64
Orderliness	2.39	1.09
Attention to detail	3.67	1.01
Self-control (reinspections)	22.64	13.73

Identifying the Profiles

An exploratory factor analysis (EFA) with Varimax rotation was conducted on the six primary eye-tracking variables. The Kaiser-Meyer-Olkin measure verified sampling adequacy (KMO = .72), and Bartlett's test of sphericity was significant, $\chi^2(15) = 179.21$, $p < .001$, supporting the factorability of the correlation matrix. Three factors emerged with eigenvalues greater than 1, explaining a total of 72.6% of the variance: (1) Strategic Search, (2) Detail-Oriented Evaluation, and (3) Impulsive Scanning.

A two-step cluster analysis based on the factor scores identified two distinct visual-attentional profiles. The silhouette coefficient (.62) indicated good cohesion and separation. The clusters were labeled as Perfectionists (n = 43) and Impulsives (n = 57) based on their processing characteristics. Figure 3 illustrates the cluster composition and key dimensions. Discriminant function analysis confirmed the robustness of the classification with an overall prediction accuracy of 91%.

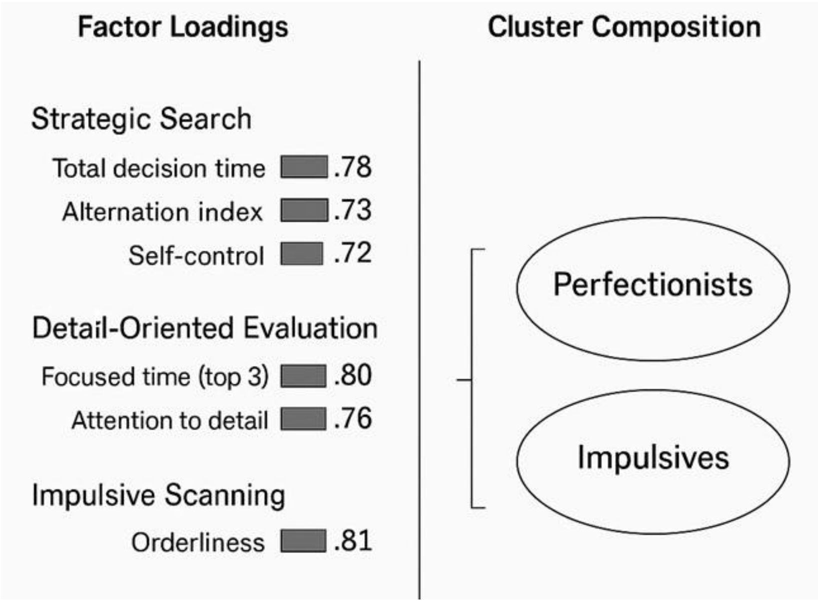

Figure 3. Factor loadings and cluster composition from EFA and cluster analysis.

Group Comparisons

As shown in Table 2, one-way ANOVAs revealed significant group differences on all eye-tracking indicators. Compared to Impulsives, Perfectionists spent significantly more time making decisions, $F(1, 98) = 22.15$, $p < .001$, $\eta^2 = .18$, and focused more intensively on the best alternatives, $F(1, 98) = 13.44$, $p = .001$, $\eta^2 = .12$. They also showed higher alternation indices, $F(1, 98) = 26.82$, $p < .001$, $\eta^2 = .21$, greater attention to detail, $F(1, 98) = 11.92$, $p = .001$, $\eta^2 = .10$, and more frequent reinspections (self-control), $F(1, 98) = 16.87$, $p < .001$, $\eta^2 = .14$. Two example videos illustrating the decision-making behavior of Impulsive and Perfectionist participants, recorded via eye-tracking, can be accessed at the following links: https://www.youtube.com/watch?v=RnDMfLqmPek (impulsive) and https://www.youtube.com/watch?v=Plj9q_hwRyo (perfectionist).

Table 2. Cluster Differences on Decision Accuracy and Processing Styles.

Variable	Perfectionists (n = 43)	Impulsives (n = 57)	F	p	η²
Decision Accuracy	.86	.24	37.07	<.001	.29
Total Time (s)	349.44	114.94	22.15	<.001	.18
Focused Time (s)	27.06	16.96	13.44	<.001	.12
Alternation Index	1.94	0.64	26.82	<.001	.21
Attention to Detail	4.11	3.23	11.92	<.001	.10
Self-Control	25.35	13.21	16.87	<.001	.14

Note. Decision accuracy is coded as 1 = correct, 0 = incorrect. All measures refer to aggregated task performance across the two conditions.

Decision Accuracy

Perfectionists demonstrated significantly higher decision accuracy than Impulsives ($M = .86$ vs. .24), $F(1, 98) = 37.07$, $p < .001$, $\eta^2 = .29$. This result suggests that more detailed and systematic information inspection was associated with a higher probability of selecting one of the expert-defined optimal options in this task.

Correlational Analysis

Spearman’s correlations revealed that decision accuracy was positively associated with age ($\rho = .34$, $p = .001$) and conscientiousness ($\rho = .31$, $p = .002$), and negatively associated with impulsivity ($\rho = -.28$, $p = .004$). Among the eye-tracking indicators, focused time ($\rho = .38$, $p < .001$) and alternation index ($\rho = .43$, $p < .001$) showed the strongest positive correlations with decision accuracy.

DISCUSSION

The present study aimed to investigate how different patterns of visual attention, as indexed by eye-tracking data, are associated with economic decision-making in an online shopping context. Rather than assuming that eye-tracking reveals decision quality directly, the present findings are interpreted as showing how different forms of visual engagement with a digitally structured choice environment are related to task-specific decision accuracy. In this sense, the study identified two distinct visual-attentional profiles: Perfectionists, who engaged in more detail-oriented and systematic evaluations, and Impulsives, who showed faster and less controlled patterns of information inspection.

These profiles can be interpreted as broad processing tendencies that are consistent with dual-process distinctions, but they should not be understood as pure or fixed embodiments of System 2 and System 1, respectively. Although the Perfectionist profile was characterized by focused attention, strategic comparison, and self-control, and the Impulsive profile by faster and more selective scanning, the present results do not suggest that participants relied exclusively on one mode of processing. Rather, they point to recurrent differences in how individuals navigated the task and engaged with the informational structure of the interface. This more cautious interpretation is important because real-world consumer decisions are unlikely to emerge from fully separate cognitive systems operating in isolation. Instead, they are better understood as resulting from a dynamic interplay between intuitive responses, reflective monitoring, personal tendencies, and the design features of the choice environment.

The observed differences in decision accuracy between the two profiles nevertheless remain meaningful. Participants classified in the Perfectionist cluster spent more time examining the available options, focused more on the top-rated alternatives, alternated more frequently between them, and revisited information more often than participants in the Impulsive cluster. These patterns were associated with a higher probability of selecting one of the expert-defined optimal plans within the task. However, this should be interpreted carefully: the outcome variable used in the present study refers to decision accuracy in relation to predefined task criteria, not to a universal or context-free measure of good decision-making. Thus, the results suggest that more extensive and systematic visual inspection was advantageous in this specific online comparison task, rather than demonstrating that slower or more effortful processing is always superior across consumer contexts.

In this regard, the findings are broadly compatible with previous work suggesting that greater comparison, attentional persistence, and self-regulation can support more accurate judgments in information-rich environments. At the same time, the present study does not claim that longer viewing times or more fixations are inherently better. In some contexts, rapid decisions may be adaptive, efficient, or even preferable, especially when options are familiar, stakes are low, or information is redundant. What the present data indicate is that, under the conditions of this task - multiple alternatives had to be compared and only a limited subset met expert-based efficiency criteria - participants who engaged in more systematic inspection were more likely to arrive at those optimal selections (Vogrincic-Haselbacher et al., 2021; Kool et al., 2010; Gigerenzer & Brighton, 2009).

This point is particularly relevant for the theoretical interpretation of dual-process theory. In the original framing of the manuscript, the distinction between Perfectionists and Impulsives risked being read too mechanically as a straightforward confirmation of System 2 versus System 1 processing (Evans & Stanovich,2013; Fabio & Caprì, 2023). The revised interpretation is more nuanced. The identified clusters are best understood as empirical visual-attentional profiles that can be discussed in relation to dual-process theory, but not as direct behavioral equivalents of two isolated mental systems. Indeed, some participants may have begun with an intuitive orientation and then shifted toward more reflective comparison, whereas others may have alternated between careful inspection and rapid heuristic selection. Such fluidity is more consistent with contemporary accounts that emphasize the interdependence and mutual modulation of automatic and controlled processes.

From this perspective, the present findings contribute not only to consumer psychology, but also to the study of human–technology interaction. The online interface was not merely a neutral container of information; it structured the decision space by making some attributes salient, some comparisons easier, and some attentional paths more likely than others. The observed profiles therefore reflect not only internal differences between participants, but also different ways of interacting with a technologically mediated environment. This point strengthens the relevance of the study for Human Technology, as it highlights how digital environments participate in shaping attention, comparison behavior, and ultimately decision outcomes.

The associations found for age and conscientiousness further enrich this interpretation. Older participants and those scoring higher in conscientiousness tended to show more systematic processing and higher decision accuracy. Rather than viewing these variables as deterministic causes of better decision-making, they may be understood as characteristics that increase the likelihood of sustained comparison, attentional persistence, and more deliberate engagement with the task. This suggests that personal dispositions may shape how users respond to the demands and affordances of online choice environments, again underscoring the relational nature of decision-making in digital settings.

From a methodological perspective, the study also highlights both the value and the limits of eye-tracking. A major strength of the method is that it allows researchers to observe, in real time, how attention is distributed across alternatives during the unfolding of a decision. This provides an important complement to self-report measures, which may be affected by memory bias or post hoc rationalization. At the same time, eye-tracking cannot by itself reveal the full reasoning process, the subjective meaning attributed to information, or the emotional and motivational states that may also guide choice. For this reason, the present findings should be interpreted as evidence about patterns of information inspection and visual engagement, rather than as exhaustive measures of cognitive quality.

These considerations also have practical implications for digital marketing, consumer education, and interface design. If different users engage with information in different ways, online platforms may benefit from offering interfaces that better support both rapid orientation and deeper comparison. For example, designers might provide layered information structures, clearer comparison tools, or customizable displays that allow users to move more easily between summary-level and detailed inspection. Importantly, the goal should not be to steer users toward one presumed “ideal” cognitive style, but to create environments that reduce unnecessary overload and support more transparent, informed, and user-appropriate decisions.

Overall, the present study supports the idea that systematic visual engagement is associated with better task performance in a complex online consumer setting, while also suggesting the need for a more flexible theoretical account than a strict one-to-one mapping between observed behavior and dual-process categories. By integrating the reviewer’s concern, the revised discussion therefore positions the study not as a simple confirmation of two pre-existing cognitive types, but as an empirical exploration of how visual attention, individual tendencies, and digital environments interact during online consumer choice.

LIMITATIONS AND FUTURE DIRECTIONS

Several limitations of the present study should be acknowledged. First, although the sample size was adequate for the analyses conducted, the relatively limited and context-specific sample reduces the generalizability of the findings across broader populations, age groups, and consumer domains. Future research should therefore examine whether similar visual-attentional profiles emerge in more diverse samples and in other decision-making contexts, such as health, finance, or public service platforms.

Second, while eye-tracking provides valuable real-time information about how participants visually inspect alternatives during a choice task, it should not be considered a direct or exhaustive measure of the underlying reasoning process, nor of decision quality in a general sense. Eye movements can indicate where attention is allocated, for how long, and in what sequence, but they do not by themselves capture the meanings participants assign to information, the strategies they consciously report using, or the emotional and motivational processes that may shape a decision. For this reason, future studies would benefit from integrating eye-tracking with complementary methods such as think-aloud protocols, post-task interviews, process tracing, or physiological measures.

Third, the cross-sectional and task-based nature of the present design does not allow for strong causal inferences. The study identifies associations between visual-attentional patterns and task-specific decision accuracy, but it cannot determine whether these patterns cause better performance, result from it, or co-develop in interaction with other personal and situational factors. Longitudinal and experimental designs would be especially useful for clarifying how attentional strategies evolve over time and how they may be shaped by repeated exposure to particular digital environments.

From a theoretical perspective, the present findings support the relevance of dual-process approaches, but they also suggest the need for a more nuanced interpretation than a strict two-system reading. Rather than considering Type 1 (automatic) and Type 2 (controlled) processes as entirely distinct and independently operating systems, the results are more consistent with the idea that consumer decisions emerge from a dynamic interaction between rapid intuitive responses and more reflective forms of monitoring and evaluation. Even participants classified within the same profile may not rely exclusively on one mode of processing. Instead, they may shift between rapid orientation, selective comparison, reconsideration, and more deliberate inspection depending on task demands and interface structure.

This more integrative view is particularly important in technologically mediated decision settings. Online choice environments do not simply display information; they also organize, prioritize, and visually frame it in ways that can channel attention and shape the conditions under which reflection or impulsivity become more likely. Future research should therefore examine more explicitly how interface design features - such as layout complexity, comparison tools, visual hierarchy, defaults, or persuasive cues - interact with individual tendencies to produce different decision patterns.

Finally, although the present study identified two clusters that were analytically meaningful, consumer behavior is unlikely to be fully captured by a rigid two-profile classification. The profiles observed here are better understood as empirical patterns within this specific task rather than as fixed and universal consumer types. Future work could explore more fine-grained distinctions, continuous dimensions of attentional behavior, or within-person shifts between impulsive and deliberative modes across time and contexts.

Overall, the main limitation of the study is not that eye-tracking lacks value, but that its value must be interpreted with appropriate theoretical and methodological caution. At the same time, this limitation also points to an important opportunity: by combining eye-tracking with richer theoretical models and multimethod designs, future research may offer a more complete understanding of how people make decisions in complex digital environments.

CONCLUSIONS

This study advances our understanding of economic decision-making by showing how different patterns of visual engagement are associated with task-specific decision accuracy in online consumer environments. The findings are discussed in relation to dual-process theory, but they are interpreted more cautiously as empirical visual-attentional profiles emerging from the interaction between individual tendencies and the structure of the digital interface.

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Human Technology
ISSN 1795-6889
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