“Deciphering the temporal dynamics of consumer decisions: the interplay of cognitive load and response correctness”

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DECIPHERING THE TEMPORAL DYNAMICS OF CONSUMER DECISIONS: THE INTERPLAY OF COGNITIVE LOAD AND RESPONSE CORRECTNESS

Abstract

This study delves into the impact of visual marketing stimuli on consumer response times, focusing on the complexity and subjectivity of the questions posed. Conducted in Slovakia, the research involved 40 participants (20 men and 20 women, aged 30 to 50 years), all holding university degrees in economics to ensure consistent decision-making experience. Participants were presented with visual stimuli representing four well-known FMCG brands. The stimuli included simple brand preference questions and complex evaluative judgments of offer efficiency. Response times were measured in milliseconds and analyzed using statistical methods, including the Mann-Whitney U test and one-way ANOVA. Results revealed that responses to simple stimuli averaged 1212 ms, while complex stimuli elicited slower responses, averaging 2504 ms. A significant difference was observed for "No" answers in the offer evaluation tasks, with correct "No" responses taking 3000 ms compared to 2297 ms for incorrect ones ($p < 0.05$), highlighting the cognitive load involved in accurate decision-making. These findings provide valuable insights into the cognitive processes driving consumer decision-making and contribute to the theoretical understanding of how question complexity and subjectivity influence response times.

Keywords consumer behavior, consumer decision-making, marketing stimuli response

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INTRODUCTION

The study of consumer behavior has evolved significantly since the mid-20th century, offering profound insights into the factors influencing purchasing decisions. However, notable gaps persist, particularly in understanding the immediate cognitive and emotional reactions during the decision-making process. This research is driven by the necessity to delve deeper into these instantaneous responses, particularly how consumers process and react to varying levels of cognitive load when faced with marketing stimuli. Given the increasing complexity of the marketplace and the diverse array of choices presented to consumers, understanding these rapid decision-making processes is of paramount importance.

Consumer decision-making is a multifaceted process influenced by various factors, including the complexity and subjectivity of the information presented. Previous research has established that cognitive load plays a significant role in decision-making efficiency and accuracy (Kahneman, 2011). However, there is a lack of empirical evidence on how these factors specifically affect response times in real-time consumer settings. This gap in the literature highlights the need for research that not only examines these instantaneous decisions, but also contextualizes them within the cognitive frameworks consumers use daily.

In Slovakia and across Europe, the retail sector has experienced substantial growth, with FMCG sales increasing by 5.7% in Slovakia and showing similar upward trends in other European countries (European Statistical Office, 2023). This surge underscores the necessity for businesses to refine their marketing strategies to better capture consumer attention and influence their purchasing decisions. By examining the response times to various marketing stimuli among Slovak and European consumers, this research aims to provide actionable insights that can enhance marketing effectiveness in this dynamic market.

Statistical data underscore the importance of this field. For instance, a report by IBM and the National Retail Federation (2022) indicates that 65% of consumers make purchase decisions within moments of encountering a product or advertisement. This statistic highlights the critical need to understand the factors that influence these split-second decisions.

The relevance of this research is further emphasized by the growing importance of personalized marketing strategies. As consumers across Europe are bombarded with information, the ability to gauge their preferences and decision-making processes becomes crucial. This study addresses this scientific problem by focusing on how question complexity and subjectivity impact consumer response times, thereby contributing to a more nuanced understanding of consumer behavior in real-time decision-making scenarios.

1. LITERATURE REVIEW

Response times analysis has its relevance in studying consumer behavior, as it provides insight into the decision-making process. In the research community, response time is often interchangeably used with reaction time. Both terms, however, describe the period between stimulus perception and stimulus response, reflecting the ability to recognize, process, and react to stimuli (Jain et al., 2015). This section covers key components related to response times in cognitive processing, the influence of stimulus complexity, and applications in consumer behavior.

Response times are a crucial measure in studying cognitive processes. Research has identified three main types of response time experiments: simple, recognition, and choice response time experiments. Simple response time experiments involve a single stimulus and response, recognition experiments require identifying specific stimuli, and choice experiments involve selecting a response from multiple options (Luce, 1986). The studies consistently show that response times increase with task complexity. For example, Laming (1968) found that simple tasks like reacting to a light signal had significantly shorter response times compared to more complex tasks requiring decision-making.

Welford (1980) expanded on this by examining response times across different types of tasks, demonstrating that as the complexity of a task increases, so does the response time. Teichner and Krebs (1974) further confirmed these findings, showing that response times in choice reaction tasks are significantly longer than in simple reaction tasks. These studies collectively highlight the foundational role of task complexity in determining response times.

These studies provide a foundational understanding of response times; however, they often do not consider real-world complexities and variables that might affect consumer decision-making in live environments. Most experiments are conducted in controlled settings, which might not accurately reflect the dynamic nature of consumer environments where multiple stimuli and decision-making factors interact simultaneously. This gap is particularly relevant for marketing applications where decisions are influenced by numerous concurrent factors.

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The complexity of stimuli significantly affects response times. Henry and Rogers (1960) found that more complex responses require accessing more information, thus taking longer. This is supported by Hick's law, which states that reaction times increase logarithmically with the number of stimulus-response choices (Hick, 1952). For example, he demonstrated that when participants had to choose between multiple responses, their reaction times increased predictably with the number of choices.

Sternberg (1969) demonstrated a linear increase in recognition task times with the number of memory set items. In his memory scanning experiments, participants were asked to recall a set of items, and the response time increased linearly with the number of items they had to remember. These findings indicate that cognitive load and task complexity are critical factors in response time studies.

Klapp (2010) revisited these concepts and validated that the complexity of motor responses also influences reaction times, suggesting that both cognitive processing and motor execution contribute to overall response latency. O'Shea and Bashore (2012) highlighted the importance of considering both cognitive and motor components in understanding reaction times, noting that neglecting either aspect could lead to incomplete conclusions.

Although these studies highlight the relationship between stimulus complexity and response time, they often use highly controlled settings that may not accurately reflect consumer environments. Furthermore, there is a lack of focus on how these dynamics play out in real-time consumer interactions with marketing stimuli.

Beyond the type and complexity of the stimulus, numerous other factors influence response times. Following aspects are crucial for understanding the nuances of cognitive processing and their implications for consumer behavior:

Arousal: Arousal, including muscular tension and state of attention, affects response time. An intermediate level of arousal yields the fastest response times, while extremes in relaxation or tension deteriorate performance (Welford, 1980).

Age: Response times vary with age, decreasing from infancy to the late 20s, then increasing through the 50s and 60s, and more rapidly increasing thereafter (Jevas & Yan, 2001; Surwillo, 1973).

Stimulus relevance to survival: Responses to unpleasant stimuli relevant to survival are faster and more accurate compared to pleasant ones (Boesveldt et al., 2010).

Gender: Males generally have faster response times across almost all age groups, a difference not mitigated by practice (Adam et al., 1999).

Hand preference: Response times may differ based on hand preference and the specialization of cerebral hemispheres (Boulinquez & Bartélémy, 2000).

Vision type: Response times vary with the part of the eye perceiving the stimulus. Responses are faster for stimuli seen by cones than those detected by rods (Ando et al., 2002).

Practice and errors: Response times shorten with practice but become more variable following errors (Ando et al., 2002).

Fatigue: Both physical and mental fatigue increase response times (Van den Berg & Neely, 2006).

Distraction: Distractions lead to increased response times, with the impact based on the individual's emotional state and prior experiences (Trimmel & Poelzl, 2006).

Understanding these factors is essential for developing comprehensive models of consumer behavior. In marketing, response times can provide insights into how different stimuli and conditions affect decision-making processes. For example, high arousal levels might enhance the speed of decision-making in high-pressure sales environments, while fatigue or distractions could negatively impact consumer attention and reaction.

In consumer behavior research, response times provide insights into decision-making processes. Studies have shown that consumers' response times can vary based on the type and intensity of stimuli. Milosavljevic et al. (2011) found that consumers can make decisions in as little as a third of a second, illustrating the speed of implicit decision-making. Their research demonstrated that rapid decisions are often based on visual processing and instinctive reactions, highlighting the importance of first impressions in consumer choices.

Van Rullen and Thorpe (2001) identified two visual processing mechanisms: a fast general perceptual process and a slower, more in-depth process. Their study involved participants classifying animals or vehicles appearing among distractors, showing that initial categorization is quick and automatic, but more detailed processing takes longer. This distinction between fast and slow processing is critical for understanding how consumers evaluate products under different conditions.

Implicit attitudes influenced by associative learning can shape consumer responses, particularly under high cognitive load conditions. Gibson (2008) and Nevid (2010) suggest that attitudes formed through associative learning significantly impact consumer choices, especially when quick decisions are required. For example, Gibson's study used the Implicit Association Test to show that brands associated with positive emotions were chosen more quickly, even under time constraints.

Pieters and Warlop (1999) found that visual attention and time pressure significantly affect brand choice decisions. In their eye-tracking study, participants made quicker and more efficient brand choices under time pressure, suggesting that visual cues and time constraints play significant roles in consumer decision-making.

While these studies offer valuable insights, they often fail to capture the immediate cognitive and emotional reactions during actual consumer decision-making processes. Moreover, the existing literature does not sufficiently address the interplay between response accuracy and response time, particularly in complex decision-making scenarios. This study seeks to fill these gaps by providing empirical evidence on how question complexity and subjectivity affect consumer response times.

The aim of the study is to investigate how question complexity and subjectivity impact consumer response times, providing actionable insights to enhance marketing effectiveness and deepen the understanding of real-time consumer decision-making.

The literature reviewed provides a foundation for the current study's research questions, which examine the impact of question complexity and subjectivity on consumer response times. Specifically, this study seeks to answer the following research questions and address identified gaps:

RQ1: What is the response time difference between positive ("Yes") and negative ("No") responses?

RQ2: How do response times vary between subjective and objective questions?

RQ3: What is the relationship between the complexity of a question and the response time?

RQ4: How do subjective and objective decision-making processes differ in terms of response accuracy?

2. METHODOLOGY

Response times analyzed in this study were obtained from study participants, who responded to specific stimuli related to marketing. The sample size consisted of 40 individuals, evenly divided between 20 men and 20 women, all within the age range of 30 to 50 years. This demographic was carefully selected to ensure a balanced representation of genders and to capture a broad spectrum of cognitive stability and economic decision-making experience, typically well-developed in this age group. All participants held a university degree in economics, ensuring a consistent level of knowledge and understanding of economic concepts, which is critical for the validity and reliability of the study. This educational homogeneity minimized variability in responses attributable to differing levels of economic literacy, thereby allowing for a more focused analysis of the cognitive and emotional reactions to the visual marketing stimuli.

The methodology involved two types of questions. The first, concerning brand preference, asked participants to respond to logos from

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four different FMCG (Fast-Moving Consumer Goods) brands with a simple “Yes” or “No”, reflecting their subjective preference. The second question, more complex, presented two different price offers on banners and asked objectively whether the offer was advantageous (the response remained binary as “Yes” or “No”). The correctness of each response was assessed, informing about the evaluative accuracy of participants. The experiment was captured on video to measure response time – the interval between the visual stimuli presentation and the participant’s verbal response. It was all conducted in a controlled setting to minimize external distractions.

Participants were fully aware of the recording, and their consent was obtained before the experiment. Each participant was presented with the stimuli in a standardized sequence. For response time data analysis, the following statistical methods were used:

(1) descriptive statistics: create a baseline for each respondent’s mean response time and assess consistency through standard deviation and variability using minimum, maximum, and percentile values;

(2) variability analysis: explores individual differences by examining the range and interquartile range, highlighting central tendencies and dispersion in the data;

(3) one-way ANOVA: checks for significant differences in mean response times across individuals by comparing variances within and between groups;

(4) post-hoc analysis (Tukey’s HSD test): Tukey’s HSD test follows ANOVA to identify pairs of subjects with significant response time differences while controlling for error in multiple comparisons;

(5) Mann-Whitney U test: applied to analyze binary and accuracy-dependent answers, particularly useful given the non-normal distribution of data.

Descriptive statistics allowed understanding the basic structure of the response time data. Then, variability analysis helped to uncover individual differences in response times, because it reveals the data heterogeneity. One-way ANOVA assessed the significance of response time differences between various question types. For a more detailed view, Tukey’s HSD post-hoc analysis enabled to search for specific group response time differences. As the response time data were not normally distributed, the non-parametric Mann-Whitney U test was used for comparison between relevant group pairs related to brand preference and decision accuracy assessment.

During data collection, priority was given to ethical considerations. It involved mainly obtaining the informed consent of each participant and keeping the anonymity of the participants during the process of study.

3. RESULTS

Participants of the study responded to two questions. In the first phase of the study (question 1, simple, subjective), they were exposed to a selection of brand logos, which were standardized in size, resolution, and background. Participants were asked to indicate whether the presented brand was their favorite, responding with a simple “Yes” or “No”. This allowed to measure response times in connection with brand familiarity, yielding 160 observations. The second phase (question 2, complex, objective) involved presenting diverse promotional offers, including deals like “2 + 1 free” and various discounts. The participants assessed the efficiency of each offer based on the presented product’s price and the promotional discount (some offers were intentionally misleading). This task was designed to test the evaluative abilities of participants (80 observations in total) and to analyze response times differences under changing purchase scenarios.

This subsection examines response times related to the first question: “Do you consider this brand to be your favorite?”. Response times of participants were recorded, distinguishing between affirmative (“Yes”) and negative (“No”) answers. Table 1 provides a statistical description of the data.

Table 1. Descriptive statistical analysis of response times for brand preference inquiry (question 1)

Indicator	Group	N	Mean	Median	SD
Response time (ms)	No	101	1,237	1,080	516
	Yes	59	1,187	1,040	703

The Shapiro-Wilk test was conducted to assess the normality of response time data, revealing a non-normal distribution for both response categories (p-value < 0.05). Consequently, the Mann-Whitney U test compared data between both groups. The test yielded a p-value of 0.212, suggesting no statistically significant difference in response times between affirmative and negative answers.

Table 2. Comparative summary of response time differences based on answer type for brand preference inquiry

Comparison	p-value	Statistical significance
No vs. Yes	0.212	No (p > 0.05)

The findings from the Mann-Whitney U test indicate an absence of positive bias towards faster "Yes" responses over "No" responses. This outcome challenges the hypothesis of significant variation in response times based on the nature of the answer. It is crucial to recognize that this statement is based on the data used and the methods applied. There may be other external factors that were not considered in this study and may influence response times – ideally this should be addressed in further research for a more comprehensive understanding.

In the assessment of the second question ("Do you consider this offer to be advantageous?"), response times were analyzed based on the correctness of the answer and whether the answer was "Yes" or "No". For incorrect "No" responses (16 observations), a mean response time of 2,297.5 milliseconds, a standard deviation of 619.33 ms, and a median time of 2,240 ms were recorded. Correct "No" responses (10 observations) had a longer mean response time of 3,000 ms, a standard deviation of 565.06 ms, and a median of 2,900 ms. Incorrect "Yes" responses (16 observations) recorded a mean of 2,327.5 ms, a standard deviation of 792.39 ms, and a median of 2220 ms. Correct "Yes" answers (38 observations) were more frequent and had a mean response time of 2,504.21 ms, a standard deviation of 726.19 ms, and a median of 2,580 ms.

The longest mean response time is associated with correct "No" responses, averaging 3,000 ms. Conversely, the shortest mean response time relates to incorrect "No" responses, at 2,297.5 ms. Additionally, correct "Yes" responses show a higher mean response time of 2,504.21 ms when compared to incorrect "Yes" responses, which have a mean response time of 2,327.5 ms.

The Mann-Whitney U statistical test evaluated the differences in response times across various group pairs, considering both the answer type and its accuracy. The outcomes, indicated by p-values, are as follows: (1) the comparison between incorrect "No" and correct "No" answers yielded a p-value of 0.0131, suggesting a statistically significant difference; (2) there was no significant difference in response times between incorrect "No" and incorrect "Yes" answers, with a p-value of 0.8063; (3) incorrect "No" answers compared to correct "Yes" answers resulted in a p-value of 0.2008, indicating no significant difference; (4) a p-value of 0.0349 for correct "No" versus incorrect "Yes" answers suggest a significant difference; (5) the test comparing correct "No" and correct "Yes" answers resulted in p-value of 0.0373, also indicating a significant difference; (6) lastly, incorrect "Yes" versus correct "Yes" answers had p-value of 0.3242, showing no significant difference.

Table 3. Descriptive statistics for response times to price offer evaluations (question 2), distinguished by answer correctness and type

Indicator	Group	N	Mean	Median	SD
Response time (ms)	No – incorrect	16	2,297.5	2,240	619.33
	No – correct	10	3,000	2,900	565.06
	Yes – incorrect	16	2,327.5	2,220	792.39
	Yes – correct	38	2,504.2	2,580	726.19

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Table 4. Statistical analysis of response time differences by answer type and correctness (Mann-Whitney U test results)

Comparison	p-value	Statistical significance
No – incorrect vs. No – correct	0.0131	Yes (p < 0.05)
No – incorrect vs. Yes – incorrect	0.8063	No (p > 0.05)
No – incorrect vs. Yes – correct	0.2008	No (p > 0.05)
No – correct vs. Yes – incorrect	0.0349	Yes (p < 0.05)
No – correct vs. Yes – correct	0.0373	Yes (p < 0.05)
Yes – incorrect vs. Yes – correct	0.3242	No (p > 0.05)

The outcomes imply that the response correctness influences the time taken to respond, especially in the case of "No" answers. However, when not considering response correctness, the distinction between "Yes" and "No" answers does not result in a significant response time variation. These findings show nuances related to the type of response and its correctness, and how it may impact the response times of respondents.

Figure 1 illustrates the distribution of response times, categorized by the answer type (Yes/No) and answer correctness (correct/incorrect). It depicts the interquartile range of response times for each group and highlights the median within the box. Whiskers on the plot extend to demonstrate the full range of data, barring any outliers.

Key observations from Figure 1 include: (1) there is a noticeable variation in median response times across the different groups; (2) the "No – correct" group exhibits a higher median response time relative to other groups, as was already mentioned and presented in Table 4; (3) response times variability, as depicted by the interquartile range and whiskers, differs among the groups and indicates varying levels of dispersion in response times for each group.

Among the 40 participants (each of them provided 4 responses), response times vary significantly, between 650 and 2,640 ms, as presented in Figure 2. The standard deviation of response times also varies and indicates different levels of consistency. Lower standard deviations suggest higher response times consistency while higher deviations indicate greater variability – possibly due to fluctuating attention or cognitive load.

Figure 2 represents the average response times for each of 40 respondents to the question "Do you consider this brand to be your favorite?" One-way ANOVA revealed significant differences in average response times across participants (F-statistic = 2.814, p-value < 0.001). Subsequent Tukey's HSD post-hoc analysis identified specific pairs of re-

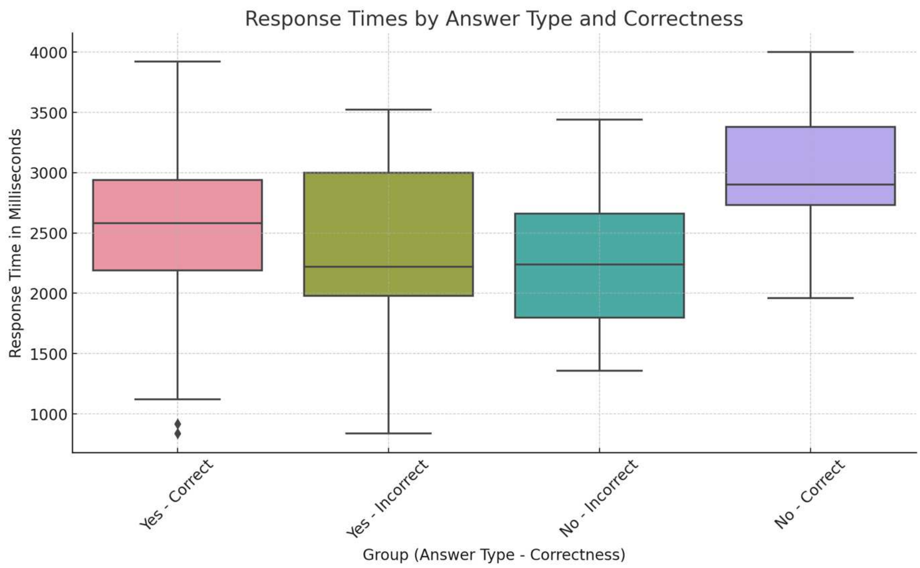

Figure 1. Comparison of response times by group based on answer type and correctness

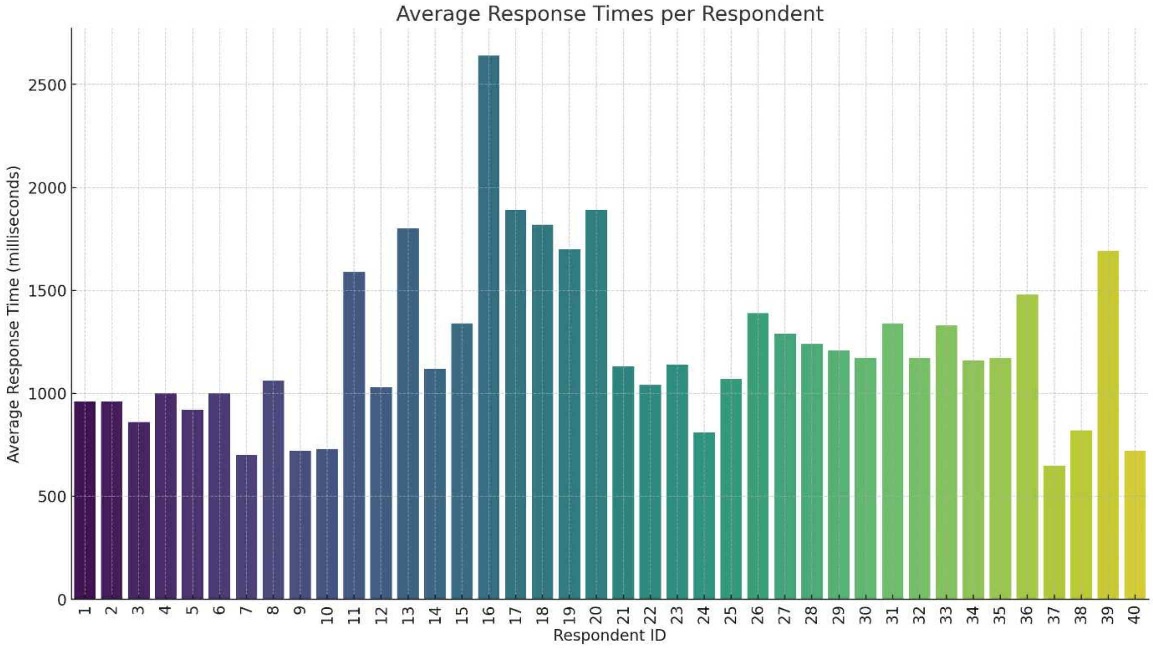

Figure 2. Average response time per respondent (ms)

spondents, such as (participant 1 vs. participant 16), with significantly different mean response times, with mean difference of 1,680 ms and p-adj value of 0.0024.

The results show individual differences in response time variability. It provides interesting findings in the field of consumer psychology and underlines the importance of personalized marketing and complex consumer decision-making research.

Related to the offer assessment question, all respondents provided two responses (totaling 80 observations). Mean response times vary from 1,080 to 3,620 ms, and they reflect individual differences in the decision-making process (Figure 3). The standard deviation also varies, showing fluctuation in response times possibly caused by stimulus complexity.

Variability analysis revealed individual differences in response times. Some participants showed

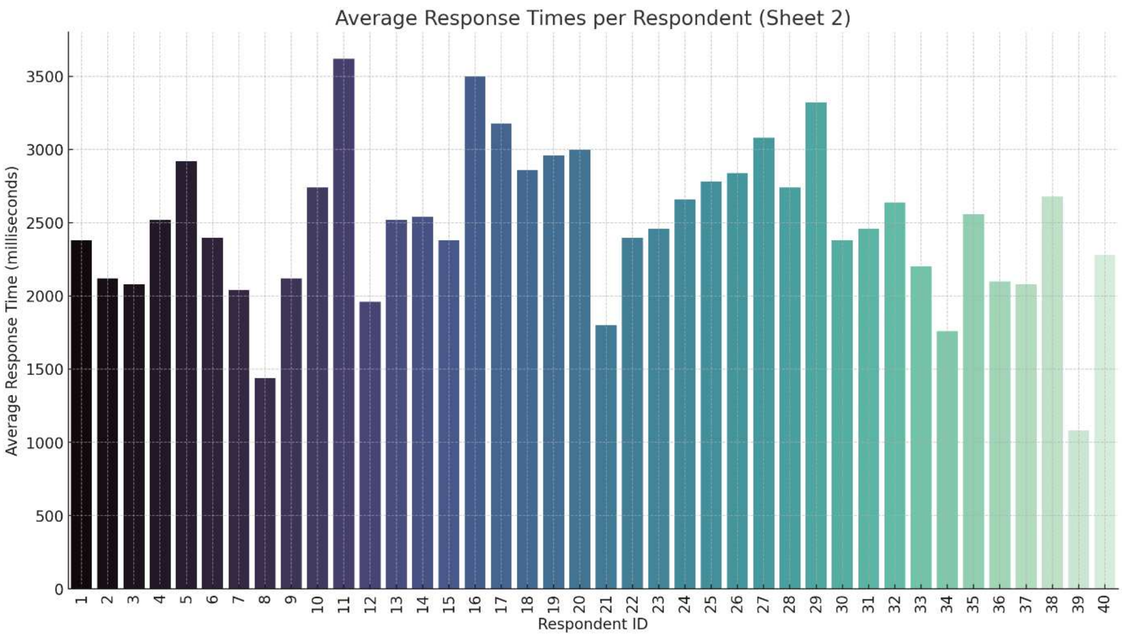

Figure 3. Average response time per respondent (ms)

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moderate to high response time variability, others exhibited lower variability with more consistent response patterns to presented stimuli. These findings point out how complex and unique human psychology and decision-making are.

Figure 3 above represents the average response times for each respondent to the question "Do you consider this offer to be advantageous?" The results of one-way ANOVA prove there are no significant differences in mean response times across participants (F-statistic = 1.0816; p-value = 0.4027). Tukey's HSD post-hoc analysis confirmed the absence of significant differences between most pairs of respondents. This suggests response patterns uniformity across the whole sample of participants.

4. DISCUSSION AND FUTURE RESEARCH

The results of this study provide significant insights into consumer decision-making and the factors influencing response times. The findings indicate that response times to simple stimuli, such as brand preference choices, are generally shorter compared to complex stimuli, like evaluating the efficiency of offers. This supports existing theories in cognitive psychology that simpler tasks are processed more quickly due to lower cognitive load (Laming, 1968; Teichner & Krebs, 1974).

For subjective brand preferences, the results revealed rapid processing of stimuli across the entire research sample. This suggests that preference-based decisions are instinctual and can be quickly made, aligning with Kahneman's (2011) dual-system theory, which distinguishes between fast, intuitive thinking and slow, analytical thinking. This rapid processing is crucial for marketers aiming to leverage branding and messaging to create strong, immediate consumer preferences.

Conversely, the analysis of offer evaluations showed longer response times and significant variability, particularly for correct responses. This indicates deeper cognitive engagement and supports the cognitive load theory presented by Henry and Rogers (1960). The longer response times for correct evaluations highlight the cognitive effort required for tasks demanding accuracy, as suggested by Klapp (2010). This is crucial for marketers when designing promotional materials that require consumers to make more analytical decisions.

The study's findings align well with previous research on cognitive processing and consumer behavior. For example, Pieters and Warlop (1999) demonstrated that visual attention and time pressure significantly affect brand choice decisions, which is consistent with the rapid processing observed in this study for brand preferences. Similarly, Milosavljevic et al. (2011) found that consumers can make decisions in as little as a third of a second, supporting the notion that brand preference decisions can be made quickly and instinctively.

Additionally, the study extends the work of Gibson (2008) and Nevid (2010) by showing that implicit attitudes formed through associative learning significantly impact consumer choices under quick decision-making scenarios. The longer response times for more complex stimuli also corroborate findings by Sternberg (1969) and Klapp (2010), which indicated that task complexity and the need for accurate responses increase cognitive load and response time.

The results also resonate with recent findings by Costa and Kallick (2015) who highlighted the importance of question complexity and intention in shaping response times. Similarly, Šostar and Ristanović (2023) emphasized the need to consider a variety of influencing factors, such as cultural nuances and digital versus physical presentation of stimuli, which are crucial for understanding consumer behavior in different contexts.

This study enriches current knowledge by providing empirical evidence on the impact of question complexity and subjectivity on consumer response times. It highlights the importance of cognitive load in consumer decision-making and provides practical insights for marketers on how to tailor their strategies based on the complexity of the decisions they want consumers to make. The study also bridges gaps in existing literature by focusing on real-time consumer responses in live environments, rather than controlled laboratory settings.

Furthermore, the findings support Evans' (2008) dual-process theory of reasoning, which posits that decision-making involves both intuitive and analytical processes. The study also aligns with Bellini-Leite's (2022) work on dual-process theory, suggesting that both embodied and predictive processes play a role in consumer decision-making, particularly when dealing with complex stimuli.

Despite its contributions, this study has several limitations. The sample size was relatively small and homogeneous, which may limit the generalizability of the findings. Additionally, the research methodology focused on binary response tasks. The study also did not account for cultural differences or the impact of digital versus physical question presentation, which could influence response times and decision-making processes.

Future research should address these limitations by:

1) expanding the sample size and including participants from diverse backgrounds will improve the generalizability of the findings. This could involve recruiting participants from different age groups, cultures, and socioeconomic statuses;

2) including a variety of response types, such as open-ended questions and non-verbal cues, will provide a more comprehensive understanding of consumer decision-making processes;

3) investigating the impact of digital versus physical presentation of stimuli on response times and decision-making will help understand the influence of different environments;

4) examining how cultural differences affect response times and decision-making processes will provide a more nuanced understanding of consumer behavior across different contexts;

5) implementing studies in more naturalistic settings to better capture real-world consumer behavior and decision-making processes.

This paper advances theoretical and practical knowledge of consumer psychology and decision-making within the marketing context. By examining the impact of question complexity and subjectivity on response times, the findings contribute to a deeper understanding of the cognitive processes underlying consumer decisions. These insights can help marketers design more effective strategies that cater to the cognitive and emotional needs of their target audiences.

CONCLUSION

The purpose of this study was to examine the impact of question complexity and subjectivity on consumer response times within an experimental setting that simulates real-world decision-making scenarios. The obtained results revealed that simple stimuli, related to brand preferences, elicited quicker response times compared to complex stimuli, which required evaluative judgments of offer efficiency. It was found that the correctness of the responses significantly influenced response durations, particularly for "No" answers in the offer evaluation tasks, where correct "No" responses took notably longer than incorrect ones. Furthermore, the study demonstrated significant individual variability in response times, suggesting the potential for personalized marketing strategies.

From these findings, several key conclusions can be drawn: first, the complexity and subjectivity of marketing stimuli markedly influence consumer decision-making times, supporting the cognitive load theory which posits that more complex decisions require longer processing times. Second, accurate decision-making, especially in rejecting offers, involves a deeper cognitive engagement as evidenced by the longer response times. Lastly, the variability in individual response times underscores the necessity for personalized marketing approaches to cater to different consumer processing speeds and decision-making styles. These insights contribute to the broader understanding of consumer psychology and offer practical implications for enhancing marketing strategies to better engage and influence consumers.

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