UNIVERSITY OF TARTU

Faculty of Social Sciences

School of Economics and Business Administration

Yevheniia Baranovych

VISUAL ATTENTION AND DECISION-MAKING PATTERNS IN ONLINE SHOPPING: A CLUSTERING ANALYSIS OF EYE-TRACKING DATA

Bachelor Thesis

Supervisor: Junior Lecturer Kristian Pentus

Tartu 2026

I have written this Bachelor Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Table of contents

Introduction………………………………………………………………………………… 4
1. Consumer decision-making and visual attention in online shopping……………………….6
1.1. Decision-making strategies and information processing in consumer choice……… 6
1.2. Eye-tracking in studying visual attention in online shopping……………….........10
2. Empirical analysis of gaze-based decision-making patterns……………………………… 17
2.1. Methodology and pre-processing of data…………………………………………..17
2.2. Clustering results and attention distribution analysis……………………………... 26
2.3. Interpretation of clustering results and decision-making patterns………………… 34
Conclusion……………………………………………………………………………………37
List of references……………………………………………………………………………..39
Appendices…………………………………………………………………………………... 45
Appendix A. Example of AOI mapping used for eye-tracking data preparation……… 45
Appendix B. Attention transition probability heatmaps for three clustering solutions... 46
Appendix C. Normalised fixation time per AOI type for all three clustering solutions..47
Resümee……………………………………………………………………………………... 48

Introduction

Online shopping has become an important part of everyday consumer behaviour, changing how consumers search for information and make purchase decisions. In the European Union, the share of individuals who purchase goods and services online has risen steadily, reflecting the growing role of digital retail in everyday consumption (Eurostat, 2025). Compared with traditional retail, online shopping gives consumers immediate access to a large number of products and product-related cues, making them complex and information-rich decision settings (Cheng et al., 2014).

In information-rich online shopping environments, consumers rarely evaluate every alternative and attribute in detail. Instead, they adapt their information search and decision-making strategies to task demands, producing different patterns of information processing (Niza Braga & Jacinto, 2022; Schaffer et al., 2016). Since consumers cannot physically inspect products online, this process is strongly visual and relies on product cues such as images, prices, descriptions, and reviews (Grewal et al., 2004; Veale et al., 2006). Visual attention is therefore important for understanding online decision-making because it shows which cues consumers notice, compare, and process during choice.

Eye-tracking provides a suitable method for studying these processes because it records consumers' eye movements, fixations, gaze duration, and transitions between visual elements in real time (Duchowski, 2007). In online shopping research, eye-tracking has been used to examine how consumers allocate attention to product cues and how this relates to evaluations, attitudes, and purchase decisions (Cortiñas et al., 2019; Hwang & Lee, 2015, 2018; Johnson et al., 2022; Kim & Lee, 2020; Modi & Singh, 2023). Prior studies show that attention is unevenly distributed: product images usually attract the most attention, while prices, reviews, and descriptions are processed more selectively depending on task and consumer involvement (Cortiñas et al., 2019; Johnson et al., 2022; Kim & Lee, 2020; Liu et al., 2024). Eye-movement transition studies further show that gaze transitions can distinguish attribute-based from alternative-based search (Chen & Dai, 2025; Ryan-Lortie et al., 2023).

However, existing eye-tracking research in online shopping has several limitations. Many studies focus on single-product pages or isolated product cues, which limits their ability to capture how consumers compare multiple products and attributes simultaneously (Chen et al., 2022; Johnson et al., 2022; Kim & Lee, 2020). Studies using multi-product layouts often analyse average attention patterns or prediction outcomes rather than distinct forms of information acquisition (Cortiñas et al., 2019; Liu et al., 2024). Moreover, individual differences are usually examined through predefined groups rather than derived directly from gaze behaviour (Hwang & Lee, 2015, 2018; Modi & Singh, 2023). As a result, naturally occurring visual attention patterns on multi-product search pages remain underexplored.

Cluster analysis offers a way to address this limitation. Clustering identifies groups directly from the data based on behavioural similarity, unlike predefined group comparisons. Applied to eye-tracking data, this makes it possible to detect naturally occurring patterns of visual attention that may cut across demographic categories and reflect different ways consumers process information in online shopping environments.

This thesis investigates decision-making patterns in online shopping by applying unsupervised clustering method to eye-tracking data in order to analyse consumers' visual attention to product-related cues. Decision-making patterns are understood as recurring gaze-based information-acquisition patterns that can be interpreted in relation to decision-making theory, rather than as directly observed internal decision rules. The main input used for the analysis is eye-movement transition sequences. The empirical focus is placed on reusable water bottles, treated here as a medium-involvement product category because they require comparison of functional and aesthetic attributes, but do not involve high financial, social, or safety risk. This makes them suitable for observing natural attention allocation across multiple product cues.

The aim of this thesis is to identify gaze-based decision-making patterns in online shopping by clustering eye movement transition sequences and analysing fixation time duration on multi-product search pages.

To achieve the aim of the thesis, the following research tasks are formulated:

- Present theoretical framework on decision-making strategies and information processing modes in consumer choice.
- Provide an overview of prior eye-tracking research on visual attention in online shopping.
- Develop the methodology of the analysis and pre-process eye-tracking data.
- Identify decision-making patterns of visual attention using sequence-based and fixation-based analysis.
- Interpret the identified decision-making patterns in the context of consumer decision-making theory and prior eye-tracking research.

The thesis consists of two chapters. The first chapter presents the theoretical and methodological background of the study. It introduces decision-making theories and strategies, alternative-based and attribute-based processing, and the use of eye-tracking in online shopping research. The second chapter presents the methodology and empirical analysis of secondary eye-tracking data collected at the Neuromarketing Laboratory of the University of Tartu under the supervision of Kristian Pentus in cooperation with Jason Bell from Oxford University. It describes the dataset, stimulus materials, pre-processing procedure, feature engineering, clustering approach, and interpretation of the identified attention patterns. The author contributed to the methodological development of the broader project, but not to the final data collection.

Keywords: online shopping; decision-making patterns; visual attention; eye-tracking; clustering.

1. Consumer decision-making and visual attention in online shopping

1.1. Decision-making strategies and information processing in consumer choice

The first subchapter provides the theoretical foundations of decision-making, framework within theories. It introduces the distinction between compensatory and heuristic strategies as well as the alternative- and attribute-based processing modes through which strategies are implemented. The subchapter concludes by positioning online shopping as an information-rich environment where visual product cues are central to decision-making, providing a foundation for understanding why decision patterns vary across individuals and contexts.

Decision-making is broadly understood as a cyclical process through which individuals perceive and appraise stimuli, form preferences, select and execute actions, and evaluate the resulting outcomes to inform future choices (Ernst & Paulus, 2005). Given the complexity of this process, scholars have developed a range of theories to conceptualize decision-making and examine the conditions under which choices are formed. Accordingly, these theories are commonly organized along three interacting dimensions: normative, descriptive, and prescriptive (Bell, Raiffa & Tversky, 1988; Luce & von Winterfeldt, 1994).

Normative theories specify how an idealized rational agent should decide, typically by assuming stable, internally consistent preferences and expected utility maximization (Bell, Raiffa & Tversky, 1988; Edwards, 1954). Frameworks such as Multi-Attribute Utility Theory provide formal rules for deriving the option that best satisfies the decision maker's preferences (von Winterfeldt & Edwards, 1986 as cited in Jansen, 2011). Friedman and

Savage (1948) also showed that expected utility maximization could rationalize seemingly inconsistent behaviors through the shape of a utility function.

Descriptive theories, by contrast, examine how people actually decide, and consistently document systematic deviations from normative prescriptions (Bell, Raiffa & Tversky, 1988; Kahneman & Tversky, 1979). Due to limited cognitive capacity, people often rely on heuristics and elimination rules that reduce computational effort (Gigerenzer & Goldstein, 1996; Simon, 1955; Tversky, 1972). Dual-process accounts further specify that decisions emerge from the interaction of fast, intuitive processing and slower, deliberative reasoning, with the balance shifting according to task and context (Chaiken, 1980; Kahneman, 2011; Petty & Cacioppo, 1986). Descriptive work also shows that choices under risk are shaped by reference points, loss aversion, and affective reactions, including feelings experienced at the moment of decision, rather than by pure utility maximization (Kahneman & Tversky, 1979; Loewenstein et al., 2001; Zajonc, 1980).

Prescriptive theories occupy the space between these two: they ask how real people can be helped to decide more wisely (Bell, Raiffa & Tversky, 1988). Rather than relying only on idealized assumptions of fully coherent preferences, prescriptive analysis often uses structured reflection, decomposition, and preference elicitation to help decision makers clarify trade-offs, drawing selectively on normative axioms and descriptive findings (Bell, Raiffa & Tversky, 1988; Luce & von Winterfeldt, 1994).

Within these broad theoretical dimensions, decision-making research has examined the concrete strategies that individuals apply when making choices. These strategies differ fundamentally in how decision attributes are weighed and combined (Payne, Bettman & Johnson, 1988), which can be grouped as compensatory and heuristic strategies. Compensatory strategies are approaches in which positive attributes of an option can offset, or "compensate for", negative ones (Bettman et al., 1998). When evaluating alternatives in this way, decision-makers consider all available information and make explicit trade-offs between attributes (Bettman et al., 1998; Payne, Bettman & Johnson, 1988). Such strategies are typically applied when the decision-maker faces two alternatives and aims to make a thorough, well-reasoned choice (Schaffer et al., 2016). Heuristic, or non-compensatory, strategies operate on a different principle: a poor value on one attribute cannot be offset by a superior value on another (Bettman et al., 1998; Payne, Bettman & Johnson, 1988). These strategies are typically implemented as task complexity and the number of alternatives increase, and they are characterized by more selective information processing and elimination-based approaches (Payne, 1982).

Importantly, compensatory and heuristic strategies are not mutually exclusive options or stable individual characteristics. Instead, decision-makers flexibly adapt their strategy choices depending on task demands such as the number of available alternatives, time constraints, and perceived decision importance (Payne, Bettman & Johnson, 1988). According to Bettman et al. (1998), an increase in the number of alternatives prompts people to adopt more non-compensatory strategies, whereas an increase in attributes typically results in greater selectivity rather than a change of strategy. Greater selectivity and not strategy change was also confirmed by Jenke et al. (2021). Furthermore, Schaffer et al. (2016) shows that non-compensatory strategies are often used during the initial filtering of options, after which decision-makers tend to switch to compensatory strategies for the final evaluation. Additional factors such as time pressure, completeness of information, and attribute correlation have also been shown to influence strategy change (Bettman et al., 1998). This adaptivity suggests that observed decision behaviour reflects situational strategy selection rather than fixed cognitive styles.

Understanding how these strategies are implemented requires examining two distinct processing modes: alternative-based and attribute-based. These processing modes explain the cognitive mechanisms underlying compensatory and heuristic decisions. Moreover, they describe how information is sampled and compared during decision-making, whereas strategies reflect broader rules for integrating or excluding information (Bettman et al., 1998). Even though, compensatory strategies are commonly associated with alternative-based processing and heuristic strategies with attribute-based processing, this relationship should not be interpreted as one-to-one or deterministic.

Alternative-based processing involves evaluating each option as a whole by integrating its attributes into an overall value and then comparing these values across alternatives sequentially (Bettman et al., 1998; Glickman et al., 2019; Goh & Stevens, 2021; Russo & Dosher, 1983). Evidence shows that in risky choice, this mode often relies on multiplicative integration of amounts and probabilities, consistent with normative models such as Expected Utility Theory and Cumulative Prospect Theory (Glickman et al., 2019). In contrast, attribute-based processing compares options attribute by attribute simultaneously, shifting attention across alternatives within the same dimension (Bettman et al., 1998; Goh & Stevens, 2021; Noguchi & Stewart, 2018; Russo & Dosher, 1983). This approach underlies heuristic strategies and is central to the Decision by Sampling framework, where evidence is accumulated through ordinal comparisons of single attributes (Noguchi & Stewart, 2018).

These adaptive strategies and processing modes are particularly visible in online shopping environments, where consumers must navigate large amounts of information using primarily visual cues. People use online shopping because it is convenient, timesaving and less effortful (Beldad et al., 2010; Grewal et al., 2004). However, people are exposed to a massive amount of information (Cheng et al., 2014) which does not specifically imply additional cognitive load to consumers but might possess some inconveniences. Grewal et al. (2004) mentioned that consumer cannot touch or feel the product in online shopping – limitation that still exists nowadays. While this may be acceptable in some cases, it makes people rely purely on visual sense and cues (Veale et al., 2006).

Figure 1 summarizes the conceptual framework guiding the present thesis. The framework takes the online shopping environment as its starting point: a visually rich, information-dense context in which task demands such as the number of alternatives, time pressure, risk, and product type shape how consumers adapt their decision-making strategies. These strategies are in turn associated with alternative-based and attribute-based processing modes respectively, though not exclusively. Together, these processing modes drive patterns of visual attention and information processing, which ultimately feed into the interpreted decision-making process.

Understanding how individuals allocate attention during choice provides insight into the underlying cognitive processes guiding decisions. This suggests that patterns of visual attention may inform interpretations of decision-making processes and strategies, a possibility that is observed with eye-tracking and discussed further in the following subchapter.

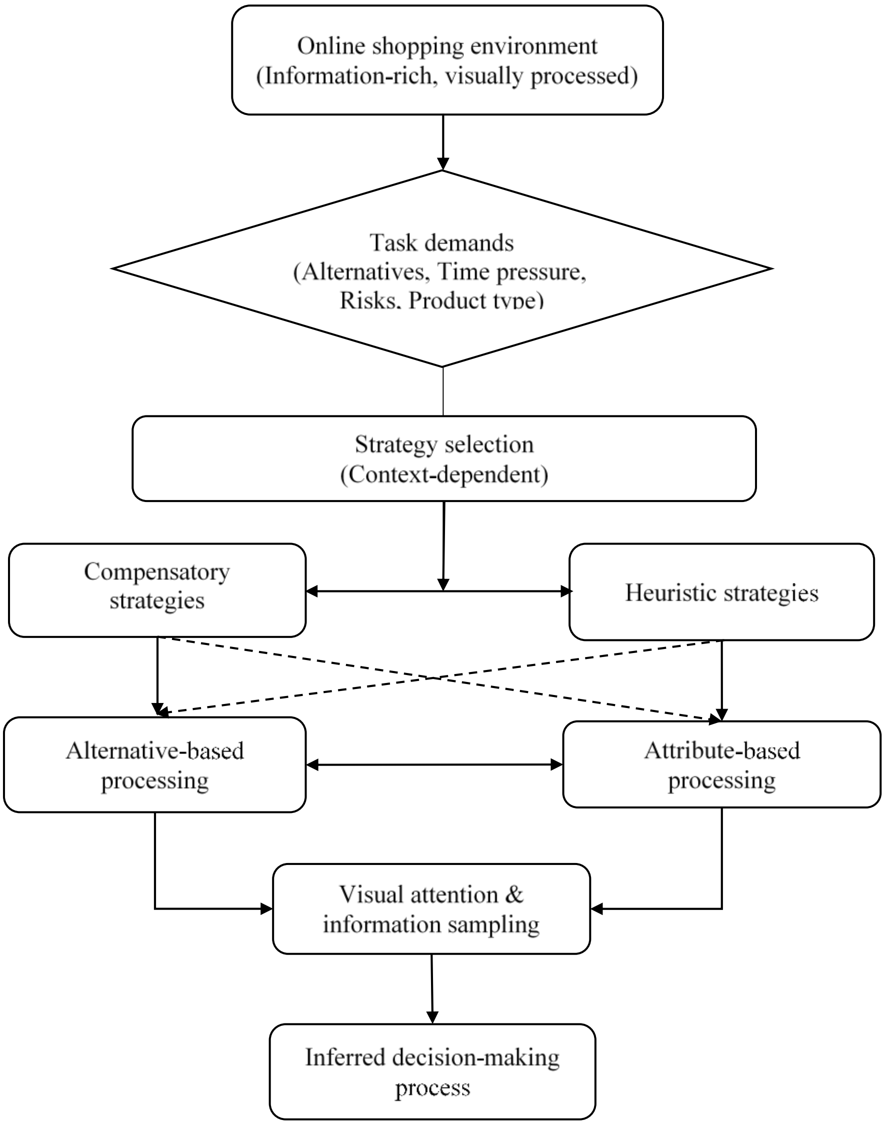


Figure 1. Conceptual framework for interpreting decision-making processes in online shopping

Source: Compiled by the author based on Bettman et al. (1998); Cheng et al. (2014); Glickman et al. (2019); Goh & Stevens (2021); Jenke et al. (2021); Noguchi & Stewart (2018); Payne (1982); Russo & Dosher (1983); Schaffer et al. (2016); Veale et al. (2006)

1.2.Eye-tracking in studying visual attention in online shopping

The second subchapter examines how eye-tracking is used to study visual attention in online shopping. It introduces core metrics and concepts, reviews how visual product cues shape attention allocation, and discusses individual differences in gaze behaviour. The subchapter concludes by reviewing clustering approaches in consumer behaviour research, identifying the methodological gap this thesis addresses.

Eye-tracking is a widely used approach in applied and scientific studies as a more objective way to quantify human attention. Researchers apply eye-tracking to investigate participants' gaze across different tasks in order to understand the cognitive mechanisms that drive human behavior (Glaholt & Reingold, 2011; Ryan-Lortie et al., 2023; Santos et al., 2015; Sun et al., 2022).

Eye-tracking research commonly operationalizes visual attention using eye-movement events and fixation-based metrics. Fixation is “a relatively stable eye-in-head position within some threshold of dispersion (typically ~2°) over some minimum duration (typically 100-200 mS), and with a velocity below some threshold (typically 15-100 degrees per second)” (Jacob & Karn, 2002, p. 7). By contrast, Duchowski (2007, p. 42) states that “saccades are rapid eye movements used in repositioning the fovea to a new location in the visual environment”. Fixation durations, fixation count, and time to first fixation provide quantitative indicators of attentional allocation and information processing, although the interpretation of these metrics depends on the task and experimental context (Duchowski, 2007). Table 1 summarizes the definitions and interpretative meaning of these core metrics as used in prior eye-tracking literature.

To give these metrics spatial context, researchers define Area of Interest (AOI), also referred to as a Region of Interest (ROI). AOI is a researcher-defined portion of a display or visual environment that holds high importance based on the semantic information of the stimulus (Borys & Plechawska-Wójcik, 2017; Jacob & Karn, 2002). AOIs are defined manually by the research or design team to facilitate the quantitative analysis of specific objects or regions (Jacob & Karn, 2002).

Beyond isolated fixations, researchers also analyze the sequence of eye movements, known as scanpaths (Jacob & Karn, 2002). Analyzing scanpath similarity allows researchers to compare the visual search strategies of different users (Duchowski, 2007). At a more granular level, transitions between AOIs can be classified as either alternative-based – moving between elements within the same product – or attribute-based – comparing the same element across different products (Ryan-Lortie et al., 2023). A third category, diagonal, captures shifts where both the product and element type change simultaneously and represents exploratory or unstructured gaze that cannot be attributed to either processing mode (Banerjee & Masters, 2021).

Table 1

Eye-tracking metrics and their interpretation

Eye-Movement metric	**Definition**	**Possible interpretation**	**Reference**
Fixation Count (also as Fixation per AOI, the number of fixation)	The total number of times the eyes remain stable on specific targets during the viewing period.	Higher fixation counts may reflect increased attention allocation or repeated inspection.	Duchowski (2007); Hwang & Lee (2015); Jacob & Karn (2002)
Fixation per AOI and adjusted for text length	"The mean number of fixations per area of interest was divided by the mean number of words in the phrase"	Shows a difference between high fixation rates caused by long text versus difficulty or poor recognition.	Poole et al., (2004, p. 370)
Fixation duration	Total time spent on a series of consecutive fixations within a specific area.	Longer fixation durations may indicate deeper processing, increased interest, greater difficulty, or higher visual salience.	Duchowski (2007); Jacob & Karn (2002)
Total Fixation Duration (also as Gaze, Dwell)	The cumulative sum of all fixation durations within a specific region during the entire trial.	Highly correlated with the total number of fixations in that region.	Duchowski (2007); Hwang & Lee (2015)
Time to First Fixation	The duration of time from the start of the stimulus until the user first fixates on a specific AOI.	Detect speed	Hwang & Lee (2015); Modi & Singh (2023)
First Fixation Duration	The length of the very first fixation recorded within a specific region.	—	Duchowski (2007)

Note: "—" – not addressed

Source: Compiled by author based on the sources presented in the table

To quantify the relative prevalence of these transition types the Payne index (PI) (Payne, 1975) and the Search index (SI) (Böckenholt and Hynan, 1994) have been developed. Both indices have been validated under controlled conditions: when decision strategies are explicitly instructed, gaze transitions reliably align with the specified strategy (Chen & Dai, 2025; Ryan-Lortie et al., 2023). However, Chen & Dai (2025) found that in free-choice settings, transition patterns showed no correspondence with strategies inferred from behavioral modeling, suggesting that in naturalistic contexts these metrics should be interpreted as indicators of information acquisition tendencies rather than direct proxies for underlying decision strategies. Accordingly, this thesis does not treat gaze behaviour as direct evidence of strategy use. Attention patterns serve as interpretive reference points for describing how information is sampled, with the focus on identifying meaningful patterns in visual attention.

Together, fixation-based metrics, AOI definitions and sequences of eye movements provide a methodological basis for examining how visual attention is distributed across different elements of an online product page. In the context of online shopping, AOIs typically correspond to distinct visual cues, like image, price, description, etc., which differ in both perceptual salience and informational value. As a result, eye-tracking enables researchers to move beyond self-reported preferences and directly observe how consumers allocate attention across cues during decision making.

Prior research consistently shows that visual attention in online shopping is not uniformly distributed but follows a hierarchy shaped by cue type and individual involvement. The product image dominates fixation time across both utilitarian and hedonic product categories, functioning as the primary entry point before consumers engage with other information (Cortiñas et al., 2019; Liu et al., 2024). Secondary cues – price, reviews, and textual descriptions – attract attention more selectively. Review-related cues are processed asymmetrically: negative ratings and lower star scores draw disproportionately more attention than positive ones, suggesting that consumers are particularly sensitive to quality signals that fall below expectations (Chen et al., 2022; Johnson et al., 2022). Price attention similarly depends on perceived value, intensifying when a product appears overpriced relative to expectations (Johnson et al., 2022). Textual descriptions, by contrast, are processed primarily by highly involved consumers who seek detailed specifications, while low-involvement consumers largely bypass them in favour of visual and numerical shortcuts (Kim & Lee, 2020).

However, the existing literature differs considerably in both stimulus structure and analytical focus. Several studies that examine how specific cues shape attention do so in single-product layouts, where only one product is visible at a time and cross-product comparison is not possible (Chen et al., 2022; Johnson et al., 2022; Kim & Lee, 2020). Other research that use multi-product layouts tend to examine attention distribution either at the sample level – reporting how attention is divided across cue types on average across all participants (Cortiñas et al., 2019) – or for predictive modelling purposes rather than to characterise individual differences in information processing (Liu et al., 2024). What remains largely unexamined is how individual consumers differ in the way they navigate a multi-product search page displaying multiple products and multiple cue types simultaneously and whether those differences reflect meaningful variation in decision-making behaviour. This is the condition the present thesis directly examines.

Building on this gap, three studies come closest to the present approach by examining multiple visual attributes and individual differences within a single experimental design (Hwang & Lee, 2015, 2018; Modi & Singh, 2023). A methodological comparison is presented in Table 2.

Table 2

Methodological comparison of eye-tracking studies

Factors	**Modi & Singh (2023)**	**Hwang & Lee (2018)**	**Hwang & Lee (2015)**
Usage of Eye-Tracking	+ (Webcam-based)	+ (Stationary)	+ (Stationary)
Type of pages analyzed	Home page, search page, one-product page	One-product pages	One-product pages
Type of products	Utilitarian (headphones)	Utilitarian (notebook) and hedonic (perfume)	Utilitarian (notebook) and hedonic (perfume)
No of Attributes	16	4	9
Metrics used	FF, FC	TFD, FC	FF, TFD, FC
Pre-defined groups for Comparison	Gender (male vs female)	Gender (male vs female)	Cognitive style (systematic vs intuitive)
Statistical tools used	Independent sample t-test, heat maps, gaze sequence	Independent t-test, regression for attitude effects	Descriptive and comparative analysis, heat maps

Note: “FF” – First Fixation, “FC” – Fixation Count, “TFD” – Total Fixation Duration, “+” – addressed

Source: Compiled by author based on the sources presented in the table

Despite differences in research focus, all three studies share a core finding: attention allocation is non-random and systematically connected to individual characteristics, with product-related cues – images, prices, specifications, and reviews – consistently attracting the highest visual attention, although their relative importance differs across individuals (Hwang & Lee, 2015, 2018; Modi & Singh, 2023). Studies interpreting these differences through gender find that female consumers generally show longer fixation durations and higher fixation counts, while male consumers display more selective attention focused on prices and comparative attributes (Hwang & Lee, 2018; Modi & Singh, 2023). Hwang & Lee (2015) show that systematic and intuitive processors exhibit distinct differences in attention distribution independent of gender, with systematic consumers attending longer to analytical cues such as reviews, and intuitive consumers prioritising visual and experiential information.

However, a fundamental methodological limitation is shared across all three studies: participants are assigned to categories prior to analysis, and group differences are tested using independent-sample t-tests or descriptive comparisons (Hwang & Lee, 2015, 2018; Modi & Singh, 2023). While this confirms that predefined groups differ in attention allocation, it cannot reveal decision-making patterns that emerge naturally from gaze behaviour itself. Gaze sequences, where present, are used illustratively rather than as inputs for classification (Modi & Singh, 2023). As a result, hybrid or unexpected attention patterns that cut across demographic labels remain invisible to this approach.

This creates a methodological gap specific to the reviewed studies: while all three demonstrate that gaze behaviour differs systematically across individuals, none derives decision-making patterns directly from behavioural sequence data. Instead, participants are classified into groups prior to analysis, and gaze metrics are used to confirm differences between those groups rather than to discover patterns within the data itself. Consequently, attention patterns that cut across demographic or cognitive-style labels remain undetectable within this framework.

One of the approaches used to examine heterogeneity in consumer behaviour is clustering analysis. Rather than testing differences between predefined groups, clustering identifies groups directly from the data based on behavioural similarity, making it possible to uncover attention patterns that demographic or cognitive-style frameworks may not anticipate. However, clustering approaches vary considerably in terms of the data analysed and the interpretive claims they support. Therefore, it is useful to consider the approach adopted in this thesis within the broader context.

Several studies apply clustering methods to retail consumer behaviour, though not specifically to eye-tracking data. Doğan et al. (2018), for example, use K-Means and two-step clustering on RFM (recency, frequency, monetary) indicators derived from loyalty card data to identify behaviourally distinct customer groups. Even though the study uses the data about aggregate purchase behaviour rather than process-level attention, it demonstrates the value of unsupervised clustering for identifying consumer types.

Kucharský et al. (2020) demonstrate a more systematic algorithmic alternative. They propose clustering eye movement sequences by first converting each individual scan path into a transition probability matrix, which encodes the likelihood of moving between each pair of predefined areas of interest and then apply K-means clustering to these matrices. The method reliably identifies latent behavioural groups that differ in their sequential gaze patterns on an item-by-item basis. However, it is in the context of cognitive tasks, more specifically Deductive Mastermind Game (DMM). (Kucharský et al., 2020)

This transition-based clustering logic has also been adopted to consumer decision-making contexts: Chen and Dai (2025) apply K-Means to average transition frequencies across AOIs in an intertemporal choice task, successfully distinguishing alternative- and attribute-based information search patterns across participants in explicitly instructed conditions.

Several studies apply clustering directly to visual attention data in retail contexts. Agost and Bayarri-Porcar (2024) qualitatively classify participants into three gaze behaviour patterns by manually reviewing gaze plots and heat maps from an eye-tracking study of wardrobe selection. Tupikovskaja-Omovie and Tyler (2020) similarly derive mobile shopping journey clusters through visual inspection of scan path maps on fashion retail websites. Both approaches are valuable in identifying descriptively distinct patterns, but the classification is performed by the researcher through observation rather than computed algorithmically from the data, which introduces subjectivity and limiting scalability.

Studies examining online shopping dynamics more broadly have applied statistical clustering to clickstream data. Park and Park (2016) identify latent visit clusters from online browsing sequences using a Bayesian changepoint framework, showing that purchase conversion differs across visit patterns. Currim et al. (2015) demonstrate that the information consumers actually access during a purchase task provides more meaningful behavioural insight than information merely available to them. Although neither study uses eye-tracking, both highlight that the sequence and pattern of information acquisition are what differentiate consumer types.

Overall, prior research establishes that visual attention during online decision-making is non-random and shaped by both cue characteristics and individual differences. Yet two limitations persist. First, studies examining individual differences in gaze behaviour assign participants to groups prior to analysis using gaze metrics to confirm those differences rather than to discover patterns within the data itself. Second, clustering approaches applied in online shopping contexts rely either on qualitative visual inspection of gaze plots or on aggregate behavioural indicators such as clickstream and purchase data. As a result, naturally occurring attention patterns that emerge directly from gaze behaviour remain undetected. This thesis addresses both limitations by applying unsupervised clustering to eye-tracking behavioural data, allowing decision-making patterns to be derived from visual attention behaviour.

2. Empirical analysis of gaze-based decision-making patterns

2.1. Methodology and pre-processing of data

This subchapter describes the data used in the empirical analysis, the initial tests, the structure of the stimulus materials, and the methodological approach applied to identify gaze-based decision-making patterns in online shopping by analyzing visual attention to product-related cues using eye-tracking methodology.

The data used in this thesis are secondary eye-tracking data collected at the Neuromarketing Laboratory of the University of Tartu under the supervision of Kristian Pentus in cooperation with Jason Bell from Oxford University. The author participated in the methodology development, and in initial first tests of the data collection which was conducted on real webpages within the internal browser of Tobii Pro Lab. During this stage, the author assisted in data collection by recruiting and running participants through the experimental sessions, and contributed to the mapping of Areas of Interest (AOIs) on the webpages for subsequent analysis. Following this, the author was further involved in the methodology development for the second and final stage of the study. The final experimental setup and data collection procedure were developed and implemented by the laboratory research team independently of the present thesis.

The choice of the product for the analysis was intentional. Reusable water bottles were selected as a medium-involvement product category that sits between purely utilitarian and hedonic goods. Consumers typically weigh functional and visual attributes without bearing high risks. This makes the category well suited for observing differentiated attention allocation across multiple cue types.

The stimulus set consisted of 15 Amazon product page screenshots in total: 5 multiple-bottle layouts, each displaying 10 products simultaneously in a two-row grid (search pages), and 10 single-bottle layouts. Data collection procedure was the following. Participants were shown screenshots of 15 Amazon product pages displaying reusable water bottles in randomized order and were asked to select the water bottle they would choose to take to work or school, making one choice per page displayed. Eye-tracking data were collected using a stationary Tobii Pro Spectrum eye-tracking device. No video recording was used; data capture was limited exclusively to eye-tracking measurements. Immediately after the eye-tracking task, participants completed a brief structured questionnaire covering age, gender, ethnicity, and ownership of a reusable water bottle. Responses were recorded manually by the experimenter and were not audio-recorded. Ethnicity was recoded as a binary variable (Estonian vs international) to enable group comparisons with adequate sizes.

Participants were recruited on a convenience basis in the Delta building of the University of Tartu. A total of 90 participants took part in the study. The demographic characteristics of the sample are presented in Table 3. Importantly, participants aged 17 are international students who began university studies before the age of 18, which is permitted under applicable admission policies. To assure anonymization and confidentiality, all participants signed an informed consent form prior to participation. In accordance with the consent form, contact information was retained for 14 days only and subsequently deleted, making retrospective identification of individuals impossible.

Table 3

Demographic characteristics of participants

Variable	Category	N	%
Gender	Female	29	32.22
	Male	61	67.78
Age	Min	17	
	Max	44	
	Mean	23.5	
Ethnicity	Estonian	44	48.89
	International	46	51.11
Ownership	Yes	65	72.22
	No	13	14.45
	Unknown	12	13.33

Note: Total sample size = 90 respondents

Source: Compiled by author based on the VSC output

After the data were collected, full access to the raw data was provided to the author, enabling independent empirical analysis. This data is providing the granularity of fixation-level measurements needed for the analysis and was purpose-built for studying consumer visual attention in an online shopping environment. The present analysis focuses exclusively on the five search pages displaying 10 products simultaneously in a two-row grid. The example of stimuli is shown in Figure 2. The order was randomised across participants to control for learning and fatigue effects. Across these pages, five visual cue types were predefined as Areas of Interest (AOIs) in Tobii Pro Lab prior to data collection: product image (BOTTLE), textual description (DESCRIPTION), price (PRICE), review score (REVIEW), and delivery information (DELIVERY) (see Appendix A). This yielded 50 AOIs per page.

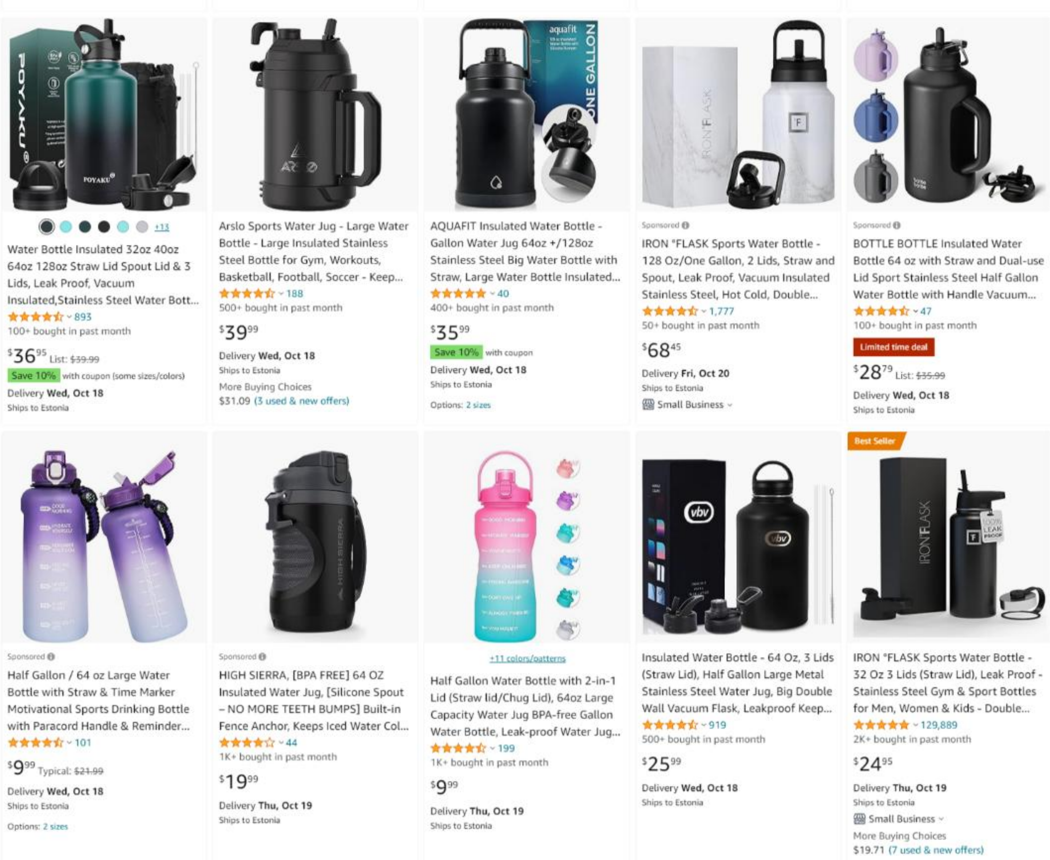


Figure 2. Example of experimental stimulus page shown to participants

Source. Laboratory research project materials based on screenshots captured in Tobii Pro Lab from Amazon product search result pages displayed through the software’s internal browser

However, the data has several limitations: uneven distribution across gender and missing AOIs elements on specific pages. Regarding gender, while ethnicity was relatively evenly distributed, the sample showed an uneven gender distribution, which represents a limitation of the dataset. To assess whether this imbalance may have influenced the findings, gender was included in the post-hoc demographic analysis examining whether cluster membership was associated with specific behavioural patterns. Regarding missing some product cues, two pages contain structural absences reflecting real-world variation in product listing completeness: Page 2 is missing the REVIEW for Product 2 and the DELIVERY for Product 8, while Page 4 is missing the DELIVERY for Product 4 and the REVIEW for Product 8. Since these cues were not present in the original stimuli, they were not mapped as AOIs and therefore did not enter the AOI-based transition computations for the affected products. As the analysis was conducted at the grouped cue-element level, these absences were documented as a limitation but are unlikely to have substantially influenced the overall clustering results.

The raw data were exported from Tobii Pro Lab as a single tab-separated file containing one row per gaze sample recorded continuously at 300Hz across all 90 participants and all five search pages with one row being 3.333ms. The file contains two groups of columns. The first captures event-level metadata: participant and recording names, the name of the stimulus being displayed, the eye movement type (Fixation, Saccade, Unclassified, or EyesNotFound), the duration of the current eye movement event in milliseconds, and a sequential event index that orders fixations within each recording session. The second group consists of 246 binary AOI hit columns, one per defined Area of Interest across all five pages. A value of 1 indicates the gaze sample fell within that AOI, 0 indicates it did not, and NA indicates the AOI did not exist on the page being shown at that moment, meaning for any given row only the 50 columns belonging to the currently displayed page contain non-missing values.

Pre-processing followed five sequential steps implemented in Python (pandas). First, rows classified as EyesNotFound or Unclassified were removed, as these do not represent valid gaze behaviour. Second, because the eye tracker samples continuously, each fixation generated multiple rows sharing the same fixation index; deduplication on the combination of participant identifier, page, and fixation index collapsed these into one row per fixation event, making the fixation the unit of observation. Third, a minimum fixation duration threshold of 100 milliseconds was applied, consistent with the standard definition of a fixation as a period of stable gaze exceeding 100-200 milliseconds (Jacob & Karn, 2002). Fourth, fixations that did not land inside any defined AOI were excluded, as these represent gaze directed at whitespace or page borders and carry no information about which product element was being processed. Finally, participant-page trials with fewer than five AOI-hitting fixations were excluded from the analysis.

Figure 3 summarises the pre-processing pipeline and the resulting reduction of the dataset at each stage.

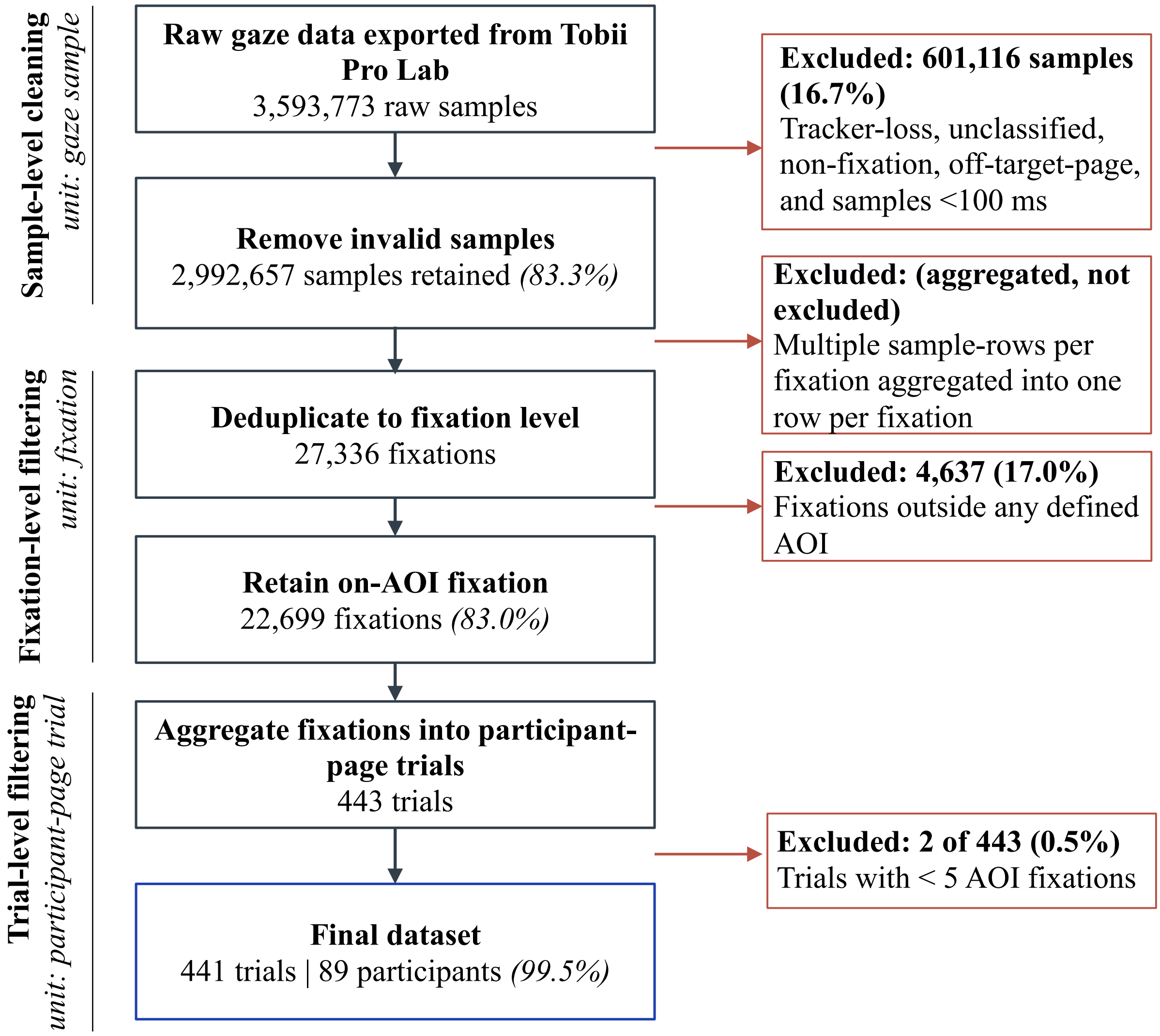


Figure 3. Pre-processing pipeline from raw gaze samples to analytical participant-page trials Sources: compiled by the author based on the raw data exported from Tobii Pro Lab, Jacob & Karn (2002), output from VSC

Starting from 3,593,773 raw gaze samples exported from Tobii Pro Lab, sample-level cleaning retained 2,992,657 valid samples (83.3%). Deduplication then reduced the dataset to 27,336 unique fixation events, of which 22,699 fixations (83.0%) landed within predefined AOIs and were retained for analysis. Then, fixations were aggregated into participant-page trials (hereafter trials), and two trials containing fewer than five AOI-hitting fixations were excluded due to insufficient engagement and unstable transition-rate estimates. The final dataset comprised 441 trials from 89 participants across five pages, with a mean of 51.5 AOI fixations per trial (SD = 45.6, range 5-402).

The analysis proceeds in six stages as described in Table 4. The logic of the analysis begins with the raw trial-level eye-tracking data, which captures the sequential order in which participants viewed page elements. From these sequences, transition rates and indices are derived to quantify each participant's scanning behaviour. These features are then organised into three independent feature sets (rate-based, Payne Index and Search Index), each of which serves as the input to a separate K-Means clustering procedure. K-Means clustering is the sole classification model employed, the three parallel solutions allow to test clustering across different feature representations. Once the optimal number of clusters is selected for each solution, the resulting clusters are characterised and visualised using transition heatmaps, descriptive statistics, and scatterplots to make behavioural differences between clusters interpretable. The distribution of visual attention across product cue types is revealed by comparing attention allocation across clusters using normalised TFD. Then demographic variables are merged into the dataset to examine whether cluster membership is associated with participant background. Finally, the three clustering solutions are cross-examined using agreement metrics to assess the consistency of participant assignments.

Table 4

Methodology for eye-tracking data analysis

Stage	**Procedure**	**Purpose**
1	Sequence feature engineering	Quantify the sequential structure of each trial and define three feature sets
2	K-Means clustering	Identify behavioural groups from each feature set independently; select optimal number of clusters for each solution
3	Cluster characterisation	Describe and visualise differences between clusters using descriptive statistics, statistical comparisons, transition heatmaps, and scatterplots
4	Total Fixation Duration (TFD) analysis	Compare clusters by total fixation duration across product cue types
5	Demographic profiling	Examine whether clusters differ by gender, age, nationality, or product ownership
6	Cross-method comparison	Assess the agreement between the three clustering solutions

Note: AOI = Area of Interest; TFD = Total Fixation Duration; ARI = Adjusted Rand Index

Source: Compiled by the author based on the analysis procedure

Stage 1 engineers the sequence features that form the input to clustering. The sequence feature engineering approach follows Kucharský et al. (2020), who proposed representing eye movement behaviour as a transition matrix over AOIs and applying clustering to identify distinct processing patterns. If the original method was implemented, transitions would produce a 50×50 matrix per trial in the present dataset (10 products × 5 element types). However, a 50×50 transition matrix yields extremely sparse data at the trial level, as most cells receive zero or one observation per participant-page session. This sparsity makes the matrix unsuitable as a direct clustering input. The present analysis therefore aggregates transitions to the element-type level, reducing the representation to normalised rates computed over five attribute types (image, description, delivery, review, and price). This modification preserves the core logic of Kucharský et al. (2020) while producing features that are dense enough for stable estimation across trials. Transition-based features of this kind have also been used as direct input to K-Means clustering in studies of intertemporal choice, where the algorithm successfully distinguished alternative- and attribute-based search patterns across participants (Chen & Dai, 2025).

For each consecutive pair of fixations within a trial, the transition is classified into one of four mutually exclusive categories (within-product, cross-product, persistence, diagonal) based on whether the product number and the attribute type change between fixations. The count of each category is divided by the total number of valid transitions – pairs where both endpoints have a resolved AOI – to yield a normalised rate that guarantees all four sum exactly to 1.0 for every trial. Sequence-derived transition rate features used in clustering are summarized in the Table 5.

Two primary rate features (within-product and cross-product rates) correspond to the two information-processing modes discussed in the theoretical framework. Specifically, within-product rate captures alternative-based processing, where consumers evaluate multiple attributes within the same product before moving to another alternative, while cross-product rate captures attribute-based processing, where consumers compare the same attribute across multiple products (Bettman et al., 1998).

The classification of diagonal rate – where both the product and the element type change simultaneously – as a distinct category follows the conceptual distinction introduced by Banerjee and Masters (2021). Such gaze shifts are neither purely alternative-based nor purely attribute-based and would introduce classification error if forced into either category. Including diagonal rate as a separate rate therefore ensures that within-product and cross-product rates capture only clean within-alternative and within-attribute transitions respectively.

Table 5

Sequence-derived transition rate features used in clustering

Rate features	What it captures	Decision-making interpretation
Within-product rate	Proportion of transitions that are cross-element within the same alternative (e.g. Product 3 Image → Product 3 Price)	Alternative-based processing: evaluating one product holistically before moving to the next (Bettman et al., 1998)
Cross-product rate	Proportion of transitions that cross product boundaries on the same attribute (e.g. Product 1 Price → Product 4 Price)	Attribute-based processing: comparing the same attribute across multiple products simultaneously (Bettman et al., 1998)
Diagonal rate	Proportion of transitions where both the product and element type change simultaneously (e.g. Product 1 Image → Product 5 Price)	Unstructured or exploratory gaze; captured to ensure transition rates sum to 1.0 across all categories (Banerjee & Masters, 2021)
Persistence rate	Proportion of transitions that stay on the same product and same element type consecutively (e.g. Product 1 Price → Product 1 Price)	Repetitive re-inspection of a single cue type; not used as a clustering feature due to perfect collinearity with the two rates above

Source: Compiled by the author based on Bettman et al. (1998), Banerjee and Masters (2021)

Persistence rate was introduced by the author to capture repeated attention to the same product element across consecutive fixations. This type of transition reflects re-inspection behaviour, where participants repeatedly return to a single cue type without shifting either product or attribute focus. Because persistence rate is mathematically dependent on the remaining transition categories and perfectly collinear with them, it was not used directly as a clustering feature.

For the purposes of this study, the author also uses two established indices that are computed from the same transition categories to calculate the rates and serve as separate clustering inputs. Both compress the raw transition counts into a single value that places each trial somewhere on a scale ranging from purely attribute-based to purely alternative-based processing. This allows the clustering solutions to be compared and establishes whether they remain consistent when different feature representations are used.

The Payne Index (PI) is calculated as:

$$PI = \frac{(T_{alt} - T_{att})}{(T_{alt} + T_{att})}$$

where T_{alt} and T_{att} denote the number of alternative-based and attribute-based transitions respectively (Payne, 1975). Payne index ranges from -1 to 1, where values above zero indicate a predominantly alternative-based search pattern, while values below zero indicate an attribute-based one.

The Search Index (SI) is a modified version that additionally accounts for the number of alternatives and attributes in the choice set and is calculated as:

$$SI = \frac{\sqrt{N}(\frac{n_{alt}n_{att}}{N}(T_{alt} - T_{att}) - (n_{alt} - n_{att}))}{\sqrt{n_{alt}^2(n_{att} - 1) + n_{att}^2(n_{alt} - 1)}}$$

where N denotes total number of transition, n_{alt} – the numbers of alternatives and n_{att} – the number of attributes (Böckenholt and Hynan, 1994).

Stage 2 applies K-Means clustering independently to each of the three feature sets – on transition rates (rate-based clustering), the Payne Index (PI clustering), and the Search Index (SI clustering), resulting in three separate solutions. K-Means was selected as the clustering algorithm following Kucharský et al. (2020) and Chen and Dai (2025), and is applied separately to each feature set so that each approach can capture its own pattern of scanning behaviour. This also makes it possible to check whether similar clusters appear across different ways of measuring scanning behaviour. Solutions for k in the range from 2 to 9 are evaluated using the elbow method and average silhouette score, with the optimal k determined independently per solution. Transition rates are z-score standardised prior to fitting as this feature set contains multiple variables on potentially different scales. The Payne and Search indices require no standardisation as each is a single scalar measure. The three solutions are carried forward independently through the subsequent analytical stages and are compared in Stage 6.

Stage 3 characterises the clusters identified across all three feature sets in Stage 2, with the same procedure applied to the rate-based, PI-based, and SI-based solutions. Descriptive statistics (mean and standard deviation) are reported for all four transition rates and total fixation count per cluster. Kruskal-Wallis tests are applied to all four transition rates. Because clustering was performed on a subset or transformation of these rates, significant results are expected by construction and are reported as descriptive confirmation of meaningful cluster differentiation rather than as independent validation. Pairwise Welch t-tests with Bonferroni correction identify which specific cluster pairs differ on each rate. Transition heatmaps visualise the distribution of gaze movement types across clusters.

Mean pairwise normalised Levenshtein distance is computed within each cluster to measure scanpath similarity. Each trial’s fixation sequence is encoded as a character string, where B = image, P = price, R = review, D = description, and L = delivery. The distance between each pair of sequences is then normalised by the length of the longer sequence. Lower values indicate that participants within the same cluster followed more similar information-search paths. The encoding groups fixations by product element type rather than specific product, preserving the within- versus cross-product distinction but not product-specific sequence patterns. Finally, a scatter plot of within-product rate and cross-product rate visualises the spatial separation of clusters within two primary feature rates.

Stage 4 analyses Total Fixation Duration per AOI type to examine whether clusters differ in how attention time is distributed across product cues. For each clustering solution, normalised TFD (percentage of total trial fixation time) are reported per cluster and AOI type. Welch ANOVA is applied across the five AOI types; Games-Howell post-hoc pairwise tests identify which specific cluster pairs differ for each cue type.

Stage 5 examines whether cluster membership is associated with participant characteristics across all clustering solutions. Age is tested using Kruskal-Wallis; gender, nationality, and reusable water bottle ownership are tested using Chi-Square with Cramér's V as the effect size measure. Demographic variables are not used as clustering inputs; their relationship to cluster membership is examined post-hoc to assess whether the behavioural groups correspond to identifiable individual-level characteristics.

Stage 6 compares the three clustering solutions at the trial level using Pairwise ARI scores to quantify assignment agreement across solutions.

2.2. Clustering results and attention distribution analysis

The fourth subchapter presents the results of the clustering analysis. It determines the optimal number of clusters across all three feature sets and provides transition rate patterns to the resulting clusters. Descriptive labels are assigned based on the behavioural patterns observed. The subchapter then examines how TFD is distributed across product cues within each cluster, whether cluster membership is associated with demographic variables, and the degree of agreement between the three clustering solutions.

K-Means was evaluated for k = 2 to 9 on each of the three feature sets independently. Elbow plots for all three solutions are presented in Figure 4. Across all three feature sets, the elbow plots show a pronounced drop in inertia from k = 2 to k = 3 and a notably smaller reduction from k = 3 to k = 4, supporting k = 3 as the point of diminishing returns. This was further confirmed by silhouette scores: the rate-based solution peaked at k = 3 (silhouette = 0.44) and the PI-based solution similarly yielded k = 3 as optimal (silhouette = 0.63). In contrast, the SI-based solution produced the silhouette score that supported k = 2 (silhouette = 0.59). Given this ambiguity and the results of the elbow plot, k = 3 (silhouette = 0.54) was selected for the SI-based solution to maintain comparability across methods. Accordingly, k = 3 was used as the final solution across all three methods. Final cluster sizes were: rate-based – 199, 21, and 221 trials; PI-based – 164, 154, and 123 trials; SI-based – 185, 129, and 127 trials.

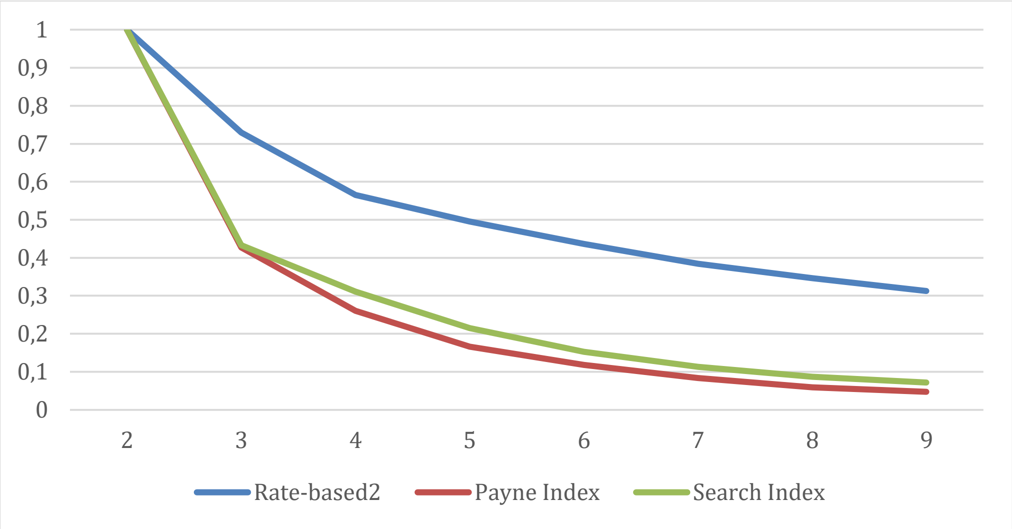


Figure 4. Normalised elbow plots for clustering solutions

Source: compiled by the author based on the output from VSC

Table 6 presents the descriptive statistics per cluster for each of the three clustering methods. For each method, clusters are characterised by their average within-product, cross-product, persistence, diagonal rates, and total fixation count, along with the corresponding standard deviations. In the rate-based solution, Cluster 0 is characterized by a high cross-product rate (M = 0.549) and a low within-product rate (M = 0.041), indicating mainly attribute-based processing. Cluster 2 shows a more balanced pattern, with moderate levels of both within-product rate (M = 0.190) and cross-product rate (M = 0.289), suggesting a hybrid search strategy that combines both attribute-based and alternative-based processing. Cluster 1 is a much smaller group consisting of 21 trials. Its values fall between Cluster 0 and Cluster

2, with within-product rate (M = 0.144) higher than in Cluster 0 but lower than in Cluster 2, while cross-product rate (M = 0.229) is the lowest among the three clusters. This cluster also has a relatively high diagonal rate (M = 0.400). Since the cluster is small, this pattern should be interpreted carefully. This group is interpreted as a shift away from pure attribute-based processing. The pattern suggests less systematic cross-product processing and more varied transition behaviour.

PI-based and SI-based solutions produce broadly similar patterns. Both identify a clear attribute-processing cluster with low within-product rate and high cross-product rate, as well as a hybrid cluster where the two rates are more balanced. The main difference appears in the intermediate cluster. In PI-based, this cluster has within-product rate = 0.138 and cross-product rate = 0.383, while SI-based the values are 0.102 and 0.430 respectively. In both cases, the cluster falls between the attribute-based and hybrid groups, although it remains more strongly oriented toward cross-product comparisons than the intermediate cluster in the rate-based solution.

Moreover, Cluster 2 showed substantially higher total fixation counts than the other two groups across all three solutions (rate-based: M = 72.4; PI-based: M = 80.0; SI-based: M = 68.0), compared to considerably lower counts in Cluster 0 (rate-based: M = 30.6; PI-based: M = 28.0; Search Index: M = 45.1) and Cluster 1 (rate-based: M = 28.3; PI-based: M = 53.6; Search Index: M = 44.3).

Across all three methods, cluster profiles reveal consistent behavioural patterns that allow descriptive labels to be assigned. Cluster 0 is characterised by the highest cross-product rate and the lowest within-product rate across all methods, reflecting a tendency to compare attributes across products, consistent with attribute-based processing. Therefore, it is labelled Attribute-based. Cluster 2 shows broadly comparable cross- and within-product rates, suggesting roughly equal use of both processing modes and is therefore labelled Hybrid. Cluster 1 occupies an intermediate position with elevated cross-product rates but a non-negligible within-product rate, indicating gaze behaviour that leans toward attribute-based processing without fully committing to it, and is labelled attribute-leaning. For ease of cross-method comparison, clusters are referred to by these behavioural labels – Attribute-based (Cluster 0), Attribute-leaning (Cluster 1), and Hybrid (Cluster 2).

Table 6

Descriptive statistics by cluster and clustering method

		Rate-Based		Payne Index		Search Index	
Rate	**Cluster**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
	0	0.0407	0.0520	0.0206	0.0311	0.0421	0.0502
Within-product rate	1	0.1444	0.0831	0.1379	0.0414	0.1016	0.0712
	2	0.1900	0.0711	0.2316	0.0645	0.2245	0.0707
	0	0.5491	0.1283	0.5623	0.1317	0.5431	0.1358
Cross-product rate	1	0.2293	0.1239	0.3827	0.0943	0.4302	0.1395
	2	0.2888	0.0986	0.2175	0.0823	0.2274	0.0863
	0	0.3835	0.1347	0.3850	0.1368	0.3830	0.1197
Persistence rate	1	0.2261	0.0972	0.3870	0.1252	0.4011	0.1351
	2	0.4200	0.1250	0.4158	0.1417	0.3955	0.1477
	0	0.0268	0.0392	0.0322	0.0772	0.0317	0.0393
Diagonal rate	1	0.4003	0.1355	0.0924	0.0852	0.0671	0.0650
	2	0.1012	0.0518	0.1350	0.1003	0.1525	0.1281
	0	30.598	17.096	28.043	14.857	45.063	29.712
Total fixation count	1	28.286	21.585	53.623	34.900	44.276	40.081
	2	72.434	54.548	79.951	64.278	68.039	59.94

Source: compiled by the author based on outputs from VSC

Kruskal-Wallis tests showed significant differences between clusters for all four transition rates in the rate-based solution. In PI-based and SI-based solutions, everything had significant differences, except Persistence rate. Since the clustering methods were designed to maximize separation, these results are treated as descriptive evidence that the clusters capture distinct viewing patterns rather than as independent validation of the models. Pairwise Welch t-tests with Bonferroni correction ($\alpha = 0.0167$) provide a more detailed view of the differences between clusters. In the rate-based solution, all cluster pairs differed significantly on diagonal rate and persistence rate. However, the comparison between Attribute-leaning and Hybrid was not significant for within-product rate ($t = -2.43$, $p = 0.023$) or cross-product rate ($t = -2.14$, $p = 0.044$), which may reflect the relatively small size of attribute-leaning. In PI-based and SI-based solutions, all cluster pairs differed significantly on within-product, cross-product, and diagonal rates. In contrast, persistence rate did not significantly distinguish any cluster pairs in either solution.

Mean pairwise Levenshtein distance within clusters is reported for all three solutions. In the rate-based solution the distances are 0.426 (Attribute-based), 0.694 (Attribute-leaning), and 0.601 (Hybrid). In PI-based solution the distances are 0.416 (Attribute-based), 0.553 (Attribute-leaning) and 0.652 (Hybrid). In SI-based solution, the distances are 0.432 (Attribute-based), 0.547 (Attribute-leaning) and 0.665 (Hybrid). The Hybrid and Attribute-leaning clusters generally showed higher within-cluster variability than the Attribute-based, reflecting the wider variety of gaze paths produced by less strictly structured gaze behaviour.

Transition heatmaps for all three clustering solutions are shown in Appendix B. Across all solutions, the Attribute-based cluster consistently shows transitions concentrated along cross-product same-element pathways. The Hybrid cluster displays a more distributed pattern with greater within-product movement across element types in all three solutions. The Attribute-leaning cluster shows a less structured pattern, with no clearly dominant transition type, which is consistent with its position between the other two groups and its lower trial count in the rate-based solution.

Scatter plots of within-product rate against cross-product rate for the rate-based, PI-based, and SI-based solutions are shown in Figures 5, 6, and 7 respectively.

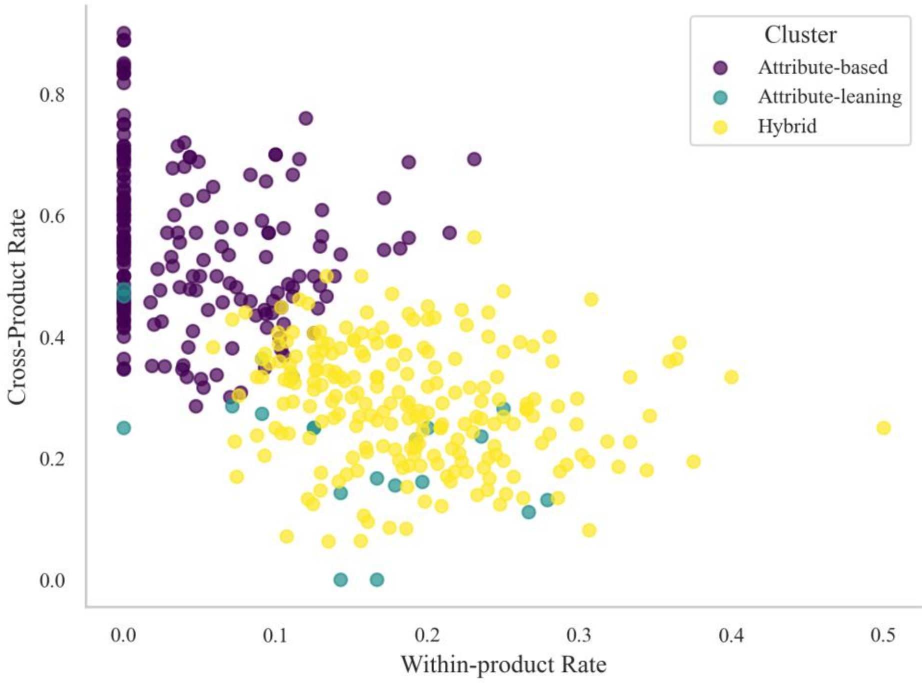


Figure 5. Rate-based cluster separation by within- and cross-product rates

Source: compiled by the author based on outputs from VSC

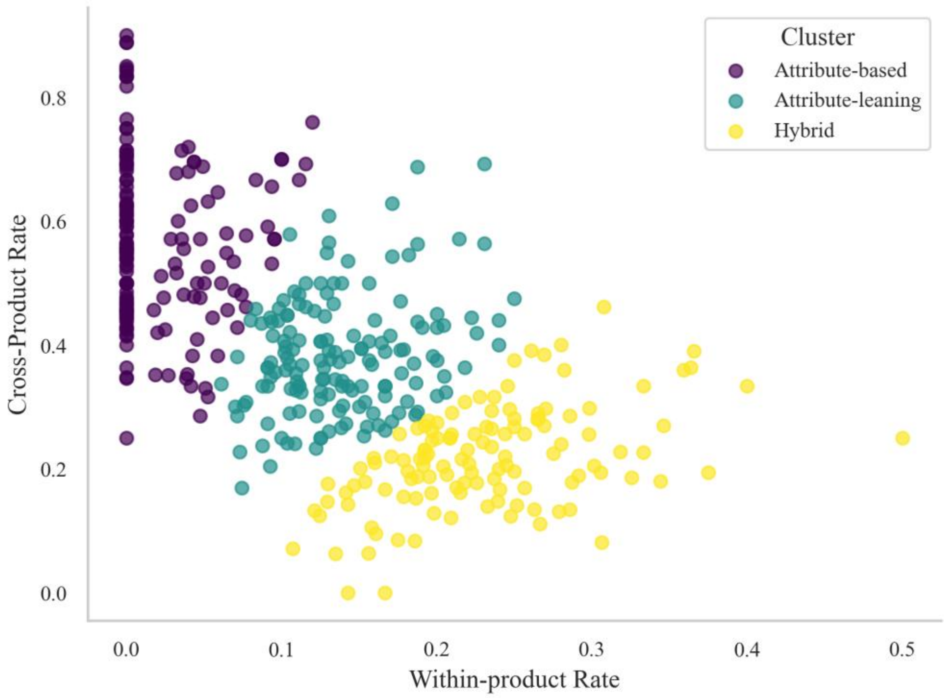


Figure 6. Payne Index cluster separation by within- and cross-product rates
Source: compiled by the author based on outputs from VSC

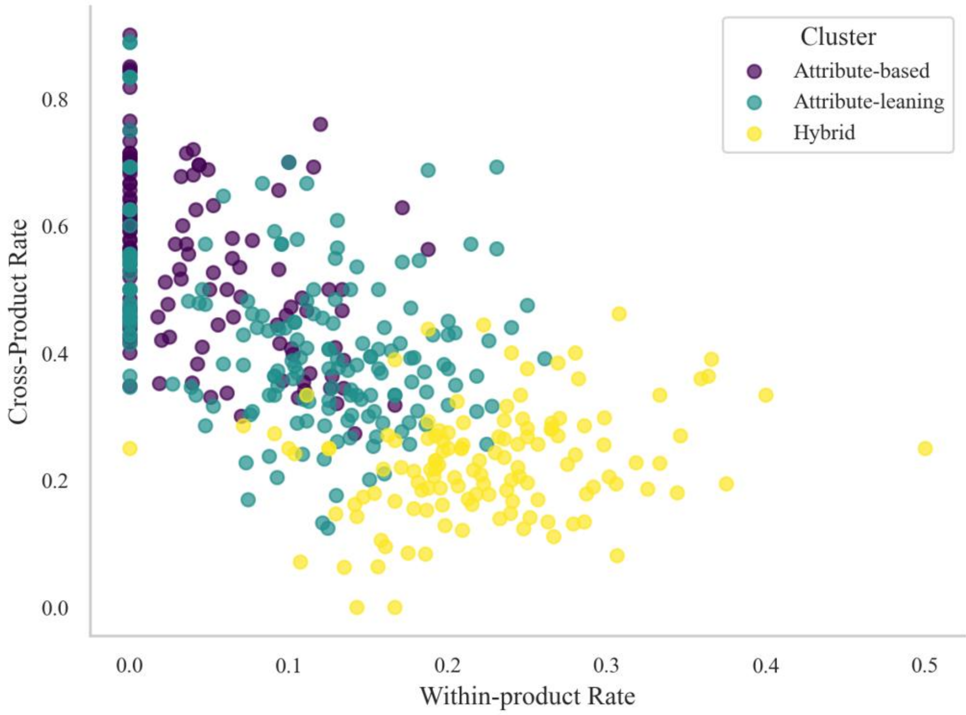


Figure 7. Search Index cluster separation by within- and cross-product rates
Source: compiled by the author based on outputs from VSC

Across all three solutions, Attribute-based occupies the upper-left region of the feature space – high cross-product rate and low within-product rate. Hybrid occupies the lower-right, reflecting higher within-product rate and lower cross-product rate. In the rate-based solution, the separation between Attribute-based and Hybrid is clear, while Attribute-leaning is scattered across the feature space without a distinct region. The PI-based solution shows the cleanest three-way separation, with Attribute-leaning forming a visible intermediate band between Attribute-based and Hybrid. In the SI-based solution, Hybrid is well separated in the lower-right, while Attribute-based and Attribute-leaning show some overlap in the upper-left region.

To examine whether clusters differ in how attention time is distributed across product cues, normalised total fixation duration (TFD) was analysed per AOI type for all three clustering solutions. Results are shown in Appendix C. Welch ANOVA confirmed significant between-cluster differences for all five AOI types across all three solutions (all $p < 0.001$), with the exception of delivery information in the PI-based solution ($p = 0.365$).

Images dominated fixation time across all clusters in all three solutions. In the PI-based and SI-based solutions, the share decreases monotonically from Attribute-based to Hybrid. The rate-based solution shows a different pattern: Attribute-leaning cluster allocated the least fixation time to image (44.5%).

Description was notably elevated in both the Attribute-leaning and Hybrid clusters across all solutions, though the relative ordering differed: in the rate-based solution the Attribute-leaning showed higher fixation (33.2%) than the Hybrid (23.3%), while in the PI-based and SI-based solutions the Hybrid showed the highest share (30.1% and 29.0% respectively), with all pairwise comparisons significant (all $p < 0.05$).

TFD to price and review were low across all clusters in all three solutions, with no practically meaningful differences. The exception is the rate-based solution, where the Attribute-leaning cluster showed somewhat higher fixation on reviews (12.3%) compared to the other two clusters, with Games-Howell tests confirming significant differences between Attribute-leaning and both other clusters ($p = 0.006$ and $p = 0.012$). Delivery information was similarly low across all clusters in the PI-based and SI-based solutions, with no significant pairwise differences. In the rate-based solution, the Attribute-leaning cluster again showed elevated fixation on delivery information (15.4%), significantly higher than the Attribute-based and Hybrid clusters ($p = 0.005$ and $p = 0.008$ respectively).

Additionally, cluster membership was tested against gender, ethnicity, bottle ownership, and age across all three clustering solutions to check the possible association. Gender was the only variable that reached significance in all three solutions, with a consistent directional pattern: Attribute-based cluster contained the highest proportion of female participants in every solution, and the effect was strongest in the rate-based and PI-based solutions and weaker but still significant in the SI-based solution. Ethnicity was not significant in any solution. Bottle ownership was significant only in the rate-based solution and did not replicate across methods. Age was significant in the rate-based and SI-based solutions but borderline in the PI-based solution; effect sizes were small across all three, indicating limited practical relevance. The inconsistency of bottle ownership and age findings across methods suggests these associations are sensitive to the choice of feature representation and should be interpreted with caution. Table 7 summarises the results.

Table 7

Association between demographic variables and cluster membership across three methods

Variable	Rate-based			Payne Index			Search Index		
	Statistic	p	Effect size	Statistic	p	Effect size	Statistic	p	Effect size
Gender	χ^2 = 21.98	<0.001	V = 0.213	χ^2 = 19.74	<0.001	V = 0.201	χ^2 = 7.16	0.028	V = 0.108
Ethnicity	χ^2 = 4.14	0.126	V = 0.070	χ^2 = 3.49	0.175	V = 0.058	χ^2 = 0.35	0.841	V = 0.000
Bottle ownership	χ^2 = 13.39	0.010	V = 0.103	χ^2 = 2.64	0.620	V = 0.000	χ^2 = 3.70	0.449	V = 0.000
Age	H = 6.67	0.036	ε^2 = 0.011	H = 5.41	0.067	ε^2 = 0.008	H = 15.11	<0.001	ε^2 = 0.031

Note: Gender, Ethnicity, and Bottle ownership tested with Chi-Square; Cramér's V reported as effect size; Age tested with Kruskal-Wallis; ε^2 reported as effect size

Source: compiled by the author based on outputs from VSC

For the cross-method comparison pairwise Adjusted Rand Index scores were computed at the trial level. Table 8 shows the pairwise ARI scores and exact trial match rates across all three solutions. The results show moderate agreement between the rate-based and PI-based solutions, as well as between the PI-based and SI-based solutions. In contrast, the agreement between the rate-based and SI-based solutions was weaker.

Attribute-based cluster showed the most consistent rate profiles across all three methods, indicating that trials with predominantly cross-product, same-element transitions are robustly identified, regardless of the feature representation used. Disagreement was concentrated among trials with Attribute-leaning or Hybrid, where the choice of feature representation has the greatest influence on cluster assignment.

Table 8

Pairwise agreement between clustering solutions

	Rate-based	Payne Index	Search Index
Rate-based	—		
Payne Index	ARI = 0.443, 62.6%	—	
Search Index	ARI = 0.238, 51.2%	ARI = 0.396, 73.2%	—

Note. ARI = Adjusted Rand Index, 0 – no better than chance, 1 – perfect agreement, % – percentage of trials assigned to the same semantically aligned cluster by both methods

Source: Compiled by the author based on the output from VSC

2.3. Interpretation of clustering results and decision-making patterns

This subchapter interprets the clustering results in relation to the theoretical framework and prior literature. All three clustering solutions pointed to a three-group structure, providing consistent evidence that consumer did not follow one uniform pattern of visual attention on multi-product search pages, but showed meaningfully distinct patterns. Despite differences in the feature representations used, the three solutions identified broadly comparable groups that can be described in terms of information processing modes.

The first group, identified as Attribute-based, is characterised by a very low within-product rate and a high cross-product rate across all three solutions. Participants in this group mainly moved across products while staying on the same element type. This pattern aligns closely with attribute-based processing as described by Bettman et al. (1998) and Payne (1975), where information is sampled by comparing alternatives on one dimension at a time rather than evaluating each option as a whole.

The other group, Hybrid cluster, shows moderate and roughly equal levels of both within-product and cross-product rates. This suggests that consumers in this group combined both attribute-based and alternative-based processing. Rather than relying clearly on one dominant processing mode, they appeared to move flexibly between comparing products across the same cue and examining several cues within the same product. This interpretation is consistent with the adaptive decision-making view of Bettman et al. (1998) and Schaffer et al. (2016), who argue that consumers often adjust their information search depending on the task and available information.

The last group, Attribute-leaning cluster, occupies an intermediate position between the other two clusters. It was more attribute-based than the Hybrid cluster but with a higher within-product rate than the pure Attribute-based cluster, suggesting a partial shift toward within-product evaluation. However, this group is the least stable across clustering methods.

The small size of this cluster in the rate-based solution reflects the geometry of the feature space under this representation rather than a universal property of the group. Under the Payne Index and Search Index solutions, the corresponding cluster reaches comparable size to the others. Overall, this indicates that the boundary between the Attribute-leaning and Hybrid clusters can be more reliably captured by scalar index representations than by raw transition rates. While the two groups are located next to each other in the feature space, they reflect meaningful differences in how they acquire information.

TFD distributions further support the interpretation derived from the transition patterns. Attribute-based cluster concentrated nearly all fixation time on images, with minimal engagement with secondary cues such as price, description, or reviews. This is consistent with a fast, image-driven scan where the visual appearance of the product serves as the primary comparative cue (Cortiñas et al., 2019; Liu et al., 2024). Hybrid and Attribute-leaning clusters allocated substantially more time to descriptions and, to a lesser extent, prices and reviews. This indicates more thorough information processing that extends beyond the product image.

Beyond fixation-time allocation, the clusters also differed in overall viewing intensity. Across all three solutions, the total fixation counts for Hybrid cluster were higher than for the other two clusters. One interpretation is that high within-product comparison is more cognitively demanding, requiring more fixations to integrate multiple attributes within each product before moving on. An alternative explanation, however, is that the clusters partly reflect different levels of engagement with the page rather than purely distinct processing modes. For instance, some attribute-based trials may represent participants who scanned briefly and moved on, rather than participants who deliberately adopted attribute-based comparison approach.

The scanpath similarity results add another layer to these findings. Attribute-based cluster consistently showed the lowest mean Levenshtein distances across all three solutions, indicating that trials in this group followed more similar gaze sequences. This is theoretically plausible: attribute-based processing imposes a relatively constrained structure on the scanpath, moving systematically across a product grid within the same element type, which leaves little room for individual variation in the order of information acquisition.

In contrast, Hybrid and Attribute-leaning cluster showed the highest within-cluster variability, reflecting the wider range of paths available when both within-product and cross-product transitions occur. Attribute-leaning cluster fell between the two, consistent with its intermediate behavioural profile. Overall, the results suggest that Attribute-based cluster represents more clear and more consistent viewing pattern, while Hybrid cluster reflects a broader mix of scanning behaviours that share a general tendency rather than one common sequence.

Although the clusters were derived purely from gaze behaviour, some demographic differences also emerged. Gender was the only demographic variable that reached significance across all three clustering solutions, with female participants more frequently assigned to the attribute-based cluster. This broadly aligns with prior findings showing that male consumers tend toward more selective, comparative scanning (Modi & Singh, 2023). However, this finding should be treated cautiously for three reasons. First, the sample is gender-imbalanced, reducing the reliability of proportional comparisons. Second, cluster assignment operates at the trial level, so a single participant may contribute trials to multiple clusters, meaning the demographic comparison approximates rather than cleanly tests between-subjects' differences. Third, the effect size was small to small-medium (Cramér's V = 0.108-0.213).

Importantly, participants were not instructed to follow any particular decision strategy, thus the present findings align with Chen & Dai (2025), who showed that in free-choice settings transition patterns reflect information acquisition tendencies rather than direct indicators for underlying decision-making strategies. The identified clusters should therefore be interpreted as descriptions of how visual attention was distributed during the task, not as evidence that participants consciously adopted a specific decision-making approach.

Overall, the evidence suggests that visual attention in multi-product environments is shaped by varying degrees of cross-product and within-product comparison. Attribute-based cluster emerges as the most stable and constrained viewing pattern, consistently identified across all three feature representations. Hybrid and Attribute-leaning, by contrast, are more heterogeneous and less consistently separable, reflecting the adaptive and flexible nature of online information acquisition. The presence of both the Attribute-leaning and Hybrid clusters suggests that consumers do not commit to a single processing mode for the entirety of a trial but adapt their scanning strategy in response to the available alternatives, task demands, or preliminary impressions formed during initial product inspection.

Conclusion

The process of making decisions online requires people to continuously allocate their visual attention between competing products and product-related cues in an information-rich environment. Although eye-tracking research has widely examined visual attention in online shopping, many existing studies rely on predefined groups' comparisons and static fixation metrics. As a result, the sequential structure of gaze behaviour remains less explored. This thesis addressed that gap by deriving eye movement transitions sequences and applying unsupervised clustering to identify naturally occurring patterns of information acquisition on multi-product search pages.

The theoretical foundation of the thesis was based on consumer decision-making research that distinguishes between attribute-based and alternative-based processing modes. It also relies on adaptive decision-making theory, which suggests that consumers do not necessarily follow a fixed processing mode, but adjust their information search according to task demands and available alternatives. Previous eye-tracking research in online shopping has shown that visual cues such as images, prices, descriptions, and reviews play an important role in guiding product evaluation and purchase decisions. However, less attention has been paid to how differently consumers move between these cues across several products. Clustering methods therefore provide a useful methodological approach, as they make it possible to identify behavioural groups directly from gaze transition data rather than relying only on predefined consumer categories.

For empirical analysis, eye-tracking data were collected from participants browsing on several screenshots of multi-product Amazon search pages for reusable water bottles. Gaze transitions between areas of interest were represented as three parallel feature sets – raw transition rates, the Payne Index, and the Search Index. Afterwards K-Means clustering was applied independently to each. Three parallel clustering converged on a three-group solution. The Attribute-based cluster, the most stable and consistently identified group, was characterised by systematic cross-product scanning within the same element type and concentrated nearly all fixation time on product images. The Hybrid cluster combined within-product and cross-product transitions at roughly equal rates and allocated substantially more fixation time to descriptions and other secondary cues. The Attribute-leaning cluster occupied an intermediate position and was the least stable across methods. Overall, the convergence of three independent clustering approaches supports the credibility of the identified patterns. The Attribute-based cluster was particularly consistent across all feature representations.

Beyond the empirical findings themselves, the study also offers several broader theoretical contributions. It demonstrates that unsupervised clustering on eye movement transition sequences can uncover behaviourally meaningful groups without relying on predefined theoretical categories. It contributes to the growing methodological toolkit of eye-tracking research in consumer behaviour. Rather than classifying participants based demographic characteristics, the approach identifies processing tendencies directly from observed gaze behaviour, offering a more grounded basis for consumer segmentation.

From a practical standpoint, the identification of distinct scanning patterns has implications for e-commerce interface design. Product ranking algorithms could be designed to prioritise image quality and visual clarity for Attribute-based consumers, while ensuring that descriptions and reviews are prominent and easily accessible for Hybrid consumers. More broadly, the coexistence of Attribute-based and Hybrid processing patterns on the same page suggests that interface design could benefit from accommodating both tendencies simultaneously. For example, through switchable layout options such as a compact grid view suited to cross-product comparison and a card-based view that expands product detail for within-product evaluation.

Several limitations should be noted. The clustering approach captures average transition patterns at the trial level, providing a static description of scanning behaviour rather than a dynamic account of within-trial strategy shifts. Cluster assignment at the trial level means that no strong claims can be made about individual-level strategy consistency, as a single participant may contribute trials to multiple clusters. The gender finding should be treated as preliminary given the imbalanced sample composition. Additionally, the low fixation time observed for prices across all clusters may reflect the laboratory setting and the absence of real financial consequences, limiting the generalisability of this finding to naturalistic shopping contexts. Finally, the higher fixation counts observed in the hybrid cluster may partly reflect differences in overall page engagement rather than processing mode alone, an ambiguity that cannot be resolved with the present data.

Future research could address the static nature of the present models by applying dynamic sequential approaches such as Hidden Markov Models, which would allow processing mode transitions to be tracked within individual trials. Replication with a gender-balanced sample would allow the demographic finding to be tested more rigorously. Extending the approach to naturalistic browsing environments with real purchase consequences would further test the generalisability of the identified patterns.

List of references

1. Agost, M. J., & Bayarri-Porcar, V. (2024). The use of eye-tracking to explore the relationship between consumers' gaze behaviour and their choice process. *Big Data and Cognitive Computing*, *8*(12). https://doi.org/10.3390/bdcc8120184
2. Banerjee, P., & Masters, T. (2021). When consumers do not compromise - An eye tracking study! (Working Paper No. IIMK/WPS/446/MM/2021/08). Indian Institute of Management Kozhikode.
3. Beldad, A., De Jong, M., & Steehouder, M. (2010). How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust. *Computers in Human Behavior, 26*(5), 857–869. https://doi.org/10.1016/j.chb.2010.03.013
4. Bell, D. E., Raiffa, H., & Tversky, A. (1988). Descriptive, normative, and prescriptive interactions in decision making. In D. E. Bell, H. Raiffa, & A. Tversky (Eds.), *Decision making: Descriptive, normative, and prescriptive interactions* (pp. 9–30). Cambridge University Press. https://doi.org/10.1017/CBO9780511598951.003
5. Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. *Journal of Consumer Research*, *25*(3), 187–217. https://doi.org/10.1086/209535
6. Böckenholt, U. and Hynan, L.S. (1994), Similarities and differences between SI and SM: A reply to Payne and Bettman. J. Behav. Decis. Making, 7: 123–127. https://doi.org/10.1002/bdm.3960070205
7. Borys, M., & Plechawska-Wójcik, M. (2017). Eye-tracking metrics in perception and visual attention research. *European Journal of Medical Technologies*, 11–23.
8. Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology, 39*(5), 752–766. https://doi.org/10.1037/0022-3514.39.5.752
9. Chen, T., Samaranayake, P., Cen, X. Y., Qi, M., & Lan, Y. C. (2022). The impact of online reviews on consumers' purchasing decisions: evidence from an eye-tracking study. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.865702
10. Chen, W., & Dai, J. (2025). Information search patterns in intertemporal choice do not always reflect decision strategies: An eye-tracking study. *Journal of Behavioral Decision Making*, *38*, e70045. https://doi.org/10.1002/bdm.70045

11. Cheng, F. F., Wu, C. S., & Lin, H. H. (2014). Reducing the influence of framing on internet consumers' decisions: The role of elaboration. *Computers in Human Behavior*, *37*, 56–63. https://doi.org/10.1016/j.chb.2014.04.015
12. Cortiñas, M., Chocarro, R., & Villanueva, A. (2019, June 25). Image, brand and price info: Do they always matter the same? *Eye Tracking Research and Applications Symposium (ETRA)*. https://doi.org/10.1145/3317960.3321616
13. Currim, I. S., Mintz, O., & Siddarth, S. (2015). Information accessed or information available? The impact on consumer preferences inferred at a durable product e-commerce website. *Journal of Interactive Marketing*, *29*, 11–25. https://doi.org/10.1016/j.intmar.2014.09.003
14. Doğan, O., Ayçin, E., & Bulut, Z. A. (2018). Customer segmentation by using RFM model and clustering methods: A case study in retail industry. *International Journal of Contemporary Economics and Administrative Sciences*, *8*(1), 1–19.
15. Duchowski, A. (2007). *Eye Tracking Methodology: Theory and Practice* (2nd ed.). Springer.
16. Edwards, W. (1954). The theory of decision making. *Psychological Bulletin*, *51*(4), 380–417. https://doi.org/10.1037/h0053870
17. Ernst, M., & Paulus, M. P. (2005). Neurobiology of decision making: A selective review from a neurocognitive and clinical perspective. *Biological Psychiatry*, *58*(8), 597–604. https://doi.org/10.1016/j.biopsych.2005.06.004
18. Eurostat. (2025). *E-commerce statistics for individuals*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=E-commerce_statistics_for_individuals
19. Friedman, M., & Savage, L. J. (1948). The utility analysis of choices involving risk. *Journal of Political Economy*, *56*(4), 279–304.
20. Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669. https://doi.org/10.1037/0033-295X.103.4.650
21. Glaholt, M. G., & Reingold, E. M. (2011). Eye Movement Monitoring as a Process Tracing Methodology in Decision Making Research. *Journal of Neuroscience, Psychology, and Economics*, *4*(2), 125–146. https://doi.org/10.1037/a0020692

22. Glickman, M., Sharoni, O., Levy, D. J., Niebur, E., Stuphorn, V., & Usher, M. (2019). The formation of preference in risky choice. *PLoS Computational Biology*, *15*(8). https://doi.org/10.1371/journal.pcbi.1007201

23. Goh, F. W., & Stevens, J. R. (2021). Attribute-Based Choice. In *Routledge Handbook of Bounded Rationality* (pp. 242–253). Routledge. https://doi.org/10.4324/9781315658353-16

24. Grewal, D., Iyer, G. R., & Levy, M. (2004). Internet retailing: Enablers, limiters and market consequences. *Journal of Business Research*, *57*(7), 703–713. https://doi.org/10.1016/S0148-2963(02)00348-X

25. Hwang, Y. M., & Lee, K. C. (2015). Exploring the impacts of consumers' systematic and intuitive cognitive styles on their visual attention patterns in online shopping environments: Emphasis on eye-tracking method. *International Journal of Multimedia and Ubiquitous Engineering*, *10*(12), 175–182. https://doi.org/10.14257/ijmue.2015.10.12.18

26. Hwang, Y. M., & Lee, K. C. (2018). Using an eye-tracking approach to explore gender differences in visual attention and shopping attitudes in an online shopping environment. *International Journal of Human-Computer Interaction*, *34*(1), 15–24. https://doi.org/10.1080/10447318.2017.1314611

27. Jacob, R. J. K., & Karn, K. S. (2002). Eye tracking in human-computer interaction and usability research: Ready to deliver the promises [Preprint]. Tufts University / Xerox Corporation.

28. Jansen, S. J. T. (2011). The multi-attribute utility method. In S. J. T. Jansen, H. C. C. H. Coolen, & R. W. Goetgeluk (Eds.), *The measurement and analysis of housing preference and choice* (pp. 101–125). Springer. https://doi.org/10.1007/978-90-481-8894-9_5

29. Jenke, L., Bansak, K., Hainmueller, J., & Hangartner, D. (2021). Using eye-tracking to understand decision-making in conjoint experiments. *Political Analysis*, *29*(1), 75–101. https://doi.org/10.1017/pan.2020.11

30. Johnson, R. L., Nambiar, D., & Suman, G. (2022). Using eye-movements to assess underlying factors in online purchasing behaviors. *International Journal of Consumer Studies*, *46*(4), 1365–1380. https://doi.org/10.1111/ijcs.12762

31. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

32. Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.

33. Kim, D., & Lee, S. (2020). A study on visual behavior for presenting consumer-oriented information on an online fashion store. *Journal of the Korean Society of Clothing and Textiles*, *44*(5), 789–809. https://doi.org/10.5850/JKSCT.2020.44.5.789

34. Kucharský, Š., Trutescu, G. O., Zaharieva, M., Visser, I., Laurence, P. G., & Raijmakers, M. E. J. (2020). Cognitive strategies revealed by clustering eye movement transitions. *Journal of Eye Movement Research*, *13*(1), 1–20. https://doi.org/10.16910/jemr.13.1.1

35. Liu, Z., Yeh, W. C., Lin, K. Y., Lin, H. C. S., & Chang, C. Y. (2024). Machine learning based approach for exploring online shopping behavior and preferences with eye tracking. *Computer Science and Information Systems*, *21*(2), 593–623. https://doi.org/10.2298/CSIS230807077L

36. Loewenstein, G. F., Hsee, C. K., Weber, E. U., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

37. Luce, R. D., & von Winterfeldt, D. (1994). What common ground exists for descriptive, prescriptive, and normative utility theories? *Management Science*, *40*(2), 263–279.

38. Modi, N., & Singh, J. (2023). Understanding Online Consumer Behavior at E-commerce Portals Using Eye-Gaze Tracking. *International Journal of Human-Computer Interaction*, *39*(4), 721–742. https://doi.org/10.1080/10447318.2022.2047318

39. Niza Braga, J., & Jacinto, S. (2022). Effortless online shopping? How online shopping contexts prime heuristic processing. *Journal of Consumer Behaviour*, *21*(4), 743–755. https://doi.org/10.1002/cb.2032

40. Noguchi, T., & Stewart, N. (2018). Multialternative decision by sampling: A model of decision making constrained by process data. *Psychological Review*, *125*(4), 512–544. https://doi.org/10.1037/rev0000102

41. Park, C. H., & Park, Y.-H. (2016). Investigating purchase conversion by uncovering online visit patterns. *Marketing Science*, *35*(6), 894–914. https://doi.org/10.1287/mksc.2016.0990

42. Payne, J. W. (1975). *Task complexity and contingent processing in decision making: An information search and protocol analysis* (CIP Working Paper No. 287). Carnegie-Mellon University.

43. Payne, J. W. (1982). Contingent decision behavior. *Psychological Bulletin, 92*(2), 382–402. https://doi.org/10.1037/0033-2909.92.2.382

44. Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. Journal of Experimental Psychology: Learning, Memory, and Cognition, 14(3), 534–552. https://doi.org/10.1037/0278-7393.14.3.534

45. Petty, R. E., & Cacioppo, J. T. (1986). *Communication and persuasion: Central and peripheral routes to attitude change*. Springer-Verlag.

46. Poole, A., Ball, L. J., & Phillips, P. (2004). In search of salience: a response-time and eye-movement analysis of bookmark recognition. In S. Fincher, P. Markopoulos, D. Moore, & R. Ruddle (Eds.), *People and Computers XVIII - Design for Life*. Springer.

47. Russo, J. E., & Dosher, B. A. (1983). Strategies for multiattribute binary choice. Journal of Experimental Psychology: Learning, Memory, and Cognition, 9(4), 676–696. https://doi.org/10.1037/0278-7393.9.4.676

48. Ryan-Lortie, J., Pelletier, G., Pilgrim, M., & Fellows, L. K. (2023). Gaze differences in configural and elemental evaluation during multi-attribute decision-making. *Frontiers in Neuroscience*, *17*. https://doi.org/10.3389/fnins.2023.1167095

49. Santos, R. D. O. J. dos, Oliveira, J. H. C. de, Rocha, J. B., & Giraldi, J. D. M. E. (2015). Eye tracking in neuromarketing: a research agenda for marketing studies. *International Journal of Psychological Studies*, *7*(1). https://doi.org/10.5539/ijps.v7n1p32

50. Schaffer, E. I., Kawashima, H., & Matsuyama, T. (2016). A probabilistic approach for eye-tracking based process tracing in catalog browsing. *Journal of Eye Movement Research*, *9*(7), 1–14. https://doi.org/10.16910/jemr.9.7.4

51. Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, *69*(1), 99–118. https://doi.org/10.2307/1884852

52. Sun, H., Wang, W., Liu, X., Zhu, B., Huang, Y., Leng, X., & Jia, L. (2022). Comparison of Self-Report Questionnaire and Eye Tracking Method in the Visual Preference Study of a Youth–Beverage Model. *Foods*, *11*(4). https://doi.org/10.3390/foods11040505

53. Tupikovskaja-Omovie, Z., & Tyler, D. (2020). Clustering consumers' shopping journeys: Eye tracking fashion m-retail. *Journal of Fashion Marketing and Management*, *24*(3), 381–398. https://doi.org/10.1108/JFMM-09-2019-0195

54. Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, *79*(4), 281–299. https://doi.org/10.1037/h0032955

55. Veale, R., Quester, P., & Karunaratna, A. (2006, July 6–8). *The role of intrinsic (sensory) cues and the extrinsic cues of country of origin and price on food product evaluation* [Conference paper]. 3rd International Wine Business & Marketing Research Conference, Montpellier, France.

56. Zajonc, R. B. (1980). Feeling and thinking: Preferences need no inferences. *American Psychologist*, *35*(2), 151–175. https://doi.org/10.1037/0003-066X.35.2.151

Appendices

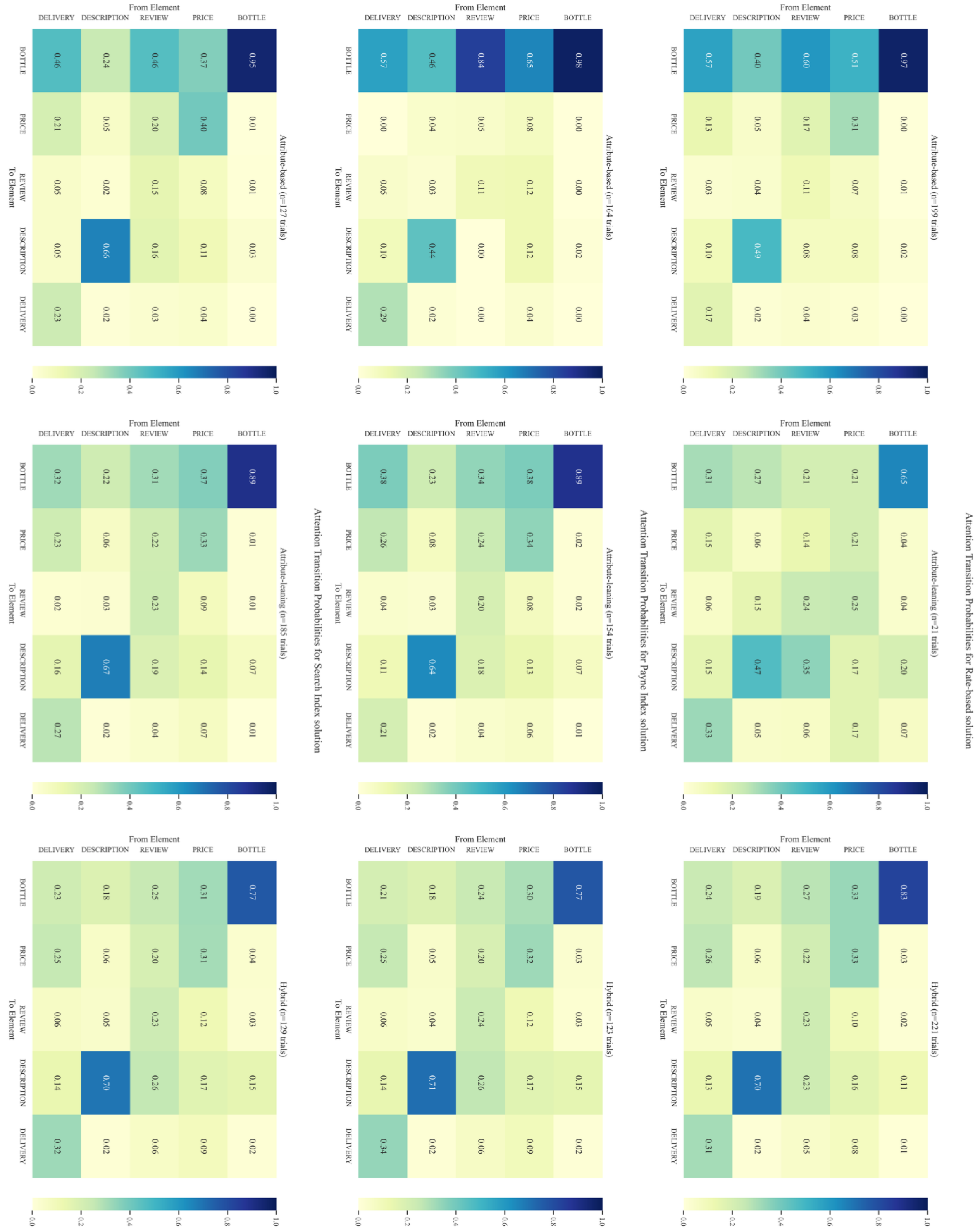
Appendix A

Example of AOI mapping used for eye-tracking data preparation

Source: Laboratory research project materials based on AOI mapping conducted in Tobii Pro Lab on Amazon product search result pages displayed through the software's internal browser

Appendix B

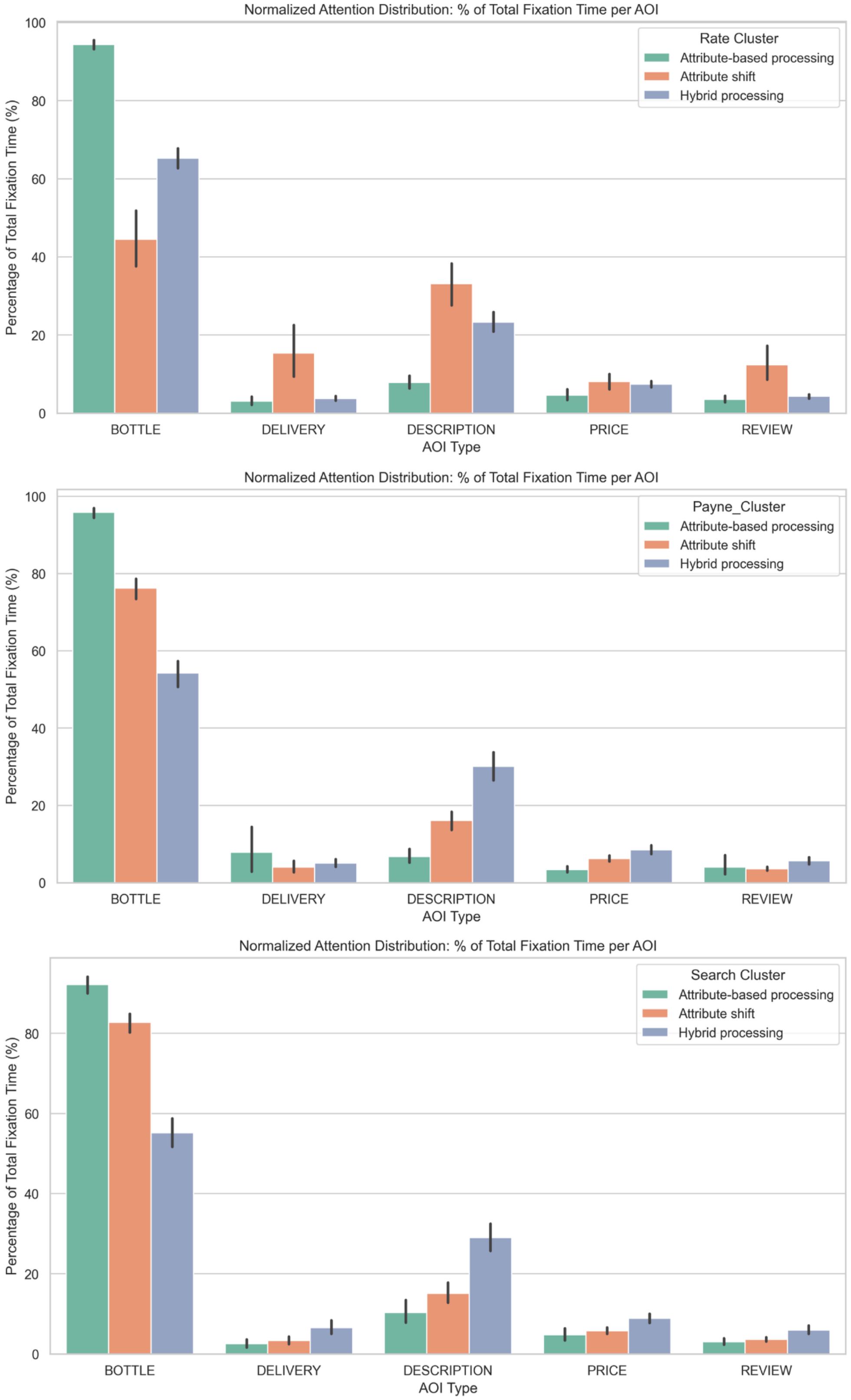
Attention transition probability heatmaps for three clustering solutions



Source. Compiled by the author based on the output from VSC

Appendix C

Normalised fixation time per AOI type for all three clustering solutions



Source. Compiled by the author based on the output from VSC

Resümee

VISUAALNE TÄHELEPANU JA OTSUSTUSMUSTID VEEBIPOES: PILGUJÄLGIMISE ANDMETE KLASTERANALÜÜS

Yevheniia Baranovych

Käesoleva bakalaureusetöö eesmärk on tuvastada veebipoes ostlemisel esinevaid otsustusmustreid, kasutades selleks pilguliikumise järjestuste põhist klasterdamist ning fikseeringute kestvuse analüüsi mitme tootega otsingutulemuste lehtedel. Kuigi on tehtud varasemaid pilgujälgimise uuringud veebipoes ostlemise teemal, ent ükski uuring ei ole rakendanud juhendamata masinõpet klastrite moodustamist mitme toote otsingulehtede pilgujälgimise andmetele, et tuvastada esinevaid otsustusmustreid.

Uuring põhineb tarbijate otsustusprotsessi teoorial, täpsemalt eristusel info töötlemise viiside vahel – omaduspõhine ja alternatiivipõhine töötlemine. Seda täiendab adaptiivne otsustusprotsessi teooria, mille kohaselt valivad tarbijad ülesande nõudmistele vastavalt paindlikult töötlemise strateegia, selle asemel et rakendada kindlat kognitiivset stiili.

Bakalaureusetöö süvendab teoreetilist arusaama tarbijate otsuste tegemisest veebikeskkonnas, näidates, et pilgujälgimise põhise üleminekujärjekorrad võivad toimida info omandamise tendentside jälgitavate näitajatena. Kontseptuaalselt ühendab uuring kognitiivse otsustamisalase kirjanduse pilgujälgimise metoodikaga, operatsionaliseerides omaduspõhise ja alternatiivipõhise töötlemise eristatavate pilguüleminekumustritena, mida on võimalik mõõta mitme toote paigutuse puhul. Analüüs annab panuse ka kontseptuaalsesse arutelusse adaptiivse strateegia valiku üle, näidates, et tarbija visuaalne käitumine ei koondu üheainsa töötlemisrežiimi ümber, vaid jaguneb kolmeks eristatavaks mustriks. Need tulemused toetavad seisukohta, et strateegia valik sõltub olukorrast ning et individuaalsed erinevused teabe omandamises peegeldavad pigem veebipõhise otsustamisprotsessi paindlikku ja adaptiivset olemust kui kindlaid töötlemis eelistusi.

Empiiriline uuring põhines Tartu Ülikooli Neuroturunduse laboris kogutud 90 osaleja pilgujälgimise andmetel, kes sirvisid Amazonis mitut toodet hõlmavaid otsingulehti. K-keskmiste klastrite moodustamine pilgujälgimise üleminekujärjekordade kolme tunnusnäitaja põhjal andis järjekindlalt kolme klastri lahenduse: omaduspõhine klaster, mida iseloomustasid süstemaatilised toodetevahelised üleminekud samade elementide vahel; hübriidklaster, milles tootesiseste ja toodetevaheliste üleminekute vahekord on tasakaalus; ning vähem stabiilne, atribuutidele kalduv klaster vahepealses positsioonis. Sugu oli ainus demograafiline muutuja, mis oli kõigi kolme lahenduse puhul klastrisse kuulumisega oluliselt

seotud, kusjuures naissoost osalejad määrati sagedamini atribuutidel põhinevasse klastrisse; väikese mõju suuruse tõttu tuleks seda tulemust siiski käsitleda esialgse järeldusena.

Erinevate visuaalsete skannimismustrite kindlakstegemisel on otsene mõju e-kaubanduse liidese disainile: toodete järjestamise algoritme ja paigutuse valikuid saaks kohandada kõigi tarbijarühmade vajadustele, näiteks vahetatavate paigutusvalikute abil, nagu kompaktne rastervaade ja laiendatud kaardipõhine vaade.