Journal of Retailing and Consumer Services 79 (2024) 103806

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

# Psychographic segmentation of multichannel customers: investigating the influence of individual differences on channel choice and switching behavior

Jan Blömker *, Carmen-Maria Albrecht

*MSB Münster School of Business, FH Münster, 48149 Münster, Germany*

A R T I C L E I N F O

Handling editor: Prof. H. Timmermans

*Keywords:*
Multichannel customer behavior
Customer journey
Individual differences

A B S T R A C T

This study investigates the role of individual differences in channel choice and switching behavior in a multichannel environment using latent class analysis on data from 1512 customers. Psychographic variables from five domains (risk attitudes, cognitive ability, motivation, personality, and decision-making style) serve as covariates for multichannel customer behavior. We identify six segments that differ significantly on six psychographic variables (readiness to take risks, need for cognition, autotelic and instrumental need for touch, and rational and intuitive decision-making styles). The results advance the theory-building of multichannel customer behavior and present insights for proactively managing customer journeys of distinct segments.

## 1. Introduction

The typical purchase decision process has become an actual journey for consumers (e.g., Lemon and Verhoef, 2016; Tueanrat et al., 2021a). With the widespread digitalization and emergence of commercial Internet (e.g., Grewal et al., 2017), companies have advanced retailing and distribution strategies to a multi- or omnichannel retailing concept (Verhoef et al., 2015). Consequently, the retail environment has experienced a proliferation of interconnected retail channels (e.g., Beck and Rygl, 2015), resulting in consumers being constantly confronted with channel choices (Verhoef, 2021). However, consumers now have unprecedented flexibility to shape their customer journey (Herhausen et al., 2019) and switch between channels and retailers (Frasquet and Miquel-Romero, 2021). Since the emergence of new, complex, and highly individual customer journeys, the predictability of multichannel customer behavior has become increasingly challenging (Ailawadi and Farris, 2017; Lemon and Verhoef, 2016).

To improve the predictability of modern multichannel customer behavior and enhance multichannel strategies, it is crucial to better understand the factors that influence channel choices during the customer journey (Mukherjee and Chatterjee, 2021). Generally, decision-making can be affected by situational factors and decision features (i.e., external factors) as well as the individual differences of the decision-maker (i.e., internal factors) (Appelt et al., 2011). Previous multichannel studies have been centered on situational factors and decision features, focusing on channel integration (e.g., Gao and Huang, 2021) or customer experience (e.g., Mishra et al., 2021). However, since utility perceptions are shaped extensively by the customer's personal characteristics, leveraging individual differences offers great potential for predicting specific outcomes of multichannel customer behavior, such as channel choices and preferences (Matz and Netzer, 2017). Knowledge of the decisional impact of individual differences has recently gained practical relevance in marketing, as psychological traits can now be retrieved from digital footprints and customer data (Matz et al., 2020). Moreover, personalizing marketing activities based on the customers' psychological traits leads to a more positive perception of the marketing activity and higher marketing effectiveness (Matz et al., 2020; Teeny et al., 2021; Zhang et al., 2024).

Pioneering research in multichannel retailing such as Konuş et al. (2008), Sands et al. (2016), and Nakano and Kondo (2018) already highlighted the importance of investigating how multichannel customer behavior is shaped by psychological traits. However, a systematic and coordinated approach for employing appropriate psychographic measures to predict multichannel customer behavior and to build on sophisticated multichannel strategies is currently lacking (Mishra et al., 2021, p. 161). We address this gap in our research by proposing a systematic theoretical framework. Since multichannel customer behavior is a representation of complex decision-making (Mukherjee and

* Corresponding author.
*E-mail address:* jan.bloemker@fh-muenster.de (J. Blömker).

https://doi.org/10.1016/j.jretconser.2024.103806
Received 4 January 2024; Received in revised form 19 February 2024; Accepted 8 March 2024
Available online 25 March 2024

Chatterjee, 2021), our research builds upon fundamental research from judgment and decision-making (Appelt et al., 2011). We systematically incorporate psychographic measures from the domains of risk attitudes, cognitive ability, motivation, personality, and decision-making style to explain large fractions of variance in channel choice behavior. With the proposed framework, we additionally aim to clarify the role of individual differences compared to the external channel choice factors (i.e., channel attributes, marketing efforts, social influences, contextual factors, and channel experiences) (Verhoef et al., 2022). Clarifying this question is critical for further research in this field.

Thus, our study contributes to the existing literature by (1) proposing and testing a theoretical framework for systematically investigating customers' individual differences affecting multichannel customer behavior and (2) highlighting the importance of individual differences in multichannel customer behavior by comparing the effect sizes of the various channel choice factors. With the help of the results of this study, we aim to better understand multichannel customer behavior and to enhance multichannel strategy building.

## 2. Literature review and theoretical framework

### *2.1. Channel choice behavior and utility perceptions*

Central to multichannel customer behavior is channel choice. Channel choice behavior includes transactional or informational exchanges with firms or other customers in commercial contexts (Herhausen et al., 2019). Verhoef et al. (2022) identified six determining factors of individual channel choices: channel attributes, marketing efforts, social influences, contextual factors, channel experiences, and consumer characteristics. While previous research has often focused on isolated determinants, such as channel attributes (e.g., Noble et al., 2005) or marketing efforts (Timoumi et al., 2022), a comprehensive comparison of their influence remains unexplored. This creates ambiguity regarding the relative importance of consumer characteristics in multichannel customer behavior and must be investigated for a better understanding of their role in multichannel customer behavior.

From a utilitarian perspective, the central assumption underlying channel choice is that customers select a channel that maximizes their personal utility in a distinct situation among all available alternatives (Noble et al., 2005). Thus, the highest subjective channel utility determines the likelihood of the channel choice. Throughout the customer journey, individuals may encounter numerous channel utility trade-offs, making multichannel customer behavior an iterative and highly individual multi-stage decision-making process (Mukherjee and Chatterjee, 2021). Under this rationale, Borghans and Schils (2021) highlighted the importance of consumer characteristics in economic utility calculations in decision-making. They showed that decision-makers' psychological traits considerably influence individual utility perceptions. Consumers choose alternatives based on their traits to achieve optimal utility. For channel choices, this implies that personal characteristics shape the perceptions of the costs and benefits of a channel, which are ultimately expressed by individual channel utility calculation (Herhausen et al., 2019; Konuş et al., 2008; Maggioni et al., 2020).

One effective approach for capturing different choice patterns and reducing the complexity of individual customer journeys is customer segmentation (Kondo and Okubo, 2022). Previous studies have conducted multichannel customer segmentation by subsuming customers with similar channel choices or usage behaviors into specified segments (see Table 1). Channel utility was measured using either ordinal utility measures (e.g., De Keyser et al., 2015; Herhausen et al., 2019) or cardinal utility measures (e.g., Konuş et al., 2008; Sands et al., 2016). Segmentation results were obtained by using data on customers' channel choices within various product categories and by describing the segments with the help of customers' individual differences as psychographic covariates (e.g., Konuş et al., 2008; Nakano and Kondo, 2018). While Schröder and Zaharia (2008) and Konuş et al. (2008) began segmenting multichannel customers at a similar time, the methodological approach of (latent class) cluster analysis by Konuş et al. (2008) has largely prevailed to date. These studies revealed certain commonalities in segment composition, which suggests that multichannel customer behavior can be translated into a robust combination of certain behavioral patterns. Each study observed at least one *store-focused segment*, one *online-focused segment,* and a segment of *multichannel enthusiasts* (also described as *research shoppers* or *true multichannel shoppers*), along with more granular segments (see Table 1). Although multichannel customer behavior produces robust types of customer segments, the psychological traits explaining multichannel customer behavior are not consistently replicable across studies (De Keyser et al., 2015; Herhausen et al., 2019; Konuş et al., 2008; Nakano and Kondo, 2018; Sands et al., 2016) and lack a unified theoretical foundation (Frasquet et al., 2015; Konuş et al., 2008; Schröder and Zahria, 2008). Extensions of Konuş et al.'s (2008) segmentation scheme mostly accounted for technological developments in multichannel retailing over the past years. However, they missed to enhance the predictive validity of psychographic covariates by systematizing the framework of psychographic variable selection. De Keyser et al. (2015) added the after-sales phase to the segmentation scheme, and Sands et al. (2016) provided the newly arisen mobile and social media channels. Nakano and Kondo (2018) used actual customer data instead of survey data to capture multichannel customer behavior. With the Technology Acceptance Model (TAM) (Davis, 1989), Frasquet et al. (2015) were the first to use a theoretical framework. However, this model primarily focuses on the motivational aspects of channel choices and does not address the influence of individual differences in decision-making processes. Therefore, our study closes this gap by proposing a systematic theoretical framework from judgment and decision-making literature for identifying reliable psychological predictors of multichannel customer behavior.

### *2.2. Individual differences in multichannel customer behavior*

Individual differences significantly influence economic utility calculation and, consequently, decision-making (e.g., Borghans and Schils, 2021). Herhausen et al. (2019) stated that individual differences between customers elicit different benefits and costs for specific channels, which lead to different marginal utilities and ultimately to different channel choices and journey patterns. In prior segmentation studies on multichannel customer behavior following the approach of Konuş et al. (2008), researchers have consistently employed a range of singular psychographic measures (such as innovativeness, loyalty, motivation to conform, shopping enjoyment, price consciousness, time pressure, and involvement) to address individual differences in the perception of the benefits and costs of channel choices, as outlined in Table 1. These studies contributed to advancing our understanding of how psychological traits influence channel selection. These studies show that certain constructs (i.e., innovativeness, shopping enjoyment, and time pressure) are promising indicators of segment membership. However, the significant influence of these variables in determining segment membership cannot be consistently replicated (see Table 1). The variables selected were initially used by Ailawadi et al. (2001) to explain customers' reactions towards brand promotions (Konuş et al., 2008). To enhance the replicability and robustness of these segmentation models, we suggest a coordinated approach of psychographic variable selection tailored to the properties of the channel choice process. Frasquet et al. (2015) initiated progress in this area by applying the Technology Acceptance Model (TAM) from Davis (1989) to identify intrinsic and extrinsic motivators for explaining channel choice. While the TAM (Davis, 1989) provides a useful framework for understanding approach or avoidance behaviors towards online channels, it does not capture the nuanced range of the patterns of multichannel behavior. Moreover, it overlooks various individual differences beyond motivational aspects. Consequently, the approaches employed by Konuş et al. (2008) and Frasquet et al. (2015) reveal avenues for further exploration to capture various factors

**Table 1**
Segmentation studies investigating individual differences in multichannel customer behavior.

| Studies | Sample | Method | Product categories | Segments | Psychographic variables | Origin of psychographic variable selection | Theoretical framework |
|---|---|---|---|---|---|---|---|
| Schröder and Zaharia (2008) | *N* = 525 (Survey data) | Discriminant analysis<br>MANOVA | Apparel<br>Housewares<br>Kitchen and gardening items<br>Consumer electronics<br>Office and school products<br>Toys | Chain store + chain store (CS + CS) (29.9%)<br>Shop within grocery store + shop within grocery store (GS + GS) (12.6%)<br>Shop within bakery + shop within bakery (BS + BS) (6.1%)<br>Catalog + catalog (CT + CT) (11.2%)<br>Online-shop + online-shop (ON + ON) (7.6%)<br>Online-shop + chain store (ON + CS) (5.9%)<br>All further usage patterns (26.7%) | Recreational orientation*<br>Convenience orientation*<br>Independence orientation*<br>Risk aversion* | Singular selection from channel choice literature | Integrative theory of patronage preference and behavior (Sheth, 1983) |
| Konuş et al. (2008) | *N* = 364 (Survey data) | LCA | Books<br>Mortgage<br>Electronics<br>Holidays<br>Clothing<br>Computers<br>Insurance | Uninvolved shoppers (40%)<br>Multichannel enthusiasts (37%)<br>Store-focused consumers (23%) | Price consciousness*<br>Shopping enjoyment*<br>Innovativeness*<br>Motivation to conform<br>Brand/retailer loyalty*<br>Time Pressure | Psychological traits as drivers of store brand and national brand promotion usage by Ailawadi et al. (2001) | – |
| Frasquet et al. (2015) | *N* = 1533 (Survey data) | Hierarchical and k-means cluster analysis | Apparel<br>Consumer electronics | Apparel \| Electronics:<br>Online shoppers (26.1% \| 26.1%)<br>Reluctant MC shoppers (12.0% \| 16.5%)<br>Uninvolved MC shoppers (11.3%); Online searchers (16.7%)<br>True MC shoppers (17.9% \| 32.2%)<br>Offline shoppers (32.7% \| 8.5%) | Usefulness*<br>Security*<br>Time pressure*<br>Ease-of-use*<br>Enjoyment*<br>Hedonic orientation<br>Product involvement* | Singular selection from channel choice literature | Technology Acceptance Model (Davis, 1989) |
| De Keyser et al. (2015) | *N* = 314 (Survey data) | LCA | Telecom | Research shoppers (after sales: store) (34%)<br>Web-focused shoppers (22%)<br>Store-focused shoppers (18%)<br>Research shoppers (after sales: Internet/store) (11%)<br>Web-focused shoppers (after sales: store/call center) (9%)<br>Call center-prone shoppers (6%) | Perceived price<br>Perceived risk<br>Innovativeness<br>Perceived product complexity<br>Loyalty*<br>Involvement | Psychological traits as drivers of store brand and national brand promotion usage by Ailawadi et al. (2001) | – |
| Sands et al. (2016) | *N* = 930 (Survey data) | LCA | Clothing<br>Holiday travel<br>Consumer electronics | ROPO, anti-mobile/social media (35.9%)<br>ROPO, multichannel enthusiasts (22.4%)<br>ROPO, social media enthusiasts (15.8%)<br>Internet-focused, anti-mobile (14.0%) | Price consciousness*<br>Shopping enjoyment*<br>Innovativeness*<br>Brand/retailer loyalty<br>Time Pressure | Psychological traits as drivers of store brand and national brand promotion usage by Ailawadi et al. (2001) | – |

(*continued on next page*)

**Table 1** (*continued*)

| Studies | Sample | Method | Product categories | Segments | Psychographic variables | Origin of psychographic variable selection | Theoretical framework |
|---|---|---|---|---|---|---|---|
| Nakano and Kondo (2018) | $N = 2595$ (Survey and purchase data) | LCA | Groceries<br>Beverages<br>Sundries<br>Cosmetics<br>Drugs | Internet-focused, multi-channel enthusiasts (11.9%)<br>Store-focused customers; Anti-digital (21.3%)<br>Store-focused light customers; Anti-digital (19.0%)<br>Store-focused light customers; Multimedia/ social (15.7%)<br>Store-focused customers; Multimedia (15.7%)<br>Uninvolved shoppers; Average (15.4%)<br>Online-favored multichannel enthusiasts; PC (6.5%)<br>Store-favored multichannel enthusiasts; Multimedia/ social (6.4%) | Price consciousness<br>Shopping enjoyment<br>Innovativeness*<br>Motivation to conform<br>Brand/retailer loyalty*<br>Time Pressure* | Psychological traits as drivers of store brand and national brand promotion usage by Ailawadi et al. (2001) | – |
| Herhausen et al. (2019) | $T_1$: $N = 2443$<br>$T_2$: $N = 2649$<br>(Survey data) | LCA | Apparel<br>Cosmetics<br>Electronics<br>Entertainment | Store-focused shoppers (22% \| 24%)<br>Pragmatic online shoppers (23% \| 22%)<br>Extensive online shoppers (21% \| 13%)<br>Multiple touchpoint shoppers (13% \| 14%)<br>Online-to-offline shoppers (20% \| 26%) | Price consciousness<br>Time pressure<br>Involvement | Singular selection from channel choice literature | – |
| Current study | $N = 1512$ (Survey data) | LCA | Clothing<br>Holiday travel<br>Consumer electronics | Desktop-focused single-channel shoppers (24.5%)<br>Mobile-focused light-multichannel shoppers (16.5%)<br>Store-focused single-channel shoppers (15.9%)<br>Mobile-focused multichannel social shoppers (15.9%)<br>Desktop-focused multichannel comparison shoppers (15.1%)<br>Store-focused analog multichannel shoppers (12.1%) | Readiness to take risks*<br>Need for cognition*<br>Chronic shopping orientation<br>Autotelic need for touch*<br>Instrumental need for touch *<br>Resistance to change<br>Exploratory buying behavior tendency<br>Neuroticism<br>Openness<br>Conscientiousness<br>Agreeableness<br>Extraversion<br>Rational style*<br>Intuitive style*<br>Dependent style<br>Avoidant style<br>Spontaneous style<br>Maximization tendency<br>Regret tendency | Based on findings from channel choice literature within the categories of risk attitudes, cognitive ability, motivation, personality, and decision-making style proposed by Appelt et al. (2011) | Decision Making Individual Differences Inventory ( Appelt et al., 2011) |

*Notes:* $T$ = Time point of measurement; *LCA* = Latent class analysis; *MANOVA* = Multivariate analysis of variance; *Covariate with a statistically significant influence ($p < 0.05$) on segment membership in LCA.

influencing channel choice more comprehensively.

To broaden and systematize the investigation of individual differences in multichannel customer behavior, we propose a novel framework by synthesizing fundamental research from the area of judgment and decision-making (Appelt et al., 2011) and recent research on channel choice determinants (Verhoef et al., 2022). According to Verhoef et al. (2022), the six categories of channel choice determinants contribute proportionally to the utility perception within channel choices. We delineate the external channel choice factors (i.e., channel attributes, marketing efforts, social influences, contextual factors, and channel experiences) from the internal channel choice factors (i.e., individual differences) to examine which specific psychological traits are relevant for utility perception. Additionally, we can identify how strong their influences are compared to the external channel choice factors. For psychographic variable selection, we draw on the research of Appelt et al. (2011) that distinguished five categories of individual differences that have a considerable influence on utility perception and personal decision-making patterns: risk attitudes, cognitive ability, motivation, personality, and decision-making style. Thus, we incorporate psychographic measures from these categories into multichannel customer segmentation as relevant determinants of channel utility formation within the channel choice process (Fig. 1). Appelt et al. (2011) recommended selecting specific measures for the five categories based on theoretical underpinnings or prior empirical work in the research field. Hence, we follow this approach and select psychological traits for our model that have previously demonstrated a significant impact on multichannel customer behavior.

### 2.2.1. *Risk attitudes*

In economic decision-making, risk attitude reflects the individual's willingness to make a trade-off between the perceived risks and returns of an option. However, the preferred level of risk-taking can vary strongly between individuals (e.g., Figner and Weber, 2011). In multichannel customer behavior, risks and uncertainties mainly occur when channels are subject to technical or procedural uncertainties. These uncertainties arise, for instance, due to distrust in the retailer or their services (e.g., Hermes et al., 2022; Nguyen et al., 2022; Singh and Rosengren, 2020). In specific cases, a low propensity for risk-taking leads to choosing more established channels to avoid procedural uncertainties (e.g., Bezes, 2016; Schröder and Zaharia, 2008). Therefore, the choice and usage of novel or unfamiliar channels are unlikely when the risk propensity is low. De Keyser et al. (2015) did not observe a direct influence of risk aversion on segment membership in multichannel customer segmentation. Hence, the role of individual risk-taking propensity in channel choices remains unclarified (e.g., Wolf and Steul-Fischer, 2022).

### 2.2.2. *Cognitive ability*

Cognitive ability represents consumer competency and commitment to engage in and solve complex and comparative decision-making tasks. This includes the decision-maker's intelligence as well as specific skills and styles of information processing (Appelt et al., 2011). To the best of our knowledge, no known study has attempted to measure the direct effect of consumer intelligence on multichannel customer behavior. However, the *need for cognition* (NFC) (Cacioppo and Petty, 1982) is a viable estimator of cognitive ability (Fleischhauer et al., 2010). Research suggests that high NFC is associated with a higher extent of information processing and search behavior in multichannel contexts, especially when the stimulus is complex (Kim, 2019; Park and Kim, 2021). Additionally, the level of cognitive deliberation could be a determining factor in overall desktop usage (Zhu and Meyer, 2017). Furthermore, conscious and deliberative information processing is higher among customers with high levels of multichannel usage (Rodríguez-Torrico et al., 2020). Presumably, high NFC leads to extensive information-seeking behavior during the search phase.

### 2.2.3. *Motivation*

Individual differences in motivation determine the extent of engagement in specific behaviors. However, different factors can potentially elicit an individual's motivation (Appelt et al., 2011). Relevant indicators of consumer behavior result from either self-regulation or psychological needs and fears. Self-regulation in shopping scenarios can be largely traced by a person's *chronic shopping orientation* (CSO) (Büttner et al., 2014). CSO is a timely and cross-categorially stable disposition of either following hedonic pleasure or being task-oriented while shopping. Konuş et al. (2008) showed that shopping enjoyment predicts segment membership and is most pronounced among multichannel enthusiasts and store-focused shoppers. In addition,

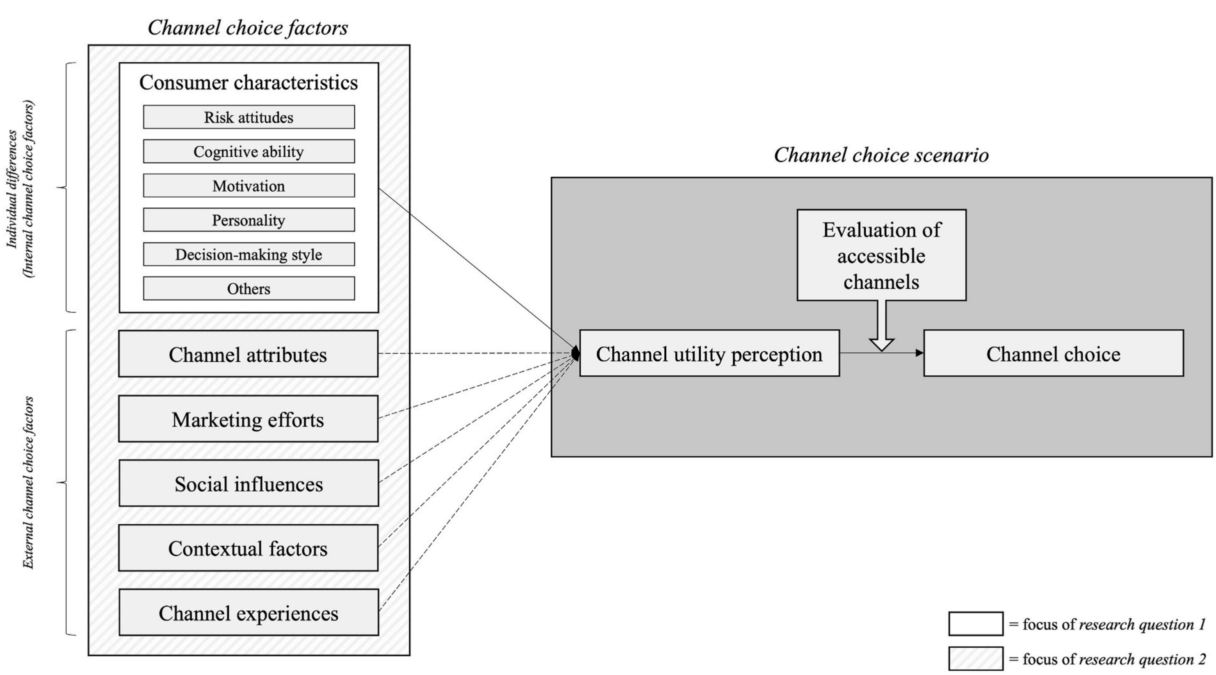


**Fig. 1.** Theoretical framework.

engagement in mobile shopping (Chimborazo-Azogue et al., 2021) and multichannel use increase when the shopping orientation is hedonic (Lee and Jung, 2020). Another motivational construct of self-regulation is the tendency to show *exploratory buying behavior* (EBBT) (Baumgartner and Steenkamp, 1996), which is also referred to as innovativeness (e.g., Konuş et al., 2008) or variety-seeking (e.g., Mukherjee and Chatterjee, 2021) in similar studies. EBBT is beneficial for online channel choices, especially during the search phase (Mukherjee and Chatterjee, 2021), and a lower degree of innovativeness is associated with strong overall anti-digital behavior (Hallikainen et al., 2019). Segmentation studies also positively associate innovativeness with using online touchpoints (Konuş et al., 2008; Nakano and Kondo, 2018; Sands et al., 2016), but there is a slight inconsistency in replicating the significance of this factor (e.g., De Keyser et al., 2015). *Resistance to change* (RTC) (Oreg et al., 2008) represents consumers' individual differences in adapting to new behaviors or adhering to old habits. High RTC leads to inertia in channel choice, which is detrimental to channel-switching intentions (Juaneda-Ayensa et al., 2016; Kazancoglu and Aydin, 2018; Valentini et al., 2011). Finally, *need for touch* (NFT) expresses how strongly a person needs to touch an object to gather information about it and consists of two subscales: autotelic and instrumental NFT (Peck and Childers, 2003). NFT is primarily associated with choosing stationary channels over online channels to fulfill customers' sensory needs for product evaluation (Aw, 2020; Hermes et al., 2022; Maggioni et al., 2020; Tueanrat et al., 2021b), suggesting that a high level of NFT leads to a higher tendency to use brick-and-mortar stores for information search. De Canio and Fuentes-Blasco (2021) provided the first evidence that strong haptic traits can benefit mobile channel usage.

#### 2.2.4. Personality

In modern psychology, personality traits are typically captured within the paradigm of the Big Five personality factors: *extraversion, neuroticism, openness, conscientiousness, and agreeableness* (Hahn et al., 2012). The Big Five personality factors, along with even more fine-grained constructs, have been the subject of research on multichannel customer behavior. Hermes and Riedl (2021) submitted that individuals with a high degree of *openness* are more susceptible to online shopping, whereas those with a high degree of *agreeableness* are less likely to choose online stores. Furthermore, *agreeableness*, *extraversion*, and *conscientiousness* are positively related to in-store purchase willingness (Hermes et al., 2022). However, the exact role of the Big Five personality traits in multichannel customer behavior remains unclear (Liu et al., 2019).

#### 2.2.5. Decision-making style

Scott and Bruce (1995) proposed five general decision-making styles to which an individual can be assigned. These decision-making styles define whether a person makes decisions rationally, intuitively, dependently, avoidantly, or spontaneously. Literature on the effect of decision-making styles on multichannel customer behavior is scarce. However, for general consumer behavior, rational decision-making corresponds to the tendency to thoroughly obtain the given (economic) information beforehand (Hamilton et al., 2016). Additionally, spontaneous decision-making correlates with compulsive buying behavior (Nori et al., 2022).

Another relevant decision-making style not represented by Scott and Bruce (1995) is the maximization tendency and its regret tendency subscale (Schwartz et al., 2002). Individuals differ in the extent to which they maximize a decisional outcome or are satisfied with the minimum acceptable outcome. A higher tendency to maximize is positively associated with channel-switching and extensive information use (e.g., Harris et al., 2021). Additionally, a higher tendency to maximize leads to greater satisfaction with the customer journey (Muthaffar and Vilches-Montero, 2023). However, Muthaffar and Vilches-Montero (2023) also argue that maximization should not only be seen as an individual trait but as a situational mindset, questioning the trait-based approach. Considering the regret tendency, webrooming behavior (i.e., searching online and purchasing offline) is hypothesized to be an expression of regret avoidance in making sub-optimal product choices (Arora and Sahney, 2019). Gensler et al. (2017) showed that anticipated regret is also higher among customers showing showrooming behavior (i.e., searching offline and purchasing online) (Schneider and Zielke, 2020), which leads to the assumption that extensive multichannel behavior is associated with high regret values.

### 2.3. Research questions and research approach

As demonstrated, the understanding of the influence of individual differences on multichannel customer behavior has been significantly enhanced by prior research. Despite these advancements, further exploration is needed in two primary areas. First, a comprehensive and systematic framework for probing individual differences in multichannel customer behaviors is currently lacking. This raises the research question: (1) What role do individual differences in risk attitudes, cognitive ability, motivation, personality, and decision-making style play in multichannel customer behavior? Second, an integrative and comparative perspective is missing when considering the effect sizes of the determining factors of channel choice. This prompts a subsequent research question: (2) What role do individual differences play in multichannel customer behavior compared to channel attributes, marketing efforts, social influences, contextual factors, and channel experiences?

To broaden the scope of observed individual differences in multichannel customer behavior and to answer these research questions, we draw on the established segmentation approach by Konuş et al. (2008). First, we apply LCA (Vermunt, 2010) to segment multichannel customer behavior. Then, we extend this approach by validating our segmentation model using ordinal and cardinal utility measures for model indications. Finally, we integrate the determining factors of channel choice (Appelt et al., 2011; Verhoef et al., 2022) as covariates into our segmentation model and calculate the effect sizes on the segmentation model for each covariate.

## 3. Method

### 3.1. Data collection

Survey data were collected from 1589 German consumers via an online research panel provider[1] in August 2022. The panelists received monetary compensation from a panel provider for participating in the survey. To assure data quality, we implemented two attention checks in the survey leading to a direct screen-out, and reviewed the data set manually for any inconsistencies or invalid responses. In total, 77 respondents were removed from the data set due to invalid responses leading to an effective sample size of $N = 1512$ respondents. The sample size was determined in advance based on methodological (e.g., Wurpts and Geiser, 2014), research-based (Herhausen et al., 2019; Sands et al., 2016), and economic considerations. Respondents were required to be at least 18 years old and have made a purchase within the product category of clothing, holiday travel, or consumer electronics within the past three months. These product categories were selected because they differ in purchase frequency, complexity, and tangibility (Sands et al., 2016). This resulted in a sample composition of 761 participants in the clothing, 374 in consumer electronics, and 377 in holiday travel categories. Quotas were set to ensure equal gender distribution (50.0% female). The mean age was $M = 47.10$ ($SD = 14.47$) years. The sample characteristics

[1] The panel provider adheres to the standards of ISO 20252:2019 and is a member of industry bodies, including the European Society for Opinion and Marketing Research (ESOMAR) and the German Society for Online Research (DGOF).

are listed in Table 2.

### 3.2. Definition and measurement of multichannel customer behavior

To measure individual multichannel customer behavior, we obtained respondents' channel choices from a recent customer journey from one of three product categories within the previous three months. We draw on the principle of ordinal utility perception and assume that channel choices represent the highest subjective channel utility in this situation (Herhausen et al., 2019). Channel choices were obtained separately for the search, purchase, and after-sales phases (De Keyser et al., 2015; Sands et al., 2016). Respondents could select from a list of channels that were based on existing multichannel literature, adapted to the characteristics of each phase of the customer journey so that all major current channel offerings were included (Herhausen et al., 2019; Lemon and Verhoef, 2016; Lynch and Barnes, 2020; Verhoef et al., 2022). Respondents could select more than one channel if required, reflecting the complex structures of the search and after-sales phases. For the after-sales phase, respondents could also indicate not having used a channel, if applicable to their customer journey.

Additionally, the respondents indicated the order in which they used the channels in the search phase and assessed the importance of these channels in their purchase decisions (on a 7-point Likert scale with 1 = not important and 7 = very important) (Herhausen et al., 2019). Using this information, three dummy-coded variables were developed a posteriori. *Moment of truth* represents the search channel rated as most important for the purchase decision. If two or more channels were rated as equally important, the channel used closer to the purchase phase was selected. The *number of search phase channels* refers to the number of channels used by respondents during the search phase (Herhausen et al., 2019). *Channel-switching* is dichotomous and can be expressed either by *switching* (i.e., the last channel used in the search phase differs from the channel used in the purchase phase) or *staying* (i.e., the last channel used in the search phase corresponds to the channel used in the purchase phase). The variables of *purchase channel* and *after-sales channel* consist of channel choices made in the purchase and after-sales phases.

In a separate section of the survey, we additionally addressed the approach of cardinal utility measurement. The respondents indicated their general utility perceptions on a 7-point Likert scale from 1 (not at all appropriate) to 7 (fully appropriate) for each channel within all three customer journey phases, now for all three product categories (i.e., clothing, holiday travel, consumer electronics) in general (Konuş et al., 2008; Sands et al., 2016). The mean values of the cardinal channel utility measures were then calculated across the three product categories, giving each channel an overall cardinal utility value (ranging from 1 to 7) for each stage in the customer journey.

### 3.3. Definition and measurement of covariates

*Psychographic covariates:* We assumed that several psychographic variables categorized by Appelt et al.'s (2011) framework can substantially shape multichannel customer behavior. Representing the category

**Table 2**
Sample characteristics ($N = 1512$).

| Gender | % | Age | |
|---|---|---|---|
| Female | 50.0 | *Mean* | 47.10 |
| Male | 50.0 | *SD* | 14.47 |
| *Household size* | % | *Education* | % |
| 1 person | 25.7 | No degree | 0.1 |
| 2 persons | 41.0 | Lower secondary degree | 8.9 |
| 3 persons | 17.3 | General secondary degree | 32.8 |
| 4 persons | 12.2 | A-levels | 24.6 |
| 5 persons | 3.0 | University degree | 31.5 |
| 6 or more persons | 0.8 | PhD | 2.1 |
| *Occupation* | % | *Marital status* | % |
| Student | 4.8 | Unmarried | 31.6 |
| Apprentice | 0.9 | Married | 55.6 |
| Self-employed | 6.9 | Widowed | 2.2 |
| Employee | 51.9 | Divorced | 10.6 |
| Civil servant | 4.4 | | |
| Worker | 5.8 | | |
| Assisting family member | 1.9 | | |
| Unemployed | 3.6 | | |
| Retired | 19.9 | | |
| *Residence* | % | *Household net income* | % |
| Rural area (under 5000 inhabitants) | 20.5 | Under 500 € | 2.0 |
| Urban area (between 5000 and 10,000 inhabitants) | 8.7 | 500 € to 1300 € | 9.5 |
| Urban area (between 10,000 and 20,000 inhabitants) | 11.1 | 1300 € to 1700 € | 6.9 |
| Urban area (between 20,000 and 50,000 inhabitants) | 12.8 | 1700 € to 2600 € | 19.9 |
| Urban area (between 50,000 and 100,000 inhabitants) | 8.5 | 2600 € to 3600 € | 20.4 |
| Urban area (between 100,000 and 500,000 inhabitants) | 16.9 | 3600 € to 5000 € | 21.2 |
| Urban area (over 500,000 inhabitants) | 21.4 | Over 5000 € | 11.0 |
| | | Not stated | 9.0 |
| *Which technological device do you own or is available to you in your household? (Multiple selection possible)* | % | *Product category* | % |
| Desktop PC | 53.4 | Clothing | 50.3 |
| Notebook | 79.2 | Holiday travel | 24.9 |
| Tablet | 61.6 | Consumer electronics | 24.7 |
| Smartphone | 91.9 | | |

*Notes: SD* = Standard deviation.

of *risk attitudes*, we obtained the construct of *readiness to take risks* (Dohmen et al., 2011). *Cognitive ability* is captured by *need for cognition* (NFC) (Cacioppo and Petty, 1982). Multichannel-relevant *motivational measures* include *chronic shopping orientation* (CSO) (Büttner et al., 2014), *need for touch* (NFT) with autotelic and instrumental subscales (Nuszbaum et al., 2010), *resistance to change* (RTC) (Oreg et al., 2008), and *exploratory buying behavior tendency* (EBBT) (Baumgartner and Steenkamp, 1996). Consumer *personality* is captured by the *Big Five personality short-scale* (Hahn et al., 2012). Decision-making styles are represented by Scott and Bruce's (1995) *five general decision-making styles*: rational, intuitive, dependent, avoidant, and spontaneous. Additionally, the *maximization and regret tendency* was assessed using the Maximizing Scale (Schwartz et al., 2002). All psychographic variables were measured on either validated or adapted 7-point Likert scales from 1 (fully disagree/does not apply at all) to 7 (fully agree/fully applies), except for *readiness to take risks* which was captured using a validated 7-point Likert scale with scale endpoints of 1 (not at all willing to take risks) and 7 (very willing to take risks). Sufficient validity values were obtained for all scales (see Appendix A), except for the spontaneous decision-making style subscale. Therefore, this scale was excluded from further analysis.

*External channel choice factors:* To account for the additional factors affecting channel choice suggested by Verhoef et al. (2022), we established control measures for *channel attributes*, *marketing efforts*, *social influences*, *contextual factors*, and *channel experience*. For channel attributes, we focused on *information* and *service quality* of the search phase channel and *service quality* of the purchase channel. Additionally, we asked whether the selected purchase channel had a substantial *price advantage* over the other channels. *Marketing efforts* was measured by asking whether a specific marketing promotion (e.g., newsletter, coupons, advertising) influenced consumers' final purchase decisions. *Social influence* was assessed using two items evaluating whether a third person influenced the purchase decision and whether it was made on behalf of another person. *Contextual factors* were covered by *time pressure* (i.e., the need for immediate possession of the product, being pressed for time during shopping), *regional accessibility* (i.e., acceptable reachability of brick-and-mortar stores), and *technological accessibility* (i.e., technical requirements to access online channels). Finally, *channel experience* is represented by *retailer loyalty*, which reflects the habit of using the selected purchase channel and the behavior of always performing the purchase in the same pattern. Each item was measured using a 7-point Likert scale ranging from 1 (fully disagree) to 7 (fully agree), except for marketing efforts, which were measured using a dichotomous response set (yes and no).

### 3.4. Data analysis

LCA was conducted to explore customer segments with similar multichannel customer behavior using the software, Latent GOLD 6.0 (Vermunt and Magidson, 2021). Following Vermunt's (2010) three-step approach, LCA forms homogeneous groups of customers by classifying the relative similarity of respondents' multichannel customer behaviors in the first step. The multinomial logit model employs probabilities by which consumers can be categorized into respective segments. Measures of multichannel customer behavior serve as indicator variables for cluster formation. In the following steps, psychographic and external channel choice factor measures were included in the final cluster model solution as covariates. Including covariates allows researchers to detect whether a shared variation in a covariate is statistically associated with membership in a behavioral segment.

## 4. Results

### 4.1. Multichannel customer segmentation

We estimated the model solutions based on the indicator variables of multichannel customer behavior for one to ten clusters. For model computation, we set the convergence criterion to 0.000001 and used 50 random sets of starting parameters to reduce the likelihood of convergence to local maxima (Sands et al., 2016). We used the Bayesian Information Criterion (BIC), which is reportedly the most reliable fit statistic for identifying the final cluster solution. A lower BIC value indicates a better model fit (Weller et al., 2020).

Among the ten model solutions, the six-cluster model recorded the lowest BIC value (15476.91) (see Table 3). Therefore, we selected a six-cluster solution as the favorable model. The interpretability of the clusters and an adequate Entropy $R^2$ value of 0.908 supported the selection of the six-cluster solution. The model was subsequently tested for local independence by analyzing the bivariate residuals (BVRs) of each pair of indicator variables. The maximum BVR (Max. BVR) of the selected six-cluster model had a value of 3.49; thus, no BVRs exceeded the proclaimed critical value of four (Vermunt and Magidson, 2021). Therefore, the assumption of local independence is not violated.

Table 4 shows the composition of the six clusters obtained from LCA. The cluster profiles represent the percentage of respondents in a cluster that indicated a specific channel usage behavior in a distinct behavioral category (e.g., 99.9% of the respondents in Cluster 3 experienced their moment of truth in a brick-and-mortar store). Based on these behavioral patterns, we labeled the six clusters as (1) *desktop-focused single-channel shoppers* (24.5%), (2) *mobile-focused light-multichannel shoppers* (16.5%), (3) *store-focused single-channel shoppers* (15.9%), (4) *mobile-focused multichannel social shoppers* (15.9%), (5) *desktop-focused multichannel comparison shoppers* (15.1%), and (6) *store-focused analog multichannel shoppers* (12.1%).

When inspecting the data, we first noticed an obvious difference between the first three clusters and the last three clusters regarding channel-switching behavior. While the first three clusters persisted in purchasing in the same channel they searched last, the last three clusters mostly switched channels before purchasing. Accordingly, we observed a lower multichannel proneness (i.e., the number of utilized search

**Table 3**
Model diagnostic and model fit criteria.

| Models | LL | AIC | BIC | Npar | Class. Err. | Smallest class size (%) | Entropy $R^2$ |
|---|---|---|---|---|---|---|---|
| 1-Class model | −9154.08 | 18348.15 | 18454.58 | 20 | 0.000 | 100.0 | – |
| 2-Class model | −8483.89 | 17049.78 | 17267.95 | 41 | 0.021 | 40.0 | 0.902 |
| 3-Class model | −7950.40 | 16024.80 | 16354.71 | 62 | 0.032 | 24.3 | 0.919 |
| 4-Class model | −7515.14 | 15196.29 | 15637.95 | 83 | 0.025 | 17.2 | 0.950 |
| 5-Class model | −7372.26 | 14952.53 | 15505.93 | 104 | 0.041 | 12.8 | 0.924 |
| **6-Class model** | **−7280.88** | **14811.76** | **15476.91** | **125** | **0.057** | **12.1** | **0.908** |
| 7-Class model | −7246.78 | 14785.56 | 15562.45 | 146 | 0.060 | 5.7 | 0.903 |
| 8-Class model | −7218.12 | 14770.25 | 15658.89 | 167 | 0.058 | 5.3 | 0.917 |
| 9-Class model | −7187.89 | 14751.78 | 15752.17 | 188 | 0.059 | 4.7 | 0.920 |
| 10-Class model | −7161.80 | 14741.59 | 15853.72 | 209 | 0.080 | 4.5 | 0.901 |

*Notes: N* = 1512; Bold text indicates the selected model solution*; LL* = Log-likelihood*; AIC* = Akaike Information Criterion; *BIC* = Bayesian Information Criterion; *Npar* = Number of model parameters; *Class. Err.* = Classification errors.

**Table 4**
Cluster profiles (%) (LCA) of multichannel customer behavior ($N = 1512$).

| | | Cluster 1 (24.5%) | 2 (16.5%) | 3 (15.9%) | 4 (15.9%) | 5 (15.1%) | 6 (12.1%) | *Overall* (100%) |
|---|---|---|---|---|---|---|---|---|
| *Moment of truth* | Online store (Desktop) | 99.6% | 0.1% | 0.0% | 10.6% | 13.4% | 15.6% | 30.0% |
| | Online store (Mobile) | 0.0% | 99.9% | 0.0% | 19.0% | 15.6% | 11.5% | 23.2% |
| | Brick-and-mortar store | 0.3% | 0.0% | 99.9% | 11.8% | 1.1% | 14.4% | 19.8% |
| | Social media & blogs | 0.0% | 0.0% | 0.0% | 9.7% | 2.8% | 1.2% | 2.1% |
| | Search eng./comp. portal | 0.0% | 0.0% | 0.0% | 33.2% | 49.4% | 14.4% | 14.5% |
| | Print media | 0.0% | 0.0% | 0.0% | 0.9% | 2.5% | 13.7% | 2.2% |
| | Personal recommendation | 0.0% | 0.0% | 0.0% | 7.5% | 8.6% | 26.4% | 5.7% |
| | Digital recommendation | 0.0% | 0.0% | 0.0% | 7.4% | 6.6% | 2.8% | 2.5% |
| *# Search phase channels* | One channel | 62.7% | 46.4% | 67.5% | 7.7% | 18.1% | 43.8% | 43.0% |
| | Two channels | 15.9% | 29.4% | 19.0% | 24.3% | 33.5% | 29.3% | 24.2% |
| | More than two channels | 21.5% | 24.3% | 13.5% | 68.0% | 48.4% | 27.0% | 32.8% |
| *Channel-switching* | Switching | 0.0% | 0.0% | 0.1% | 77.1% | 87.6% | 97.0% | 37.2% |
| | Staying | 100.0% | 100.0% | 99.9% | 22.9% | 12.4% | 3.0% | 62.8% |
| *Purchase channel* | Online store (Desktop) | 99.5% | 0.3% | 0.1% | 11.4% | 85.1% | 10.5% | 40.4% |
| | Online store (Mobile) | 0.0% | 99.7% | 0.0% | 73.9% | 14.7% | 1.8% | 30.6% |
| | Brick-and-mortar store | 0.5% | 0.0% | 99.9% | 14.7% | 0.2% | 87.7% | 29.0% |
| *After-sales channel* | Online store (Desktop) | 42.8% | 2.4% | 0.0% | 0.0% | 40.2% | 1.9% | 17.2% |
| | Online store (Mobile) | 3.6% | 52.7% | 1.8% | 34.7% | 1.9% | 0.1% | 15.7% |
| | Brick-and-mortar store | 0.5% | 2.0% | 17.4% | 1.7% | 0.0% | 16.4% | 5.5% |
| | Call center | 0.3% | 0.4% | 0.8% | 1.5% | 0.0% | 1.4% | 0.7% |
| | Social media & blogs | 1.1% | 0.4% | 0.0% | 1.2% | 1.8% | 0.7% | 0.9% |
| | Personal recommendation | 0.0% | 0.0% | 1.2% | 0.0% | 1.4% | 3.2% | 0.8% |
| | Digital recommendation | 0.3% | 0.0% | 0.4% | 0.0% | 2.9% | 1.3% | 0.7% |
| | No channel | 44.4% | 27.8% | 74.6% | 21.6% | 44.4% | 74.2% | 46.4% |
| | More than one channel | 7.0% | 14.4% | 3.7% | 39.3% | 7.3% | 1.0% | 12.2% |

*Notes:* $N = 1512$; *# Search phase channels* = Number of search phase channels; *Search eng.* = Search engine; *Comp. portal* = Comparison portal.

phase channels) for Clusters 1 to 3 than that for Clusters 4 to 6. Therefore, we labeled these clusters *single-channel* or *light-multichannel shoppers*, in contrast to the *multichannel shoppers* in Clusters 4 to 6.

Notably, we observed similar patterns of purchasing behavior throughout the clusters. Clusters 1 and 5 are called desktop-focused as they heavily rely on the desktop online store in the purchase phase. The main difference lies in the usage of search-phase channels. While consumers in Cluster 1 followed a straightforward approach to online (desktop) shopping by solely using the online store via desktop (99.6%) without switching, consumers in Cluster 5 showed more in-depth

**Table 5**
Parameter estimates of covariates (three-step LCA) of multichannel customer behavior.

| | | Cluster 1 | 2 | 3 | 4 | 5 | 6 | *Wald* | *p* |
|---|---|---|---|---|---|---|---|---|---|
| *Risk attitudes* | Readiness to take risks | **−0.130** | 0.022 | **−0.162** | **0.244** | 0.010 | 0.016 | 27.66 | >0.00 |
| *Cognitive abilities* | Need for cognition | **0.174** | **−0.138** | **−0.155** | −0.045 | **0.204** | −0.040 | 16.59 | 0.01 |
| *Motivational measures* | Chronic shopping orientation | −0.020 | 0.003 | −0.049 | 0.093 | 0.065 | −0.092 | 1.97 | 0.85 |
| | Autotelic need for touch | −0.022 | −0.052 | **−0.145** | **0.229** | 0.033 | −0.044 | 11.60 | 0.04 |
| | Instrumental need for touch | −0.082 | −0.052 | **0.354** | **−0.385** | −0.059 | **0.223** | 51.20 | >0.00 |
| | Resistance to change | 0.216 | −0.024 | −0.127 | −0.066 | −0.035 | 0.036 | 8.91 | 0.11 |
| | Exploratory buying behavior tendency | −0.062 | 0.070 | 0.097 | 0.077 | −0.057 | −0.125 | 4.87 | 0.43 |
| *Personality measures* | Neuroticism | −0.114 | 0.021 | −0.052 | 0.090 | 0.033 | 0.023 | 6.35 | 0.27 |
| | Openness | −0.028 | 0.029 | 0.058 | 0.154 | −0.128 | −0.085 | 7.22 | 0.20 |
| | Conscientiousness | −0.146 | 0.023 | 0.109 | 0.010 | −0.010 | 0.014 | 6.81 | 0.24 |
| | Agreeableness | 0.075 | 0.068 | −0.094 | 0.047 | −0.052 | −0.044 | 4.91 | 0.43 |
| | Extraversion | −0.066 | 0.007 | −0.040 | 0.081 | 0.037 | −0.019 | 3.05 | 0.69 |
| *Decision-making styles* | Rational style | 0.064 | −0.039 | **−0.255** | **0.119** | **0.200** | −0.090 | 18.51 | >0.00 |
| | Intuitive style | **−0.101** | −0.027 | **−0.174** | **0.118** | **0.137** | 0.049 | 15.20 | 0.01 |
| | Dependent style | −0.098 | 0.090 | 0.006 | 0.157 | −0.136 | −0.020 | 9.66 | 0.09 |
| | Avoidant style | 0.009 | 0.056 | −0.048 | 0.002 | 0.065 | −0.083 | 2.11 | 0.83 |
| | Maximizing | −0.036 | 0.145 | −0.128 | 0.063 | −0.030 | −0.014 | 5.87 | 0.32 |
| | Regret | 0.067 | −0.124 | 0.102 | −0.036 | −0.017 | 0.009 | 5.67 | 0.34 |
| *Channel attributes* | Information quality (Search phase channel) | **0.129** | −0.056 | −0.028 | **−0.176** | **0.149** | −0.018 | 12.75 | 0.03 |
| | Service quality (Search phase channel) | **0.204** | **0.256** | **0.229** | **−0.114** | **−0.197** | **−0.378** | 73.22 | >0.00 |
| | Service quality (Purchase phase channel) | **−0.138** | **−0.170** | −0.003 | 0.099 | **−0.179** | **0.390** | 30.76 | >0.00 |
| | Price advantage (Purchase phase channel) | 0.062 | −0.005 | **−0.130** | **0.111** | 0.082 | **−0.120** | 20.33 | >0.00 |
| *Marketing efforts* | Marketing efforts (yes)* | −0.031 | **0.227** | **−0.189** | 0.066 | **−0.120** | 0.047 | 18.06 | >0.00 |
| *Social influences* | Social influence | **−0.112** | **−0.166** | **−0.148** | **0.191** | **0.187** | 0.048 | 40.12 | >0.00 |
| *Contextual factors* | Time pressure | −0.038 | **0.149** | 0.040 | 0.044 | **−0.154** | −0.041 | 16.68 | 0.01 |
| | Regional accessibility | −0.091 | −0.066 | **0.187** | −0.066 | **−0.210** | **0.246** | 59.50 | >0.00 |
| | Technological accessibility | **−0.148** | **−0.103** | −0.012 | −0.055 | **0.317** | 0.000 | 17.07 | >0.00 |
| *Channel experiences* | Retailer loyalty | 0.060 | 0.093 | 0.065 | −0.122 | 0.025 | −0.120 | 9.70 | 0.08 |

*Notes*: $N = 1512$; Significant ($p < 0.05$) covariates and their coefficient values that exceed $\pm$ 0.1 are shown in bold font; *Analyzed separately using ML instead of BCH correction method because of nominal scale level.

shopping behavior (i.e., comparison shopping) using channels such as search engines and comparison portals (49.4%) or digital recommendations (6.6%) (Mittal, 2016). A similar observation was made for Clusters 3 and 6, which are store-focused in the purchase phase. Consumers in Cluster 3 traditionally focused on searching (99.9%) and purchasing (99.9%) within the brick-and-mortar environment, while consumers in Cluster 6 extended the store-focused purchase behavior by using classical, especially non-digital (i.e., analog) search phase touchpoints, such as print media (13.7%) and personal recommendations (26.4%). The distinction between Clusters 2 and 4 is less clear than that between the other pairs of clusters because both mobile-focused clusters inherently have a relatively high multichannel propensity. However, Cluster 4 exceeded Cluster 2 in terms of multichannel usage (i.e., the usage of more than one search phase channel, 92.3%/53.7%) and switching behavior (77.1%/0.0%). During the search phase, consumers in Cluster 2 only visited the mobile store (99.9%), whereas consumers in Cluster 4 expanded their search by using social media and blogs (9.7%), search engines and comparison portals (33.2%), or digital recommendations (7.4%).

In summary, we observed desktop-, mobile-, and store-focused clusters expressing either a straightforward approach of one-stop shopping (Viejo-Fernández et al., 2019) or an extensive multichannel-based research shopping behavior (Verhoef et al., 2007) by utilizing several related channels in the search phase. The segment profiles of the six-cluster solution were also verified using cardinal channel utilities in a distal outcome approach (Lanza et al., 2013), indicating a high conceptual fit of the model solution (see Appendix B).

### 4.2. Covariates of multichannel customer behavior

Table 5 shows the results of the psychographic covariates and external factors of channel choices. A significant outcome indicates a statistically relevant impact of covariates on cluster membership. The magnitude and direction of the coefficients suggest the likelihood of a respondent with a high score for the psychographic variables in the respective cluster. A strong positive coefficient indicates that customers within this segment scored relatively high on this variable. By contrast, a strong negative coefficient means that customers in that segment scored relatively low on this trait (Nakano and Kondo, 2018).

Overall, 6 of the 18 psychographic covariates had a significant influence on cluster membership. *Readiness to take risks* (*Wald* = 27.66; $p > 0.00$) tends to be beneficial for heavy multichannel behavior but detrimental for single-channel usage as it shows a strong positive effect for Cluster 4 ($\gamma = 0.244$) and substantial negative effects for Cluster 1 ($\gamma = -0.130$) and Cluster 3 ($\gamma = -0.162$). *NFC* (*Wald* = 16.59; $p = 0.01$) was high for the desktop-focused Clusters 1 ($\gamma = 0.174$) and 5 ($\gamma = 0.204$) and low for Clusters 2 ($\gamma = -0.138$) and 3 ($\gamma = -0.155$). *Autotelic NFT* (*Wald* = 11.60; $p = 0.04$) was positively associated with Cluster 4 ($\gamma = 0.229$) and negatively associated with Cluster 3 ($\gamma = -0.145$). *Instrumental NFT* (*Wald* = 51.20; $p > 0.00$) showed a strong positive connection with store-focused Clusters 3 ($\gamma = 0.354$) and 6 ($\gamma = 0.223$) and a negative connection with online-focused Cluster 4 ($\gamma = -0.385$). Finally, two of the four general decision-making styles attained significance. A high *rational style* (*Wald* = 18.51; $p > 0.00$) predicted cluster membership for the research-focused Clusters 4 ($\gamma = 0.119$) and 5 ($\gamma = 0.200$), whereas store-focused Cluster 3 ($\gamma = -0.255$) showed a negative relation with the construct. A pronounced *intuitive decision-making style* (*Wald* = 15.20; $p = 0.01$) leads to extensive multichannel behavior since Clusters 4 ($\gamma = 0.118$) and 5 ($\gamma = 0.137$) showed a positive influence on segment membership. The likelihood of belonging to the single-channel Clusters 1 ($\gamma = -0.101$) and 3 ($\gamma = -0.174$) is low. However, channel-switching behavior could not be explained through customers' inertia as the influence of *RTC* does not significantly predict class membership. Furthermore, our results revealed that personality measures do not have a significant influence on multichannel customer behavior. The external factors of channel choices all showed a significant influence on segment membership, except for *retailer loyalty* (*Wald* = 9.70; $p = 0.08$).

**Table 6**
Unique contribution of covariates (effect sizes).

| Covariate | Reduction in Entropy $R^2$ |
|---|---|
| Service quality (Search phase channel)* | 0.018 |
| Regional accessibility* | 0.016 |
| Instrumental need for touch* | 0.014 |
| Service quality (Purchase phase channel)* | 0.010 |
| Social influence* | 0.009 |
| Readiness to take risks* | 0.006 |
| Price advantage (Purchase phase channel)* | 0.005 |
| Technological accessibility* | 0.005 |
| Rational style* | 0.004 |
| Marketing efforts*† | 0.004 |
| Time pressure* | 0.004 |
| Need for cognition* | 0.003 |
| Information quality (Search phase channel)* | 0.003 |
| Intuitive style* | 0.003 |
| Autotelic need for touch* | 0.003 |
| Dependent style | 0.002 |
| Retailer loyalty | 0.002 |
| Openness | 0.002 |
| Resistance to change | 0.002 |
| Neuroticism | 0.001 |
| Conscientiousness | 0.001 |
| Maximizing | 0.001 |
| Regret | 0.001 |
| Exploratory buying behavior tendency | 0.001 |
| Agreeableness | 0.001 |
| Extraversion | 0.001 |
| Chronic shopping orientation | 0.000 |
| Avoidant style | 0.000 |

*Notes:* *Covariate with a significant influence ($p < 0.05$) on segment membership in the overall model; †Reference value of the reduction calculation was based on the ML correction model of *Marketing efforts.*

To investigate and compare the effect sizes of the covariates, we calculated the unique contribution of each predictor to the variance clarification. Therefore, we estimated the models and associated Entropy $R^2$ values by excluding the respective covariates. The magnitude of the reduction in Entropy $R^2$ compared with the initial cluster model reflects the unique contribution of the covariate. Table 6 shows the unique contributions of each covariate. This shows that the *service quality of the search phase channel* and *regional accessibility* have the most substantial effects on cluster formation among all the covariates. The most influential psychographic covariate was *instrumental NFT*. The variables of *service quality of the purchase channel* and *social influence* also have considerable predictive strength for multichannel customer behavior. Among the psychographic covariates, *readiness to take risks*, *need for cognition*, *rational decision-making style*, *intuitive decision-making style*, and *autotelic need for touch* are additional relevant predictors for multichannel customer behavior.

In summary, multichannel customer behavior and segment membership depend on and can be described by both consumer characteristics (i.e., psychographic variables) and the external factors following Verhoef et al. (2022). Contextual and channel-related factors shape multichannel customer behavior to a greater extent. However, psychographic variables, especially *instrumental need for touch* and *readiness to take risks*, also have considerable predictive power.

## 5. Discussion and conclusion

### 5.1. Theoretical contributions

#### 5.1.1. The use of psychographic covariates in multichannel customer segmentation

Our research overcomes the limitations of previous studies in terms of proposing an underlying systematic framework for the investigation of individual differences in multichannel customer behavior (e.g., Konuş et al., 2008; Nakano and Kondo, 2018; Sands et al., 2016). Appelt et al.'s

(2011) categorization framework helped to classify relevant domains of individual differences for multichannel customer behavior and to explain a significant portion of the variance in channel choice behavior through the identified psychological traits. The results uncover a distinct demarcation in psychological traits, critically important for advancing the theoretical understanding of multichannel customer behavior.

Personality-related traits do not influence multichannel customer behavior patterns, which supports Liu et al.'s (2019) notion of the insufficient explanatory power of personality factors. Furthermore, single motivational constructs, such as chronic shopping orientation, resistance to change, and exploratory buying behavior tendency do not significantly impact segment membership. By contrast, need for cognition, need for touch, readiness to take risks, and the complementary pair of rational and intuitive decision-making styles significantly influence multichannel customer behavior. Need for cognition and rational decision-making style function as predictors of research shopping behavior. Readiness to take risks and intuitive decision-making influence the extent of multichannel usage. Instrumental need for touch strongly indicates a preference for brick-and-mortar stores because consumers with high instrumental need for touch are captured within store-focused segments. Mobile channels can also benefit from strong haptic traits (e.g., De Canio and Fuentes-Blasco, 2021). Future research should test the relationships observed in these studies.

These results indicate a distinctive pattern regarding the behavioral influence of psychological traits. Not all domains of individual differences in general judgment and decision-making (Appelt et al., 2011) play an even role in multichannel behavior. The significant psychographic covariates share the common characteristic of being involved in the cognitive processes of information reception and processing. Contrarily, most non-significant psychographic covariates are self-referencing and self-descriptive traits (e.g., chronic shopping orientation, exploratory buying behavior tendency, resistance to change, and the Big Five personality traits). The investigation of individual differences in multichannel customer behavior could, therefore, focus on the properties and abilities that affect information reception, information processing, and (analytical) reasoning. A proposal for a comparable framework can be found in a review by Mishra et al. (2021), describing the cognitive-affective-conative model. Further investigation of cognition-based variables should be conducted in the future. Overall, the psychographic covariates considered in this study contribute to a better understanding of multichannel customer behavior and provide useful insights into potential behavioral relationships.

#### 5.1.2. *Comparison of the prediction strength of psychographic and external covariates*

To the best of our knowledge, this study is the first within multichannel customer segmentation to examine and compare the effect sizes of covariates. In addition to consumer characteristics, Verhoef et al. (2022) proposed that channel choice can also be determined by channel attributes, marketing efforts, social influences, contextual factors, and channel experiences. The results of our study show that external factors such as the accessibility of stores, service quality, and social influence crucially affect consumers' channel choices. The importance of these external factors is widely known (for a review, see Liu et al., 2018). However, the results also reveal that significant psychographic covariates influence multichannel customer behavior almost as much as external variables. The instrumental need for touch is a powerful predictor of specific multichannel customer behavior. This implies that the multichannel shopping environment is not the only relevant setscrew for understanding and influencing multichannel customer behavior. Therefore, the interaction between external factors and individual differences should be understood as an integrative structure in which the factors reciprocally affect each other. This analysis supports and encourages more systematic research on the individual differences influencing multichannel customer behavior.

### 5.2. *Managerial implications*

The segmentation results highlight the different nuances in consumer search behavior within store-, mobile-, and desktop-focused segments. They either perform a straightforward single-channel search process or conduct extensive research. Within the latter, a complementary set of channels is utilized. For instance, *desktop-focused multichannel comparison shoppers* tend to use search engines, comparison portals, and digital recommendations when purchasing online via desktop. It is crucial for retailers with a multichannel retailing strategy to understand which complementary search phase channels multichannel shoppers use to reduce friction when switching across these channels and optimize their experiences.

In addition, cognition-based psychographic variables, such as need for touch, need for cognition, risk propensity, and decision-making styles, demonstrate a similarly strong effect on the formation of multichannel customer behaviors as channel-related factors. Therefore, the investigated psychological traits can be used to proactively manage customer journeys of distinct segments. Drawing on the message-person-congruity approach (Teeny et al., 2021), channel interfaces and messages (Barann et al., 2022) can be adjusted and personalized to the prevalent psychological traits of the respective segments to achieve higher hedonic pleasure, higher advertising effectiveness, and higher customer loyalty perceptions (Schreiner et al., 2019; Tyrväinen et al., 2020; Zhang et al., 2024). Based on the results of our study, such a personalization approach might consist of desktop-based channels providing more technical information and active product comparisons to appeal to the deliberate and comparative nature (i.e., scoring high on need for cognition) of the *desktop-focused multichannel comparison shoppers* (Cluster 5). On the contrary, mobile-based channels could be designed to persuade customer segments scoring low on need for cognition (i.e., Cluster 2) on a more heuristical processing route to foster quick decision-making. Thus, knowledge about individual differences could help to navigate the customers in the early stages of the customer journey. Recent advances in machine-learning- and AI-based marketing automation promise facilitated access to the customers' psychological traits by automatically retrieving traits from the customers' digital footprints (Gao and Liu, 2023; Gladstone et al., 2019; Ramon et al., 2021). Leveraging individual differences in real-time channel customization will be a decisive factor in the development of the retail landscape (Cui et al., 2021; Matz et al., 2020). A recent example from Matz et al. (2023) shows the great potential of large language models in the context of the so-called "psychological profiling" in marketing. Personalized messages crafted by ChatGPT exhibit significantly more influence than non-personalized messages. This is the case even when the large language model is prompted with a single term naming the targeted psychological trait. Accordingly, our research establishes a foundation for the application of psychological traits in the optimization and customization of customer journeys within a multichannel retailing environment.

### 5.3. *Research limitations and further research*

This study has some limitations. Observed multichannel customer behavior is measured through self-reporting and refers to a single purchase in the past. The incorporation of two different channel utility measures (i.e., cardinal and ordinal utility) marks the first step towards cross-validating such cluster models. However, the results of similar studies have revealed that clusters and the significance of covariates are highly dependent on the study design (see Table 1). Wang et al. (2023) proposed an alternative approach for measuring such channel utilities by using stated preference choice experiments and applying a semi-compensatory independent availability logit (SCIAL) model with latent variables. Nevertheless, the use of these methods runs the risk that the results will be confounded by common method bias. Therefore, we tested our indicator variables, distal outcome variables, and covariates using Harman's one-factor test but found no statistical hint of common method variance (Podsakoff et al., 2003). Furthermore, the measurement of external channel choice factors primarily relied on self-constructed single-item measures and thus lacked further validation. Despite the mentioned data quality checks (i.e., selection of ISO-certified panel provider, quotas, attention checks, and manual data cleansing), we could not check the sample for so-called speeders since our survey tool did not measure the response time of the respondents. We recommend using the method of Greszki et al. (2015) to check for respondents who finish the survey in less than 60 percent of the median completion time to further enhance the overall data quality.

The cross-cultural interpretability and applicability of the results are limited because of the Eurocentric setting of the study. For instance, the use of travel agencies (i.e., brick-and-mortar stores in the product category of holiday travel) is typical for the German tourism sector. For this reason, the country- and culture-specific retail environment of product categories should always be considered in further studies. Furthermore, the presented channel selection is simply a curated list of all accessible channels. Therefore, the results do not reflect the complex structure of actual multichannel customer behavior. Such segmentation studies are highly complex and could lead to the misspecification of clusters (Weller et al., 2020). Hence, ideally, the results must be replicated and tested for external validity using actual purchase data. Otherwise, the reliability of statements on behavioral relationships is restricted. For instance, Kondo and Okubo (2022) conducted a segmentation study with actual purchase data of FMCG but with demographic instead of psychographic covariates. Further research should provide an integrative segmentation model for real-world customer data and psychographic measures to replicate and validate these results. In addition, future research should continue investigating the stability of the trait effects. Unstable effects may support current assumptions that shopping behavior is not exclusively driven by individual traits but also by situationally activated states (Muthaffar and Vilches-Montero, 2023).

## CRediT authorship contribution statement

**Jan Blömker:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Carmen-Maria Albrecht:** Writing – review & editing, Supervision, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Acknowledgments

We thank the EHG GmbH & Co. KG for financially supporting this research project. We also thank Oliver B. Büttner, Fumiyo N. Kondo, and Jeroen K. Vermunt for providing further information regarding their research.

## Appendix A

**Table A.1**
Reliability analysis of the covariate measures.

| *Category* | *Construct* | *Source of scale* | *Subscale* | *Item* | *M* | *SD* | *C. Alpha* | *C. Alpha (FSI)* | *Guttman split-half* | *Spearman-Brown* |
|---|---|---|---|---|---|---|---|---|---|---|
| *Risk attitudes* | Readiness to take risks | Dohmen et al. (2011) | Readiness to take risks | How willing are you to take risks, in general? | 3.63 | 1.57 | – | – | – | – |
| *Cognitive abilities* | Need for cognition | Cacioppo and Petty (1982) | Joy | I would prefer complex to simple problems. | 3.48 | 1.76 | 0.77 | 0.77 | 0.77 | 0.77 |
| | | | | I prefer my life to be filled with puzzles that I must solve. | 3.62 | 1.66 | | | | |
| | | | Engagement | Simply knowing the answer rather than understanding the reasons for the answer to a problem is fine with me. * | 4.83 | 1.72 | 0.67 | 0.67 | 0.67 | 0.67 |
| | | | | I primarily think because I have to.* | 5.07 | 1.76 | | | | |
| *Motivational measures* | Chronic shopping orientation | Büttner et al. (2014) | Hedonic shopping orientation | When shopping, I am usually looking for entertainment | 3.02 | 1.73 | 0.83 | 0.83 | 0.76 | 0.82 |
| | | | | When shopping, I try to get it over with as soon as possible.* | 3.64 | 1.79 | | | | |
| | | | | I like to kill time by shopping. | 3.44 | 1.86 | | | | |
| | | | | When shopping, I like to browse around. | 4.70 | 1.63 | | | | |
| | | | | When shopping, I mainly carry out what I have planned.* | 2.82 | 1.43 | | | | |
| | | | | When shopping, I often have fun. | 4.22 | 1.67 | | | | |
| | | | | When shopping, I act as deliberately and goal focused as possible.* | 2.87 | 1.42 | | | | |

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**Table A.1** (*continued*)

| *Category* | *Construct* | *Source of scale* | *Subscale* | *Item* | *M* | *SD* | *C. Alpha* | *C. Alpha (FSI)* | *Guttman split-half* | *Spearman-Brown* |
|---|---|---|---|---|---|---|---|---|---|---|
| | Need for touch | Nuszbaum et al. (2010) | Autotelic need for touch | When browsing in stores, it is important for me to handle all kinds of products. | 3.52 | 1.88 | 0.88 | 0.88 | 0.78 | 0.87 |
| | | | | I like to touch products even if I have no intention of buying them. | 3.38 | 1.91 | | | | |
| | | | | When walking through stores, I cannot help touching all kinds of products. | 3.28 | 1.90 | | | | |
| | | | Instrumental need for touch | I place more trust in products that can be touched before purchase. | 4.16 | 1.82 | 0.90 | 0.90 | 0.79 | 0.88 |
| | | | | I feel more comfortable purchasing a product after physically examining it. | 4.32 | 1.84 | | | | |
| | | | | The only way to make sure a product is worth buying is to actually touch it. | 3.73 | 1.84 | | | | |
| | Resistance to change | Oreg et al. (2008) | Routine seeking | I generally consider changes to be a negative thing. | 2.88 | 1.60 | 0.68 | 0.66 | 0.69 | 0.74 |
| | | | | I'll take a routine day over a day full of unexpected events any time. | 4.22 | 1.69 | | | | |
| | | | Emotional reaction | When I am informed of a change of plans, I tense up a bit. | 3.97 | 1.62 | | | | |
| | | | | When things do not go according to plans, it stresses me out. | 4.29 | 1.69 | | | | |
| | | | Short term focus | Changing plans seems like a real hassle to me. | 3.24 | 1.70 | | | | |
| | | | | I sometimes find myself avoiding changes that I know will be good for me. | 3.42 | 1.65 | | | | |
| | | | Cognitive rigidity | I often change my mind.* | 5.14 | 1.48 | | | | |
| | | | | My views are very consistent over time. | 5.06 | 1.24 | | | | |
| | Exploratory buying behavior tendency | Baumgartner and Steenkamp (1996) | Exploratory acquisition of products | When I see a new brand on the shelf, I am not afraid of giving it a try. | 4.47 | 1.64 | 0.74 | 0.74 | 0.69 | 0.69 |
| | | | | I am very cautious in trying new or different products.* | 4.32 | 1.64 | | | | |
| | | | | I enjoy taking chances in buying unfamiliar brands just to get some variety in my purchases. | 3.97 | 1.63 | | | | |
| | | | Exploratory information seeking | I do not like to shop around just out of curiosity.* | 3.90 | 2.09 | | | | |
| | | | | I like to browse through mail order catalogs even when I do not plan to buy anything. | 4.31 | 1.94 | | | | |
| | | | | I like to shop around and look at displays. | 4.05 | 1.91 | | | | |
| | | | | I often read advertisements just out of curiosity. | 3.82 | 1.99 | | | | |
| *Personality measures* | Big-Five factors | Hahn et al. (2012) | Neuroticism | I see myself as someone who worries a lot. | 4.45 | 1.78 | 0.73 | 0.72 | 0.55 | 0.64 |
| | | | | I see myself as someone who gets nervous easily. | 3.67 | 1.80 | | | | |
| | | | | I see myself as someone who is relaxed, handles stress well.* | 3.41 | 1.56 | | | | |
| | | | Openness | I see myself as someone who is original, comes up with new ideas. | 5.00 | 1.35 | 0.70 | 0.71 | 0.65 | 0.70 |
| | | | | I see myself as someone who values artistic, aesthetic experiences. | 4.34 | 1.80 | | | | |
| | | | | I see myself as someone who has an active imagination. | 4.84 | 1.59 | | | | |
| | | | Conscientiousness | I see myself as someone who does a thorough job. | 5.73 | 1.16 | 0.68 | 0.72 | 0.63 | 0.73 |

(*continued on next page*)

**Table A.1** (*continued*)

| *Category* | *Construct* | *Source of scale* | *Subscale* | *Item* | *M* | *SD* | *C. Alpha* | *C. Alpha (FSI)* | *Guttman split-half* | *Spearman-Brown* |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | I see myself as someone who tends to be lazy.* | 4.93 | 1.74 | | | | |
| | | | | I see myself as someone who does everything efficiently. | 5.59 | 1.19 | | | | |
| | | | Agreeableness | I see myself as someone who is sometimes rude to others. * | 4.78 | 1.70 | 0.59 | 0.61 | 0.57 | 0.68 |
| | | | | I see myself as someone who has a forgiving nature. | 5.11 | 1.43 | | | | |
| | | | | I see myself as someone who is considerate and kind to almost everyone. | 5.62 | 1.19 | | | | |
| | | | Extraversion | I see myself as someone who is talkative. | 4.66 | 1.60 | 0.74 | 0.74 | 0.67 | 0.74 |
| | | | | I see myself as someone who is reserved, quiet.* | 3.79 | 1.68 | | | | |
| | | | | I see myself as someone who is outgoing, sociable. | 4.70 | 1.55 | | | | |
| *Decision-making styles* | General decision-making style | Scott and Bruce (1995) | Rational style | I make decisions in a logical and systematic way | 5.13 | 1.28 | 0.76 | 0.76 | 0.71 | 0.77 |
| | | | | I double-check my information sources to be sure I have the right facts before making a decision. | 5.20 | 1.32 | | | | |
| | | | | My decision making requires careful thought. | 5.06 | 1.36 | | | | |
| | | | Intuitive style | When making a decision, I rely upon my instincts. | 4.79 | 1.36 | 0.85 | 0.85 | 0.79 | 0.86 |
| | | | | When I make a decision, I trust my inner feelings and reactions. | 4.99 | 1.32 | | | | |
| | | | | When I make decisions, I tend to rely on my intuition. | 4.74 | 1.38 | | | | |
| | | | Dependent style | I often need the assistance of other people when making important decisions. | 3.27 | 1.72 | 0.77 | 0.77 | 0.58 | 0.65 |
| | | | | I like to have someone to steer me in the right direction when I am faced with important decisions. | 3.04 | 1.66 | | | | |
| | | | | I rarely make important decisions without consulting other people. | 4.05 | 1.73 | | | | |
| | | | Avoidant style | I generally make important decisions at the last minute. | 3.04 | 1.65 | 0.78 | 0.78 | 0.69 | 0.76 |
| | | | | I put off making many decisions because thinking about them makes me uneasy. | 3.33 | 1.76 | | | | |
| | | | | I often procrastinate when it comes to making important decisions. | 3.73 | 1.70 | | | | |
| | | | Spontaneous style | I generally make snap decisions. | 4.20 | 1.49 | 0.48 | 0.48 | 0.42 | 0.44 |
| | | | | When making decisions, I do what seems natural at the moment. | 4.86 | 1.32 | | | | |
| | | | | I often make impulsive decisions. | 2.86 | 1.64 | | | | |
| | Maximization tendency | Schwartz et al. (2002) | Maximizing | When I watch TV, I channel surf. often scanning through the available options even while attempting to watch one program. | 3.34 | 1.87 | 0.73 | 0.72 | 0.75 | 0.75 |
| | | | | No matter how satisfied I am with my job, it is only right for me to be on the lookout for better opportunities. | 4.00 | 1.74 | | | | |
| | | | | I often fantasize about living in ways that are quite different from my actual life. | 3.70 | 1.91 | | | | |

(continued on next page)

**Table A.1** (*continued*)

| *Category* | *Construct* | *Source of scale* | *Subscale* | *Item* | *M* | *SD* | *C. Alpha* | *C. Alpha (FSI)* | *Guttman split-half* | *Spearman-Brown* |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Regret | Whenever I make a choice, I am curious about what would have happened if I had chosen differently. | 3.32 | 1.75 | | | | |
| | | | | When I think about how I am doing in life, I often assess opportunities I have passed up. | 3.78 | 1.80 | | | | |
| | | | | Once I make a decision, I do not look back.* | 3.70 | 1.57 | | | | |
| *Channel attributes* | Information quality | own construction | Search phase channel | I chose the channel to finalize my information search because it offered me the best information. | 5.65 | 1.44 | – | – | – | – |
| | Service quality | own construction | Search phase channel | I chose the channel to finalize my information search because it gave me the best service. | 5.23 | 1.63 | – | – | – | – |
| | | | Purchase channel | I chose the channel for product purchase because it offered me the best service. | 5.49 | 1.48 | – | – | – | – |
| | Price advantage | own construction | Purchase channel | I chose the channel for the product purchase because it offered the significantly better prices in comparison. | 5.06 | 1.76 | – | – | – | – |
| *Marketing efforts* | Marketing efforts | own construction | Marketing efforts | Did a certain marketing promotion (e.g., coupons, discount codes, advertising) contribute to where you ultimately made the purchase? (dichotomous: yes/no) | – | – | – | – | – | – |
| *Social influences* | Social influence | own construction | Social influence | Another person influenced me during my purchase decision. | 2.87 | 2.07 | 0.75 | 0.76 | 0.75 | 0.76 |
| | | | | I only made this purchase decision because another person wanted it. | 2.03 | 1.70 | | | | |
| *Contextual factors* | Time pressure | own construction | Time pressure | I was pressed for time during the shopping phase. | 2.14 | 1.75 | 0.61 | 0.62 | 0.61 | 0.62 |
| | | | | I needed the purchased product immediately. | 3.48 | 2.08 | | | | |
| | Regional accessibility | own construction | Regional accessibility | It is easy for me to reach the stationary retail stores (such as downtown stores or shopping centers) within a short period of time. | 4.80 | 1.86 | – | – | – | – |
| | Technological accessibility | own construction | Technological accessibility | I have the technical requirements (such as internet access, mobile devices, computer) to access online channels. | 6.35 | 1.15 | – | – | – | – |
| *Channel experiences* | Retailer loyalty | own construction | Channel habit | If possible, I always buy this type of product through this channel. | 5.38 | 1.55 | 0.68 | 0.68 | 0.68 | 0.68 |
| | | | Purchasing Habit | I usually do my shopping in the same pattern. | 5.24 | 1.51 | | | | |

*Note: M* = Mean*; SD* = Standard deviation*; C. Alpha* = Cronbach's Alpha*; C. Alpha (FSI)* = Cronbach's Alpha for standardized items; *Guttman split-half* = Guttman's split-half reliability coefficient; *Spearman-Brown* = Spearman-Brown reliability coefficient; *reverse-coded item.

## Appendix B

**Table B.1**
Parameters of mean cardinal channel utility perceptions (distal outcomes).

| | | *Cluster* | | | | | | *Wald* | *p* |
|---|---|---|---|---|---|---|---|---|---|
| | | *1* | *2* | *3* | *4* | *5* | *6* | | |
| *Search* | Online store (Desktop) | 0.576 | −0.172 | −0.361 | −0.201 | 0.437 | −0.279 | 141.13 | >0.00 |
| | Online store (Mobile) | −0.331 | 0.640 | −0.327 | 0.583 | −0.067 | −0.499 | 164.22 | >0.00 |
| | Brick-and-mortar store | −0.135 | −0.315 | 0.429 | −0.212 | −0.179 | 0.412 | 89.27 | >0.00 |
| | Social media & blogs | −0.335 | 0.321 | −0.397 | 0.925 | −0.159 | −0.355 | 120.60 | >0.00 |
| | Search eng./comp. portal | −0.209 | −0.003 | −0.276 | 0.592 | 0.323 | −0.429 | 94.02 | >0.00 |
| | Print media | −0.189 | −0.055 | 0.042 | 0.199 | −0.189 | 0.193 | 13.02 | 0.02 |

(*continued on next page*)

**Table B.1** (*continued*)

| | | Cluster | | | | | | Wald | p |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | | |
| | Personal recommendation | −0.357 | 0.019 | −0.032 | 0.387 | −0.046 | 0.029 | 33.70 | >0.00 |
| | Digital recommendation | −0.238 | 0.097 | −0.298 | 0.724 | 0.086 | −0.370 | 74.99 | >0.00 |
| *Purchase* | Online store (Desktop) | 0.534 | −0.108 | −0.399 | −0.165 | 0.558 | −0.421 | 139.57 | >0.00 |
| | Online store (Mobile) | −0.489 | 0.813 | −0.413 | 0.753 | −0.023 | −0.641 | 228.90 | >0.00 |
| | Brick-and-mortar store | −0.216 | −0.338 | 0.446 | −0.302 | −0.030 | 0.441 | 109.00 | >0.00 |
| *After-sales* | Online store (Desktop) | 0.558 | −0.106 | −0.347 | −0.118 | 0.450 | −0.437 | 110.25 | >0.00 |
| | Online store (Mobile) | −0.335 | 0.659 | −0.395 | 0.695 | −0.026 | −0.598 | 155.49 | >0.00 |
| | Brick-and-mortar store | −0.133 | −0.245 | 0.496 | −0.196 | −0.142 | 0.220 | 57.68 | >0.00 |
| | Call center | 0.007 | 0.149 | −0.355 | 0.354 | 0.074 | −0.230 | 24.79 | >0.00 |
| | Social media & blogs | −0.271 | 0.250 | −0.402 | 0.928 | −0.109 | −0.395 | 100.47 | >0.00 |
| | Personal recommendation | −0.330 | 0.190 | −0.218 | 0.698 | −0.172 | −0.168 | 51.92 | >0.00 |
| | Digital recommendation | −0.255 | 0.220 | −0.292 | 0.792 | −0.077 | −0.387 | 67.24 | >0.00 |

*Notes: N* = 1512; *Search eng.* = Search engine; *Comp. portal* = Comparison portal.

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