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Topic

The Influence of AI-Generated Product Recommendations on Purchasing Behaviour in E-Commerce based on the Customer Journey - a Comparison of FMCG vs. SMCG

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List of Abbreviations

AI .... Artificial Intelligence
E-Commerce .... Electronic Commmerce
FMCG.. Fast Moving Consumer Goods
SMCG... Slow Moving Consumer Goods
B2C.. Business to Consumer
B2B... Business to Business
M-Commerce .... Mobile-Commerce
CJM .... Customer Journey Mapping
ML .... Machine Learning
DL .... Deep Learning
NLP .... Natural Language Processing
GDPR .... General Data Protection Regulation
SPSS .... Statistical Package for the Social Sciences
n .... Number of Participants
SD .... Standard Deviation
M .... Mean
P .... Probability
R^2 .... Coefficient of Determination
IV .... Independent Variable
DV .... Dependent Variable
ANOVA .... Analysis of Variance
RM-ANOVA .... Repeated Measures Analysis of Variance

Abstract

This thesis examines how consumers respond to AI-generated product recommendations in various product categories, customer journey phases, and in relation to their individual characteristics. A quantitative dual-method research design was employed, combining a standardised online survey (n = 103) and a simulated scenario-based online experiment (n = 30). The research analyses the perceived usefulness, purchase intention and acceptance factors of fast-moving consumer goods (FMCG) and slow-moving consumer goods (SMCG). The findings reveal that the effectiveness of AI-generated product recommendations is highly context-dependent. SMCG recommendations were generally perceived as more useful, whereas FMCG recommendations did not increase purchase intention, and instead reduced it in the experimental condition. Perceived usefulness declined systematically across customer-journey phases, with the highest ratings occurring during the early inspiration and search phases, and the lowest occurring after the purchase phase. Individual dispositions exhibited selective effects: a sense of urgency reduced responsiveness to recommendations; openness to AI was associated with trust in well-established e-commerce channels; however, trust did not significantly predict perceived helpfulness in the experimental setting. Overall, the results highlight that AI-generated product recommendations influence consumer decision-making when they align with product type, decision phase, and consumer characteristics. This study contributes to a more nuanced understanding of AI-supported decision-making in e-commerce, offering practical guidance on designing context-sensitive, phase-appropriate, consumer-centred recommendation systems.

Keywords: AI-generated product recommendations, e-commerce, FMCG, SMCG, customer journey, perceived helpfulness, purchase intention, trust, quantitative methods, online survey, online experiment.

1 Introduction

1.1 Relevance of the Topic

Over the past decades, digitalisation has fundamentally transformed economic and social life, with electronic commerce (e-commerce) emerging as one of the most dynamic domains of this transformation (OECD, 2019, p. 11). Online shopping has become an integral part of everyday consumer behaviour, driven by convenience, variety and accessibility (Sun *et al.*, 2025, p. 45). At the same time, the rapid growth of digital marketplaces has created an environment of information overload, in which consumers are often confronted with an overwhelming number of product choices (Yoon *et al.*, 2013, p. 890).

Artificial Intelligence (AI) has become a key instrument in addressing this challenge (Huang and Rust, 2021, p. 30). In particular, AI-generated product recommendation systems have established themselves as one of the most widely used applications in e-commerce (Heinemann, 2025, p. 136). These systems analyse consumer behaviour and preferences to generate personalised recommendations that are intended to simplify decision-making, enhance customer satisfaction and ultimately, increase conversion rates. As a result, AI-generated product recommendations are now embedded into multiple phases of the customer journey – from inspiration and consideration to purchase and even post-purchase communication. (Harwardt and Köhler, 2023, p. 35)

Despite their widespread adoption, the actual effectiveness of such recommendations is far from uniform (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021, p. 9). Existing research indicates that their impact depends on several factors, including the type of product (fast-moving consumer goods [FMCG] versus slow-moving consumer goods [SMCG]) (Mazzù *et al.*, 2024, p. 1), the perceived necessity of the purchase, psychological processes such as trust and openness towards technology, (Stüber, 2013, p. 77) as well as the phase of the customer journey in which the recommendation is presented (Harwardt and Köhler, 2023, p. 35). However, an integrative perspective that systematically combines these dimensions and directly compares FMCG and SMCG in the context of AI-generated product recommendations remains limited (Li and Karahanna, 2015, p. 100).

This thesis aims to address this research gap by investigating the conditions under which AI-generated product recommendation systems are perceived as useful, when they influence purchase intention, and how trust, involvement and perceived necessity shape consumer responses in e-commerce.

1.2 Research Question, Hypotheses and Objectives

The overall objective of this thesis is to examine the influence of AI-generated product recommendations on consumer purchase behaviour within the business to consumer (B2C) e-commerce context. Particular attention is given to variations across product categories (FMCG vs. SMCG), phases of the customer journey and individual-level dispositions such as trust, openness and perceived necessity.

Accordingly, the central research question guiding this thesis is formulated as follows:

How do AI-generated product recommendations affect consumer purchasing behaviour along the customer journey in e-commerce, and do these effects differ between fast-moving and slow-moving consumer goods?

Based on theoretical assumptions and empirical findings, the following hypotheses were developed:

- H1: AI-generated product recommendations increase consumers' purchase intention, particularly for FMCG.
- H2: The effect of AI-generated product recommendations on consumers' purchase intention differs across the phases of the customer journey (inspiration, comparison, decision).
- H3: The perceived necessity of a product moderates the effect of AI-generated product recommendations on purchase intention.
- H4: Consumers evaluate AI-generated product recommendations for SMCG more critically than for FMCG.
- H5: Trust mediates the relationship between AI-generated product recommendations and purchase intention.
- H6: Greater openness towards AI-generated product recommendations is positively associated with trust in these systems.

The aim of this thesis is therefore to develop a differentiated, theory-driven and empirically grounded understanding of the effectiveness of AI-generated product recommendation systems, both from a consumer-psychological and a managerial perspective, thereby providing practical implications for online retailers.

1.3 Methodological Approach

In order to address the central research question, a quantitative dual-method research design was employed, grounded in insights derived from a systematic literature review. The overall methodological approach consisted of two complementary studies.

First, a standardised online survey (n = 103) was conducted, comprising predominantly closed-ended questions (Likert-scale, single- and multiple-choice) capturing general consumer perceptions and attitudes regarding product types, perceived necessity, trust in AI-generated product recommendations, purchase intention and customer-journey phases.

Second, a simulated scenario-based online-shopping experiment (n = 30) was implemented, employing an A/B-test logic within a between-subjects design. Participants were randomly assigned to one of four scenarios representing a 2x2 design: FMCG vs. SMCG x AI-generated product recommendation vs. no recommendation. The simulated shopping journey comprised a homepage, product-detail page and shopping cart, enabling the measurement of both behavioural and self-reported responses to recommendation exposure.

The theoretical component of the thesis builds upon established concepts and models in the fields of AI in e-commerce, AI-generated product recommendation systems research, consumer goods classification and the customer journey theory. Collectively, these elements provide the analytical framework for the empirical analysis, which is conducted employing both descriptive and inferential statistical methods (e.g., mean comparisons, correlations, regression analyses) to identify significant differences and correlations in consumers' perceptions and decision-making processes.

1.4 Scope and Structure of the Thesis

To ensure conceptual clarity and methodological feasibility, this thesis concentrates on the business-to-consumer (B2C) online retail sector in the German-speaking e-commerce market. While product recommendations are also employed in social media (e.g., influencer marketing), brick-and-mortar retail and business-to-business (B2B) environments, these contexts are beyond the scope of the present analysis. The rationale for this restriction is that AI-generated product recommendations in B2C e-commerce represent one of the most prevalent and economically significant use cases of AI in consumer markets (Heinemann, 2025, p. 136).

Moreover, this thesis focuses specifically on AI-generated product recommendations that are based on consumer behaviour and similarity logics. Hybrid forms of recommendations, which involve human curation or explicit social interaction, are excluded, as are other AI-generated tools in e-commerce, such as chatbots or dynamic pricing, to maintain conceptual clarity.

The structure of the thesis is organised into eight chapters. Following this introduction, Chapter 2 expands upon the theoretical framework by discussing the fundamentals of e-commerce, the classification of consumer goods and the customer journey as the structural model, followed by an overview of AI and recommendation systems as well as the current state of research. Chapter 3 outlines the methodological approach, including hypothesis development, research design, data collection and analysis procedures. Chapter 4 presents the results of the two empirical studies, while Chapter 5 interprets these findings and relates them to the theoretical framework and research question. Chapter 6 describes the limitations of the research, whereas Chapter 7 discusses managerial and research implications and proposes directions for future research. Finally, Chapter 8 concludes the thesis with a summary of the main findings and an integrative reflection.

In order to ensure optimal readability and consistency, this thesis applies a linguistic simplification rule. Throughout the text, the generic masculine form is used for personal designations. It is imperative to note that unless an explicit statement is provided to the contrary, all references are to be applied equally to all genders. This decision is made exclusively for stylistic and readability purposes and does not imply any exclusion or bias with regard to gender diversity.

Selected passages of this thesis were translated from German into English using the tool DeepL and subsequently revised and linguistically adapted by the author. In addition, ChatGPT (version 5.1) was used as an assistive tool for language refinement, idea generation and structural suggestions. All content, arguments and final formulations were independently developed, verified and approved by the author.

2 Theoretical Framework

Before analysing the role of Artificial Intelligence (AI) and AI-generated product recommendation systems in e-commerce, it is imperative to establish a fundamental understanding of e-commerce and consumer behaviour in the digital environment. The present chapter provides the conceptual foundation for examining how AI-generated product recommendations influence consumer decision-making processes.

2.1 Fundamentals of E-Commerce and Consumer Behaviour in the Digital Context

Within a few decades, the internet has profoundly transformed modern society, particularly in terms of consumer behaviour. Its ubiquity has created new opportunities for structuring and simplifying daily life across a wide range of domains. (OECD, 2019, p. 11) One of the most visible developments is the rapid rise of electronic commerce (e-commerce), which has become firmly established across almost all consumer segments as a convenient alternative to traditional brick-and-mortar retail (Deges, 2023, p. 2).

E-commerce, frequently employed synonymously with terms such as online retail or e-retailing, describes all market activities in which business processes are conducted fully or partly through the internet (Deges, 2023, p. 3). Its defining characteristic is not necessarily the complete digitalisation of the entire transaction process, but rather the conclusion of the contract through digital channels. Consequently, e-commerce can be defined as a form of distance selling, clearly distinguished from traditional offline trade. (Deges, 2023, p. 3) In the context of distance selling, the conventional paradigm of physical interaction between buyers and sellers is rendered obsolete by the advent of interactive communication technologies, such as the internet, which effectively bridges the spatial distance (Heinemann, 2024, p. 65).

From a technological perspective, e-commerce relies on interactive information and communication technologies. Its development is closely linked to the expansion of the internet and the availability of robust digital infrastructures. (Deges, 2023, p. 8) A particularly dynamic subfield is mobile commerce (m-commerce), which focuses on transactions conducted via mobile devices (Heinemann, 2024, p. 68). In contrast to the predominant use of desktop computers in previous years, contemporary trends indicate that smartphones have emerged as the predominant device for online shopping. However, larger screens retain their relevance for more complex or high-involvement purchases. (Deges, 2023, p. 5)

Two primary market forms can be identified in electronic commerce (Chaffey, Edmundson-Bird and Hemphill, 2019, p. 22):

- B2C (business-to-consumer): direct trade between companies and end consumers, typically via online shops, marketplaces or social media platforms.
- B2B (business-to-business): transactions between companies along the value chain, conducted via dedicated B2B shops, procurement platforms or marketplaces.

In the B2C context, e-commerce has evolved beyond a mere sales channel: it now serves as a data-driven ecosystem that supports product search, comparison, purchase, and long-term customer relationship management. (Laudon and Traver, 2023, p. 250)

Furthermore, the manner in which individuals search for, purchase and consume goods has undergone a fundamental transformation as a consequence of the internet and e-commerce. The decision-making process is now increasingly detached from temporal and geographical constraints and is becoming progressively data-driven. (Heinemann, 2024, p. 82) In contradistinction to conventional commerce, where interactions are immediate and physical, online consumers actively enter the digital marketplace through personal accounts or device identifiers, such as IP addresses (Heinemann, 2024, p. 82). This shift generates both challenges and opportunities. On the one hand, consumers benefit from unparalleled access to information and products. On the other hand, companies must adapt by investing in customer acquisition and retention strategies that are highly personalised. (Heinemann, 2024, p. 82)

The fundamental objective of every consumer is to identify products that optimally satisfy their needs (Heinemann, 2025, p. 72). The internet has profoundly shaped this process by providing global product accessibility and enabling informed decision-making (Heinemann, 2024, p. 82). During the purchasing process, consumers gather information, evaluate alternatives, and increasingly rely on product information, reviews and recommendations to reduce uncertainty and facilitate decisions (Virdi, Kalro and Sharma, 2020, pp. 563–564; Heinemann, 2024, p. 82).

It is imperative to acknowledge the mounting significance of psychological factors in conjunction with functional aspects such as price, assortment and convenience (Deges, 2023, p. 132). Trust is a pivotal component in digital commerce due to the absence of physical interaction between market participants. Particularly, in the context of first-time purchases, consumers frequently require an initial level of trust in the retailer or platform. Repeated positive experiences has been demonstrated to engender system trust, thereby fostering long-term customer relationships. (Deges, 2023, p. 131)

This typology presented in Table 1 illustrates that consumer behaviour depends not solely on product characteristics, but also on psychological drivers such as habits, emotions, trust and information availability (Kroeber-Riel and Gröppel-Klein, 2019, p. 397). In the digital environment, these drivers are further shaped by technological systems such as AI-generated product recommendation systems, which actively shape and mediate decision-making processes (Heinemann, 2024, p. 82).

Table 1 Decision-making logics in online-shopping.

Decision logic	***Information search***	***Cognitive involvement***	***Typical products***	***Example behaviour***
Extensive	High	Strong rational evaluation	Electronics, furniture	Research and comparison before purchase
Limited	Moderate	Selective	Clothing, technology	Relies on past experience or few sources
Habitual	Low	Routine-based	Groceries, everyday products	Repeated purchases without reconsideration
Impulsive	Minimal	Emotion-driven	Snacks, small items	Spontaneous, triggered by stimuli

Note. Own illustration based on (Deges, 2023, p. 133).

Table 1 summarises the four typical decision-making logics in online-shopping, highlighting how consumers' level of involvement, price sensitivity and cognitive effort determine their purchasing behaviour (Deges, 2023, p. 133). These behavioural patterns range from extensive and limited processes to habitual or impulsive decisions and provide an essential foundation for understanding how consumers respond to digital stimuli, such as AI-generated product recommendations and how these responses may differ across different product categories and phases of the customer journey.

The combination of technological infrastructure, evolving decision-making logics, and increasing personalisation underscores that e-commerce is not merely a new distribution technology, but rather an independent consumption environment with its own behavioural patterns (Huang and Rust, 2021, p. 30). As the complexity of decision-making increases and consumers are confronted with an expanding array of products and information, companies must demonstrate strategic agility, investment and technological adaptability to maintain competitiveness. (Heinemann, 2024, p. IX)

This evolution in digital consumption behaviour lays the framework for understanding how different categories of goods shape online decision-making processes, which will be examined in the following section.

2.2 Classification of Economic and Consumer Goods

Before examining the influence of AI-generated product recommendation systems in greater depth, it is essential to clarify what types of goods are traded in e-commerce. The nature of the product has been shown to exert a significant influence on the manner in which digital technologies impact consumer behaviour (Meffert *et al.*, 2024, p. 25). Consequently, this section provides a conceptual classification of economic and consumer goods as the theoretical foundation for subsequent analyses.

The exchange of goods has been identified as a fundamental principle of human interaction. As early as antiquity, philosophers reflected on the forms and challenges of barter trade. Adam Smith, widely regarded as a pioneering theorist of the industrial division of labour, identified exchange behaviour as an anthropological constant, one which is profoundly embedded within the fabric of human nature. (Meffert *et al.*, 2024, p. 2) From this perspective, marketing can be historically understood as the systematic organisation of exchange processes aimed at efficiently satisfying needs. Consequently, marketing is not only a tool for increasing sales, but also a comprehensive concept for aligning corporate performance with the consumer demands. (Meffert *et al.*, 2024, p. 2) Consumers allocate time and financial resources to acquire products that satisfy individual preferences, while companies commit resources to the development, production and distribution of goods. The capacity to comprehend consumer needs is directly correlated with the precision and success of their offerings. (Meffert *et al.*, 2024, p. 2)

Although marketing management processes are generally similar across industries, the exchange processes are found to differ depending on the type of goods and the underlying market structure. It is imperative that these differentiations are given full consideration in any strategic marketing analysis. (Meffert *et al.*, 2024, p. 25) Therefore, the subsequent section provides a systematic classification of economic goods and their key characteristics.

2.2.1 The Concept of a Product

From a consumer perspective, a product can be defined as a bundle of attributes that provides value and satisfies needs (Homburg, 2020, pp. 599–600). In order to systematically classify the various forms of products observed in business practice, a variety of typifying characteristics are applied in Table 2.

Table 2 Typology of products.

Typology criteria	***Examples / categories***
Materiality of offering	Tangible goods vs. services
Type of demand	Industrial goods (business customers) vs. consumer goods (private customers)
Usage duration	Non-durable (consumables) goods vs. durable goods
Purchase habits	Convenience goods, shopping goods, specialty goods
Purchase motivation	Sought goods vs. unsought goods
Value-creation level	Raw materials, intermediate goods, finished products
Additional criteria	Brand loyalty, product complexity, usage frequency

Note. Own illustration based on Homburg (2020, p.604).

A hierarchical typology of economic goods (see Figure 3) begins with the differentiation between tangible goods and intangible goods, such as services, predicated on the materiality of the offering. These are then subdivided by the type of demand: tangible goods are classified as consumer goods (for private use) or industrial goods (for professional or institutional use), while intangible goods are distinguished as consumptive services and investment-related services. (Homburg, 2020, p. 604)

This figure is instrumental in guiding the subsequent chapters, which are dedicated to defining the relevant terminology in this thesis.

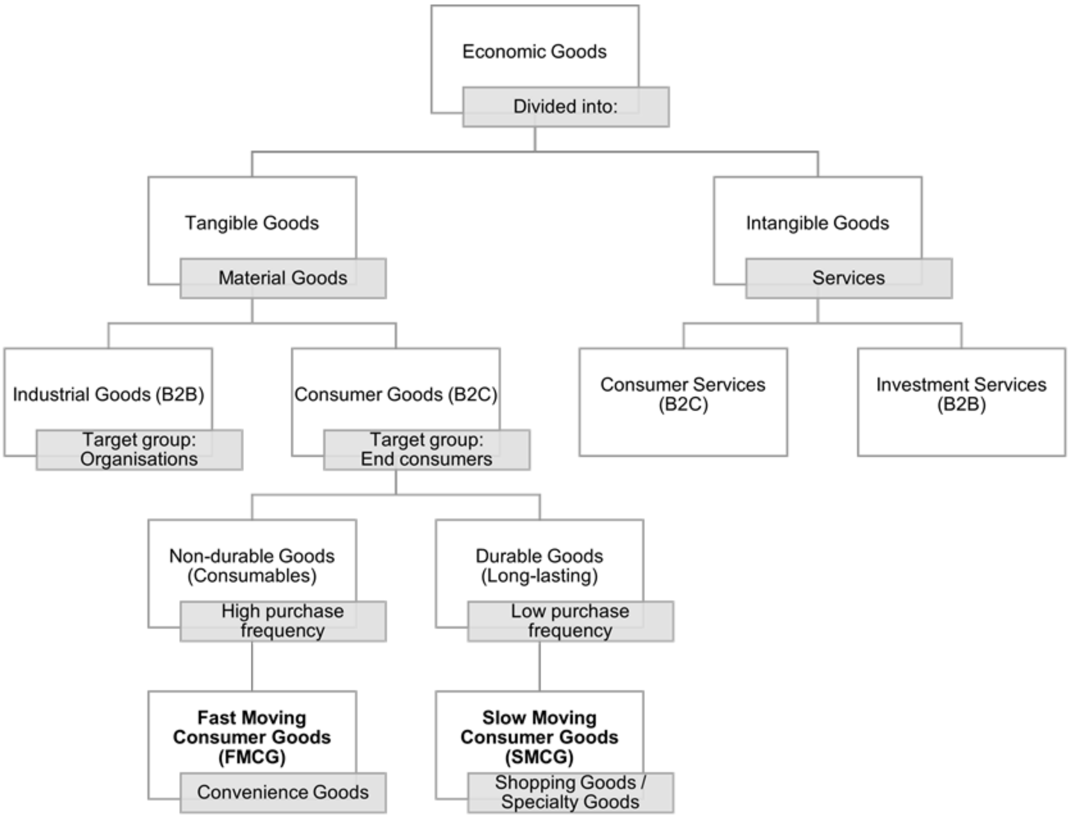


Figure 1 Hierarchical typology of economic goods.

Note. Own illustration based on (Homburg, 2020, p. 604).

2.2.2 Differentiation between Consumer and Industrial Goods

Economic goods are characterised by scarcity and the need for price-based coordination between supply and demand (Meffert *et al.*, 2024, p. 380). The primary distinction between consumer goods and industrial goods is primarily based on the type of the customer (Backhaus, 2014, p. 3).

Consumer goods include all tangible items and services that are purchased by individuals or private households for personal use and consumption. Sales are conducted either via retail channels or directly from manufacturers. In the context of large-scale commercial transactions, personal interaction between supplier and consumer is often negligible. (Meffert *et al.*, 2024, p. 25)

In contrast, *industrial goods* are procured by organisations and incorporated into production or operational processes. The customer is this context is an organisation, whether that be a company, a public authority or a non-profit institution (Meffert *et al.*, 2024, p. 55).

Beyond differences in target groups, there are also variances in transaction volume, product complexity and communication requirements between consumer and industrial markets. Industrial markets are characterised by higher transaction volumes and greater technical complexity. These differences imply that marketing concepts cannot be directly transferred between sectors. (Meffert *et al.*, 2024, p. 26)

Since this thesis focuses on consumer goods, the subsequent section provides a more detailed examination of this category and its subtypes.

2.2.3 Systematics of Consumer Goods

Within the category of consumer goods, a further distinction is made based on the usage duration:

- *Non-durable goods*: used up during consumption (e.g., food, shampoo), typically with high purchase frequency (Homburg, 2020, p. 634; Meffert *et al.*, 2024, p. 25).
- *Durable goods*: used repeatedly over an extended period (e.g., furniture, household appliances) (Meffert *et al.*, 2024, p. 25).

A further behavioural classification distinguishes consumer goods according to the consumer buying behaviour (Homburg, 2020, p. 604):

- *Convenience goods*: everyday necessities with low involvement and high purchase frequency (e.g., bread, toothpaste).
- *Shopping goods*: products requiring more information search and comparison (e.g., clothing, entertainment electronics).
- *Specialty goods*: products with high emotional attachment and brand preference (e.g., designer fashion, luxury watches).

In the field of marketing, these categories are often aligned with the broader distinction between Fast-Moving Consumer Goods (FMCG) and Slow-Moving Consumer Goods (SMCG). FMCG are defined by their association with consumables and convenience goods, as they are frequently purchased due to their low cost and short shelf life. (Homburg, 2020, p. 604; Meffert *et al.*, 2024, p. 25) Conversely, SMCG encompasses shopping goods and specialty goods, which are purchased less frequently and require a greater cognitive and emotional investment in the decision-making process (Homburg, 2020, p. 604). This distinction between FMCG and SMCG is central to this thesis, as it provides the conceptual framework for analysing how AI-generated product recommendations influence consumer decision-making across different product types.

2.3 The Customer Journey as a Structural Model

Every purchase decision, irrespective of the product category, follows a structured process of cognitive and behavioural steps (Vogrincic-Haselbacher *et al.*, 2021, p. 1). In e-commerce, companies increasingly recognise customer experience as a strategic determinant of competitive advantage, investing substantial resources in understanding and shaping digital consumer decision processes (Klaus, 2015, p. 1). In order to analyse how and when AI-generated product recommendation systems influence consumer decision-making in e-commerce and to determine where companies should allocate strategic and technological resources, it is essential to conceptualise the customer journey as both a consumer behavioural process and a structural analytical framework. This chapter outlines the theoretical foundations, underlying phase logic, and modern interpretations of the customer journey, with a specific emphasis on its relevance for AI-generated product recommendation systems.

2.3.1 Transformation of the Purchasing Decision Process

A customer journey represents a structural model that traces the consumer's progression from initially recognising a need to engaging in post-purchase evaluation (Harwardt and Köhler, 2023, p. 5). According to Harwardt and Köhler (2023, p. 6), an idealised purchasing process can be divided into five distinct phases as illustrated in Figure 2. These five phases initially include the perception of a need, followed by the search for information, the evaluation of alternatives, the decision to purchase and finally the behaviour observed in the post-purchase phase, which includes product experience, satisfaction appraisal and future purchase dispositions. (Harwardt and Köhler, 2023, p. 5)

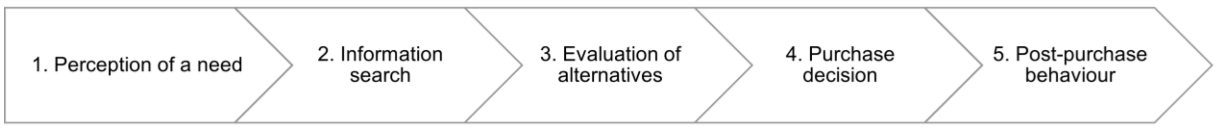


Figure 2 The five phases of the consumer decision-making process.

Note. Own illustration adapted from (Harwardt and Köhler, 2023, p. 5).

While this framework was traditionally illustrated as a linear, sequential process, the expansion of e-commerce has significantly transformed its underlying processes. In online environments, decision phases increasingly unfold in parallel, compress in duration and often recur iteratively, reflecting a fluid rather than linear progression (Harwardt and Köhler, 2023, p. 8). Within this context, consumers frequently switch dynamically between information search, alternative evaluation and product discovery, interacting with multiple digital touchpoints, including search engines, comparison platforms, online marketplaces and social media throughout their decision-making journey. (Harwardt and Köhler, 2023, p. 8)

Digital technologies exert a measurable influence on consumer perceptions and decision processes across each phase of the customer journey, with online reviews, influencer-generated content, algorithmic product rankings and AI-generated product recommendation systems representing key digital choice stimuli (Harwardt and Köhler, 2023, p. 8). These stimuli shape perceptions, reduce uncertainty and enable faster decision-making, yet may also increase cognitive load when poorly aligned with consumer needs (Roy and Dutta, 2022, p. 2).

Digital consumption environments also enable the possibility to enter and exit the journey at any point, and may purchase impulsively without engaging in formal search or evaluation. This fluidity challenges static, funnel-style perspectives and the importance of modelling customer journeys as adaptive, non-linear, and micro-moment driven decision architectures when analysing AI-generated product recommendation systems in e-commerce markets. (Bajpai and Sameer, 2025, p. Abstract)

2.3.2 Foundations and Significance of the Customer Journey

The customer journey encompasses all phases and touchpoints a consumer experiences from the initial awareness of a product or need to the ultimate purchase decision and beyond (Heinemann, 2024, p. 86). Importantly, the final purchase moment constitutes only one single element within a wider, interconnected network of digital, physical and social interactions that collectively shape the consumer's decision process (Deges, 2023, p. 148). These interactions take place across a series of Customer Touchpoints, defined as any direct or indirect, conscious or unconscious interaction between a customer and a company or platform (Harwardt and Köhler, 2023, p. 9).

In e-commerce environments, touchpoints can be systematically categorised into:

- *Company-owned* touchpoints, such as websites, mobile applications, digital product environments, email communication and newsletter-based interactions, *and*
- *External* touchpoints, including social media, influencer content, search engines, algorithmic rankings and consumer review platforms (Deges, 2023, p. 148).

As e-commerce continues to decentralise interaction environments, companies increasingly adopt customer journey models as strategic management and measurement frameworks in order to steer, evaluate and optimise customer experience within non-linear, technology-enabled retail ecosystems (Hoyer *et al.*, 2020, p. Abstract).

In the digital era, connected devices, particularly smartphones, serve as central consumer interaction interfaces, enabling companies to communicate through push-based advertising, mobile applications, cross-device browsing environments and other digitally addressable choice stimuli. (Harwardt and Köhler, 2023, p. 9)

Digitalisation has substantially increased the number and diversity of Customer Touchpoints available to consumers. Although not every consumer uses every channel, multi-device and cross-platform interactions increasingly fragment entry points into the journey. (Harwardt and Köhler, 2023, p. 12)

Taken together, the integration of these digital and social interactions across the full purchase process constitutes what is understood as the customer journey. Table 3 summarises selected academic definitions of this concept, which form the analytical basis for structuring the subsequent conceptual and empirical investigation.

Table 3 Selected definitions of the customer journey.

Author(s)	***Definition***
(Kruse Brandão and Wolfram, 2018, p. 14)	The customer journey describes the cyclical path a customer follows before deciding to purchase a product, including all contact points (touchpoints) with a brand.
(Deges, 2020, p. 81)	The customer journey connects the phases of the purchase decision process with all touchpoints, extending beyond the purchase to include after-sales services and product experiences.
(Hopf, 2021, p. 5)	The customer journey, also called the Buyer's or User's Journey, refers to all steps and touchpoints a customer experiences across communication channels on the way to purchase.

Note. Own illustration adapted from (Harwardt and Köhler, 2023, p. 11).

In contemporary research, the customer journey is increasingly conceptualised as non-linear, recursive and context-dependent, shaped by omnichannel interaction behaviour, mobile-first access patterns and algorithmically curated choice environments (Lemon and Verhoef, 2016, p. 79). These developments highlight why AI-generated product recommendations must be analysed within the structural sequence and timing of consumer decisions.

2.3.3 The AICPURA Model

While early customer journey models often relied on simplified three-phase structures (e.g., pre-purchase, purchase, post-purchase), more recent frameworks seek to capture the complexity of digital consumer purchasing behaviour (Harwardt and Köhler, 2023, p. 14). Building on the classic AIDA model (Awareness, Interest, Desire, Action), Harwardt and Köhler (2023, p. 15) propose the AICPURA model, which extends the sequence by integrating additional phases that are relevant in online contexts. The acronym AICPURA stands for:

- *Awareness:* Identification of a need or exposure to an external stimulus, frequently triggered by digital advertising, search results or social media contact.
- *Interest:* Initial orientation and broad information search within a more general set of alternatives.
- *Consideration:* More detailed evaluation and comparison of shortlisted options.
- *Purchase:* The decision and transaction phase, including payment and order confirmation processes.
- *Retention:* Post-purchase satisfaction, usage experience and relationship-building activities.
- *Advocacy:* Loyalty, positive recommendations behaviour, for example through ratings, reviews or social sharing (Harwardt and Köhler, 2023, p. 16).

Especially the post-purchase phase has gained particular importance in e-commerce. Unlike offline retail, the initial sensory encounter with the product often occurs after delivery, not prior to purchase. (Deges, 2023, p. 357) Consequently, elements such as return processes, customer service interactions, and online reviews significantly shape satisfaction and long-term loyalty, thereby determining whether consumers will make repeat purchases or act as advocates for the product or service. (Deges, 2023, p. 357)

Although the AICPURA model is typically visualised as a linear sequence, empirical and conceptual work increasingly emphasises that real consumer journeys rarely follow a purely sequential pattern. Instead, they tend to be non-linear and iterative, particularly in digital environments characterised by multiple channels, feedback loops and parallel touchpoints. (Harwardt and Köhler, 2023, p. 18) The progression between phases is strongly influenced by factors such as product involvement, perceived risk and decision complexity: for habitual, low-involvement purchases such as FMCG, consumers may compress or skip phases, relying on routine choices and minimal evaluation (Deges, 2020, p. 81). High-involvement purchases, by contrast, such as SMCG, often involve repeated search and comparison cycles, longer deliberation and a greater propensity to re-enter earlier phases before committing to a purchase. (Deges, 2020, p. 81)

The AICPURA model is particularly suitable for research on AI-generated product recommendations because it explicitly differentiates between phases in which decision support is likely to create value and phases in which recommendations are more likely to be ignored or perceived as intrusive.

2.3.4 Customer Journey Mapping

Given the increasing complexity of multi-channel environments, companies require structured, evidence-based tools to analyse and optimise customer experiences (Dwijendra Nath, Dwiivedi

Ghanashyama, and Edward Emmanuel, 2025, p. 2). Customer Journey Mapping (CJM) has evolved as a visual, user-centred analytical method for examining consumer decision pathways across multiple touchpoints. The objective is to identify critical moments, design frictionless interactions and enhance a consistently positive customer experience. (Heinemann, 2024, p. 374) In online retail, a context marked by broad assortments, algorithmic rankings, and fragmented device usage, CJM plays a vital managerial role, as it enables firms to allocate strategic resources towards the most behaviourally influential touchpoints and thereby improve conversion and long-term loyalty outcomes. Consequently, CJM is a data-driven and dynamic modelling tool that provides a strategic intelligence framework, integrating customer analytics, behaviour segmentation, and real-time data streams. This enables continuous learning from customer interactions and the prediction of future engagement patterns. (Dwijendra Nath, Dwiivedi Ghanashyama, and Edward Emmanuel, 2025, p. 2).

2.3.5 Relevance for AI-Generated Product Recommendation Systems

Understanding the structure and dynamics of the customer journey provides the conceptual foundation for analysing the situational effectiveness of AI-generated product recommendation systems. Contemporary research highlights that the impact of AI-generated product recommendation systems and other algorithmically curated decision stimuli is highly context-dependent, differing significantly across:

- Different customer journey phases,
- Product categories, *and*
- Consumers' involvement, trust and individual behaviour (Arne De Keyser *et al.*, 2015, p. 16)

Because of this phase- and involvement-dependency, theory predicts that AI-generated product recommendations are most effective when they align with the prevailing decision logic, the timing of the phase, and the touchpoint context in which they appear. When appropriately aligned, these factors can reduce uncertainty, support evaluation and increase purchase intention (Virdi, Kalro and Sharma, 2020, pp. 563–564; Heinemann, 2024, p. 82). When poorly timed or irrelevant, they risk generating cognitive friction, irritation, or being ignored altogether (Roy and Dutta, 2022, p. 2).

The customer journey framework therefore functions not only as a descriptive model of consumer progression but also serve as a strategic evaluation lens for explaining when AI-generated product recommendation systems facilitate decisions, when they stimulate impulse effects, and when they are likely to be disregarded or perceived as intrusive. This structural understanding forms the theoretical basis for the empirical analyses of this thesis, which systematically examine AI-generated product recommendations across FMCG and SMCG categories and across customer journey phases.

The following chapter thus undertakes an examination of AI and product recommendation systems as key technologies driving modern e-commerce, before linking these concepts to the hypotheses formulated in this thesis.

2.4 Artificial Intelligence in E-Commerce and Recommendation Systems

AI has gained increasing prominence in both research and practical application (Heinemann, 2024, p. 140). In e-commerce, it has become imperative for companies to leverage digital technologies strategically in order to enhance customer experience and improve efficiency throughout the entire customer journey. As one of the key innovation drivers in this domain, AI has rapidly expanded in scope and application, enabling advanced personalisation and automating decision-making processes that previously depended on human judgement. (Heinemann, 2024, p. 9)

2.4.1 Definition and Differentiation: Artificial Intelligence, Machine Learning and Deep Learning

Despite its extensive utilisation, the term A*rtificial Intelligence* (AI) remains conceptually ambiguous and lacks a universally accepted definition (Wagener, 2023, p. 19). In general, it encompasses the imitation of human cognitive abilities, including reasoning, learning and problem-solving, by technical systems. (Wagener, 2023, p. 19) A defining feature of AI is the capability for machine learning, that is, the independent processing of large datasets (big data) and the derivation of actionable patterns and using them for predictions or decisions (Wagener, 2023, p. 32,38).

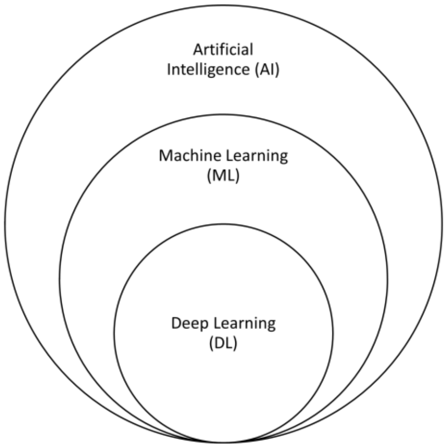
In the majority of the cases, the term AI is used as an umbrella term. In the context of systems capable of learning and adapting from data, Machine Learning (ML) and, as a subset of ML, Deep Learning (DL) are more precise terminological choices. (Heinemann, 2024, p. 141)

The conceptualisation of AI can be approached through three distinct levels of analysis:

- *Artificial Intelligence (AI)* is an umbrella term for systems with cognitive abilities. AI applications require language, speech and strategic thinking, and are capable of performing certain tasks just as well as or even better than humans (Heinemann, 2024, p. 141).
- *Machine learning (ML)* as a subfield of AI that independently learns from data, makes decisions and lays the foundation for deep learning (Heinemann, 2024, p. 141).
- *Deep learning (DL)* is a subcategory of ML that uses artificial neural networks. Applications based on deep learning use neural networks to establish connections and thereby discover patterns. It is characterised by its ability to read, convert and process input data from users. The more data available for this purpose, the better the results (Heinemann, 2024, p. 9/142).

ML enables predictive modelling, for example by anticipating customer preferences or optimising product personalisation (Heinemann, 2024, p. 9). DL, in turn, further extracts insights from unstructured data such as images, brief descriptions, or speech (Janiesch, Zschech and Heinrich, 2021, p. 689).

Figure 3 visualises the hierarchical relationship between AI, ML and DL, illustrating how deep learning builds on machine learning, which in turn represents a specialised domain within the broader field of artificial intelligence.



Note. Own illustration adapted from (Harwardt and Köhler, 2023, p. 24).
Figure 3 Hierarchical structure of AI, ML and DL.

2.4.2 Types and Potentials of AI Technologies in E-Commerce

AI technologies in e-commerce encompass a broad spectrum of applications that support customer interaction, operational efficiency and personalisation (Harwardt and Köhler, 2023, p. 32). As shown in Table 4, key technological categories include chatbots and virtual assistants for customer service, AI-generated product recommendations for personalised product discovery, predictive analytics for behavioural forecasting, and natural language processing (NLP) for interpreting text or voice input (Patil, 2025, p. 1). These technologies enable retailers to manage large assortments, automate repetitive tasks, and provide real-time, data-driven personalisation on a large scale (Chinchanachokchai, Thontirawong and Chinchanachokchai, 2021, p. 2).

Table 4 Overview of AI technologies in e-commerce and their core functions.

Technology	***Core function***
AI-generated product recommendations	Personalised suggestions based on consumer behaviour increase relevance and engagement (Ikeh, 2025, p. 5791).
Dynamic pricing	Automated price adjustments in response to market dynamics and demand patterns (Ikeh, 2025, p. 5787).
Customer segmentation	Grouping consumers in large, complex datasets into target segments based on behavioural and demographic data (Ikeh, 2025, p. 5781).
Content personalisation	Real-time adaption of website content, visuals, and recommendations to consumer profiles (Ikeh, 2025, p. 5791).

Note. Own illustration based on (Ikeh, 2025, pp. 5781–5791).

Beyond the operational efficiency that is afforded by AI, the technology also offers strategic business advantages. AI-generated systems have been shown to significantly improve key performance metrics such as average order value, conversion rate, and customer retention, while simultaneously enhancing consumer satisfaction and engagement. (Alabi, 2024, p. 1) This enables firms to expand their marketing activities, satisfy rising customer expectations for relevance and convenience, and enhance brand loyalty. Consequently, companies can leverage AI not only as a technological facilitator, but also as a strategic catalyst for growth. (Alabi, 2024, p. 9)

2.4.3 Product Recommendation Systems – Functionality and Mechanisms

AI-generated product recommendation systems represent one of the most influential and successful applications of AI in the field of digital commerce (Castells and Jannach, 2023, p. 5). They guide consumers along the customer journey by suggesting relevant products, personalising the shopping experience, and facilitating decision-making. Consequently, this approach has been shown to enhance satisfaction and conversion rates. (Nguyen *et al.*, 2024, p. 4)

Although contemporary AI research often highlights chatbots, AI-generated product recommendation systems are at least as influential in practice (Castells and Jannach, 2023, p. 56). In e-commerce, they have established themselves as a key tool for analysing consumer behaviour and generating personalised, real-time suggestions based on previous interactions, preferences or contextual signals (Castells and Jannach, 2023, p. 5).

Earlier, non-personalised systems relied on simple, rule-based logic such as ‘customers who purchased X also purchased Y’. While easy to implement, these approaches offered only limited individualisation. In contrast, modern AI-generated systems employ machine learning, collaborative and content-based filtering, deep learning, and NLP to analyse extensive behavioural datasets, including click behaviour, purchase histories, ratings or demographic characteristics and to generate precise, context-aware adaptive recommendations (Pu, Chen and Hu, 2012, p. 318). Contextual variables such as time, location or device type can further refine recommendation accuracy (Nguyen *et al.*, 2024, p. 4).

The adaptive nature of these systems enables continuous improvement, with each user interaction contributing to the refinement of the model’s precision. Empirical evidence demonstrates that AI-generated product recommendation systems have the capacity to accelerate the decision-making process, induce impulsive purchasing, elevate the average order value, and enhance cross- and upselling. (De Biasio, Navarin and Jannach, 2023, p. 2) At the same time, they serve to reduce information overload, thereby enabling customers to make more confident and satisfying purchase decisions (Fayyaz *et al.*, 2020, p. 1). This is of particular benefit to customers when searching for complex product categories, such as electronics or furniture. In the long term, positive recommendation experiences foster loyalty and repeat purchasing, as consumers perceive personalised suggestions as convenient and trustworthy (Alabi, 2024, p. 5).

2.4.4 Challenges and Ethical Considerations

The integration of AI-generated product recommendation systems introduces several ethical and operational challenges, particularly concerning data privacy, transparency, algorithmic bias, fairness and user acceptance (Milano, Taddeo and Floridi, 2020, p. 1; Deldjoo *et al.*, 2024, p. 1). It is imperative to understand how consumers perceive, evaluate and trust these systems, particularly in decision-making scenarios. Research shows that trust, perceived control, and fairness strongly influence system acceptance and utilisation. (Acharya, Sassenberg and Soar, 2022, p. 55)

Data protection remains a central issue, as effective personalisation requires access to personal and behavioural data. Under the General Data Protection Regulation (GDPR), personal data may only be permitted to be processed under a lawful basis or explicit user consent (Hoofnagle, Van Der Sloot and Borgesius, 2019, p. 76). In digital commerce, this requires organisations to ensure compliance, transparent data practices and user-centric consent mechanisms in order to maintain customer trust (Siepmann and Chatti, 2023, p. 2).

A further challenge concerns the lack of transparency of many AI-generated models. Contemporary product recommender systems, especially deep-learning-based architectures, frequently operate as 'black boxes', with unclear decision pathways, that have the potential to erode user confidence, particularly for high-involvement purchases (Alejandro Barredo Arrieta *et al.*, 2019, p. 32).

Furthermore, insufficient or biased data may lead to algorithmic bias or filter bubbles, restricting diversity and exposing users to repetitive content (Klimashevskaia *et al.*, 2024, p. 1). In addition, biases in training data can lead to algorithmic discrimination, filter bubbles or reduced diversity, reinforcing pre-existing behavioural patterns and restricting exposure to novel or serendipitous options (Werthner *et al.*, 2024, p. 421). As a result, fairness, privacy protection and explainability have become central design principles in current recommender-system research and development (Milano, Taddeo and Floridi, 2020, p. 1; Deldjoo *et al.*, 2024, p. 1).

2.4.5 Strategic Importance and Future Outlook

Despite these challenges, organisations continue to invest heavily in AI-generated product recommendation systems due to their measurable impact on consumer engagement, sales performance and long-term customer value (Khamdamov *et al.*, 2024, p. 117). Current research highlights that recommendation systems remain one of the most strategically valuable tools within the domain of digital marketing, particularly with the progression of real-time analytics and generative AI (Castells and Jannach, 2023, p. 5).

In the near future, such systems will not only shape product presentation but also dynamically influence pricing, communication, and promotional strategies (Sai Ganesh Reddy *et al.*, 2023, p. 382). With the evolution of generative and multimodal recommender models, AI-generated systems increasingly integrate visual, textual, and behavioural data, enabling highly adaptive and context-sensitive personalisation (Masrek, Baharuddin and Syam, 2025, p. 380).

In essence, AI-generated product recommendation systems represent the integration of data analytics, machine learning and customer-centric personalisation, establishing a fundamental element of future-oriented, AI-driven e-commerce strategies. Their strategic relevance within digital commerce is expected to intensify as technological capabilities continue to expand across modalities, contexts and interaction channels. (Patil, 2025, p. 1)

2.5 Research Status and Research Gaps

Building on the theoretical foundations outlined above, this section reviews the current status of academic research on AI-generated product recommendations in e-commerce and identifies the remaining gaps that motivate the present study.

2.5.1 State of the Research on AI-generated Product Recommendations

Recent literature shows that the perception and effectiveness of AI-generated product recommendations vary significantly depending on product type, purchase phase and consumer characteristics (Virdi, Kalro and Sharma, 2020, p. 555; Jin and Zhang, 2025, p. 279; Werthner *et al.*, 2024, p. 185). For instance, consumers tend to prefer AI-generated product recommendations for tangible and standardised products, whereas for experience-oriented goods such as travel or hospitality, human advice is often perceived as more trustworthy (Jin and Zhang, 2025, p. 279). Moreover, consumers' familiarity with digital technologies moderates their evaluation: individuals with greater online experience exhibit higher trust and acceptance toward automated recommendations (Hao Suan Samuel, Balaji and Kok Wei, 2015, p. Abstract).

The effectiveness of personalised recommendations also differs significantly by product type. In the case of search goods, such as electronics, characterised by objective comparability, AI-generated product recommendations are valued for their transparency and credibility (Mazzù *et al.*, 2024, p. 2). Studies emphasise that perceived credibility and informational clarity play decisive roles in determining user acceptance (Shin, 2021, p. Abstract).

Empirical findings from Chinese e-commerce contexts provide additional insights. Yin, Qiu and Wang demonstrate that consumers' click intentions increase when recommendations are perceived as trustful, relevant, inspiring, and informative (2025, p. 4). The effects are mediated by immersive experiences and technology acceptance, while privacy concerns and information quality act as moderating factors (Yin, Qiu and Wang, 2025, pp. 15–18). Similarly, Stüber identifies perceived usefulness, purchase relevance, and output quality as the strongest predictors of recommendation acceptance in the apparel sector (2013, p. 196). Among these factors, purchase relevance, defined as the degree to which recommendations align with individual needs (Stüber, 2013, p. 134), emerges as the most salient cognitive determinant (Stüber, 2013, p. 165). Interestingly, recommendations do not necessarily shorten the purchase process, instead, they may prolong browsing behaviour as users explore additional offers (Stüber, 2013, p. 204).

Conversely, dissatisfaction arises when recommendation systems are perceived as irrelevant, manipulative or misaligned with consumer preferences and 'can distort consumers' willingness to pay' (Jannach and Adomavicius, 2017, p. 2). A common methodological limitation in AI-generated product recommendation systems research is their reliance on self-reported measures such as behavioural intentions rather than observed consumer behaviour, which can diverge substantially and thus restricts external validity and generalisability (Xiaoping Zhao *et al.*, 2018, p. 668).

2.5.2 Research Gaps and Relevance of the Present Study

Despite substantial academic and practical interest, several significant research gaps remain in the field of AI-generated product recommendation systems and call for further investigation (Li and Karahanna, 2015, p. 100).

First, much of the existing research focuses on the overall impact of AI-generated product recommendations without differentiating between the different phases of the customer journey (Khamdamov *et al.*, 2024, p. 115). Although preliminary studies suggest that the influence of AI-generated product recommendations may vary across the customer journey phases, comprehensive empirical analyses spanning all phases remain limited (Böge and Eichhorn, 2019, p. 3).

A further salient deficiency pertains to the absence of adequate systematic differentiation by product category. The majority of empirical studies analyse recommendation systems independently of the product type. (Li and Karahanna, 2015, p. 93) It is evident that comparisons between FMCG and SMCG have received minimal attention, as there also is no clear definition so far in existing literature (Homburg, 2020, p. 604), despite the substantial differences in terms of purchase frequency, involvement, and decision complexity . This finding suggests that the impact of recommendations may also vary according to the characteristics of the recipient. (Li and Karahanna, 2015, p. 93) Few studies explicitly test product type as a moderating factor, leaving open how recommendation effectiveness varies between utilitarian and hedonic products (Li and Karahanna, 2015, p. 83).

Third, the cultural context of AI adaption remains unexplored. A significant proportion of empirical research originates from Chinese e-commerce platforms, leaving cross-market comparability and cultural influences insufficiently addressed (He, Du and Pu, 2025, p. 1).

Finally, psychological factors such as trust, perceived control, and privacy concerns are often analysed in isolation rather than integrated with product type or customer journey phase (Li and Karahanna, 2015, p. 83). This gap limits understanding of how individual attitudes and contextual factors interact to shape consumer responses to AI-generated product recommendations (Low *et al.*, 2023, p. 2).

The present study seeks to address these gaps by examining how AI-generated product recommendations influence consumer behaviour across different phases of the customer journey and across product types (FMCG vs. SMCG). By combining experimental methods with phase-specific analysis and cross-product analysis, it contributes to a more differentiated understanding of the mechanisms and effectiveness of AI-generated product recommendation systems in e-commerce.

3 Methods

The following chapter provides a comprehensive overview of the methodological approach used to investigate the influence of AI-generated product recommendations on consumer behaviour along the customer journey. The central research question guiding this study is:

How do AI-generated product recommendations affect consumer purchasing behaviour along the customer journey in e-commerce, and do these effects differ between fast-moving and slow-moving consumer goods?

The research design combines a systematic theoretical foundation with empirical methods to ensure both conceptual depth and analytical rigour.

3.1 Hypothesis Development

The present study was initiated with a systematic review of the existing literature on AI-generated product recommendation systems in e-commerce, in combination with theoretical concepts of consumer behaviour and the customer journey. A range of relevant sources were identified using academic databases, including but not limited to Google Scholar, SpringerLink, and ScienceDirect. These sources were then methodically evaluated with regard to their topical relevance and methodological quality.

Previous research demonstrates that AI-generated product recommendation systems are increasingly integrated at every phase of the customer journey. This ranges from the initial phases of inspiration and the search for products, to the explicit moment of purchase (Lemon and Verhoef, 2016, p. 71). Personalised recommendations have been shown to increase attention, reduce decision uncertainty and ultimately enhance purchase probability. However, prior findings suggest that their effectiveness varies according to the product type (FMCG vs. SMCG), the phase of the decision-making process, and individual dispositions of consumers such as openness or trust towards technology (Virdi, Kalro and Sharma, 2020, p. 555; Jin and Zhang, 2025, p. 279; Werthner *et al.*, 2024, p. 185).

Building upon this theoretical foundation, six hypotheses were formulated to guide the empirical investigation and to ensure conceptual alignment between literature and empirical testing. They focus on variations between product categories, the influence of recommendations across the various phases of the purchase process and the moderating roles of perceived necessity, trust and openness.

- *H1:* AI-generated product recommendations increase consumers' purchase intention, particularly for FMCG.
- *H2:* The effect of AI-generated product recommendations on consumers' purchase intention differs across the phases of the customer journey (inspiration, comparison, decision).
- *H3:* The perceived necessity of a product moderates the effect of AI-generated product recommendations on purchase intention.

- *H4:* Consumers evaluate AI-generated product recommendations for SMCG more critically than for FMCG.
- *H5:* Trust mediates the relationship between AI-generated product recommendations and purchase intention.
- *H6:* Greater openness towards AI-generated product recommendations is positively associated with trust in these systems.

These hypotheses link theoretical assumptions and empirical findings, forming the analytical framework for the research presented in the following sections.

3.2 Research Design and Method Selection

In order to empirically investigate these hypotheses, a quantitative dual-method research design was employed, combining a standardised online survey with a simulated online experiment. This combined approach enabled a comprehensive examination of both situational and behavioural indicators within controlled and realistic online environments. Moreover, enhancing internal validity through experimental control while simultaneously enhancing external validity by replicating realistic online shopping environments.

3.2.1 The Survey Design

Alongside the simulated online experiment which captured phase-specific behavioural responses, a structured online survey was administered via SoSciSurvey. This instrument ensures the expansion of the scope of the investigation by capturing general consumer perceptions of AI-generated product recommendations across the five phases of the customer journey:

- Inspiration and browsing
- Search and comparison
- Product detail pages
- Shopping cart and checkout
- Post-purchase context

Respondents evaluated the perceived helpfulness of recommendations in various product categories, including FMCG and SMCG segments such as fashion, leisure and media, household and living, and technology.

Additional constructs were measured in order to capture individual differences, specifically openness towards AI-generated product recommendations, trust across different channels such as marketplaces, specialised shops, social media and newsletters, as well as the perceived product necessity and the self-reported purchase frequency influenced by recommendations. As each respondent evaluated all phases in the online survey, these data permitted within-subject comparisons.

All constructs were measured using established and validated scales from prior literature, with minor adaptations to align with the specific requirements of the present study. Unless otherwise indicated, the measurement of items was conducted on five-point Likert scales ranging from strong disagreement (1) to strong agreement (5).

3.2.2 The Experimental Design

The experiment was implemented using Google Forms to simulate a simplified yet realistic online shopping experience. Therefore, a between-subjects experimental design with random assignment was employed to avoid carryover and learning effects that might occur if respondents experienced multiple conditions. A 2x2 factorial structured design consisting of four scenarios, labelled as Option A to D. Each scenario representing a unique combination of product type (FMCG vs. SMCG) and recommendation condition (with AI-generated product recommendation vs. without AI-generated product recommendation). Participants were randomly assigned to one of these scenarios without being informed about their condition. Following the allocation, the respondents were guided through a simulated purchase journey, starting with a homepage, progressing to a product detail page and finally ending with a shopping cart. In the experimental condition, AI-generated product recommendations were integrated at contextually relevant points of the customer journey. Conversely, in the control condition, no suggestions were displayed. This configuration reflected the central decision points in a prototypical online purchase journey, thereby enabling the systematic observation of behavioural intentions across distinct customer journey phases.

During the experimental process, a number of variables were collected at each phase, including perceived helpfulness of recommendations, purchase intention, product relevance and trust in recommendation systems. Responses initially captured as categorical text values, such as “very helpful” or “not very helpful” were later recoded into numeric scales for statistical analysis using IBM SPSS Statistics, enabling statistical comparison across participants and experimental conditions.

An integration of manipulation checks ensured that participants recognised the recommendations and correctly identified their AI-generated nature. Additionally, socio-demographic data were collected to allow a detailed sample characterisation.

3.3 Data Collection and Preparation

The data collection process was conducted in two stages. In the first stage, the participants completed the standardised online survey, designed to provide deep insights in the consumer attitudes and behaviours regarding AI-generated product recommendations. In the second stage, a subset of respondents participated in the follow-up online experiment simulating a real purchase situation. This sequential structure enabled the observation of both controlled causal mechanisms and broader attitudinal patterns, ensuring methodological complementarity between both parts of the study.

Recruitment was conducted entirely online, using social media channels such as LinkedIn, Instagram, and WhatsApp, supplemented by the SurveyCircle platform and peer-to-peer distribution within personal networks. This multi-channel dissemination strategy facilitated access to a diverse sample of digitally active consumers, reflecting typical e-commerce users. All participants provided informed consent prior to participation and were assured of anonymity and GDPR-compliant data handling. To encourage participation, SurveyCircle's point-based incentive system was employed, allowing participants to increase the visibility for their own surveys through reciprocal engagement.

The survey phase took place between 18 July and 28 July 2025, followed by the experiment, conducted between 1 August and 6 August 2025. Data collection therefore occurred shortly before the formal registration of this thesis, as part of the preparatory research process. During this period, participants were introduced to the study, informed about its objectives, and guided through the procedure. Some participants completed both the survey and the experiment, while others participated exclusively in the survey.

Following the data collection period, incomplete cases were excluded and quality filters were applied to identify so-called *speeders*. The participants were categorised as the term *speeders* if they completed the survey in less than three minutes, a well-established threshold employed within survey research. The final dataset comprised n=103 valid survey cases and n=30 valid experimental cases, with a mean completion time of 340.6 seconds (SD = 92.4 seconds).

This fully online research design strengthened ecological validity by closely mirroring real-world digital purchasing environments, where most consumer decisions occur in screen-based contexts. Although a potential self-selection bias towards digitally experienced participants cannot be entirely ruled out, the high degree of realism and experimental control of the design ensured methodological robustness and internal validity. A more thorough explanation of both samples is presented in Chapter 4.

3.4 Data Analysis

Following the above-described data cleaning process, the standardised online survey and the online experiment were analysed separately to fully exploit the methodological strengths of each approach: the experiment allowed the identification of causal effects under controlled conditions, while the online survey enabled the analysis of broader consumer attitudes and perceptions.

All statistical analyses were performed using IBM SPSS Statistics. The analytical procedure was selected according to the specific hypothesis, the study design and the measurement level of the respective variables. In general, independent-samples t-tests were applied to compare mean differences between experimental conditions, whilst repeated-measures ANOVAs were used to examine within-subject effects across customer journey phases and product categories. Finally, linear regression analyses were employed to analyse predictive and moderating relationships between individual factors and behavioural outcomes. For hypotheses concerning associative patterns, Pearson correlation coefficients and multiple regression models were applied.

Descriptive statistics were used to report mean values and standard deviations for all variables. The inferential analyses included test statistics, p-values, effect sizes (e.g., η^2, Cohen's d, R^2), and 95% confidence intervals. All statistical assumptions for parametric testing were systematically checked, and where violations occurred, corrective procedures such as Greenhouse–Geisser or Welch adjustments were applied. For multiple comparisons, Bonferroni corrections ensured control of Type I error rates. The internal consistency of all multi-item constructs was evaluated using Cronbach's α, ensuring reliability thresholds above .70.

A detailed overview of the hypotheses, dependent variables, predictors and statistical procedures is presented in Table 5. This alignment between research questions and analytical techniques underlines the methodological coherence and robustness of the present study.

Table 5 Overview of hypotheses and applied analytical methods.

Hypothesis	***Research focus***	***Statistical procedure***	***Key variables***
H1	Effect of recommendations on FMCG purchase intention	Independent-samples t-test	DV: purchase intention; IV: recommendation (yes/no)
H2	Differences in helpfulness across customer journey phases	Repeated-measures ANOVA (survey); Independent-samples t-test (experiment)	DV: perceived helpfulness; IVs: phase (within), product type (between)
H3	Moderating role of perceived necessity	Linear regression (survey & experiment)	DV: purchase frequency/helpfulness; IVs: necessity/relevance, product type
H4	Differences between FMCG and SMCG	Repeated-measures ANOVA (survey); Independent-samples t-test (experiment)	DV: helpfulness; IVs: product groups
H5	Relationship between trust and helpfulness	Pearson correlation; Multiple regression (experiment)	DV: helpfulness; IVs: trust, product type
H6	Relationship between openness and trust across channels	Pearson correlations (survey)	DV: trust (marketplaces, shops, social media, newsletters); IV: openness

Note. Own illustration based on the methodological approach.

The overall research logic and methodological framework are summarised in Figure 4, illustrating the connection between theoretical foundation, hypothesis development, empirical design and analytical procedures.

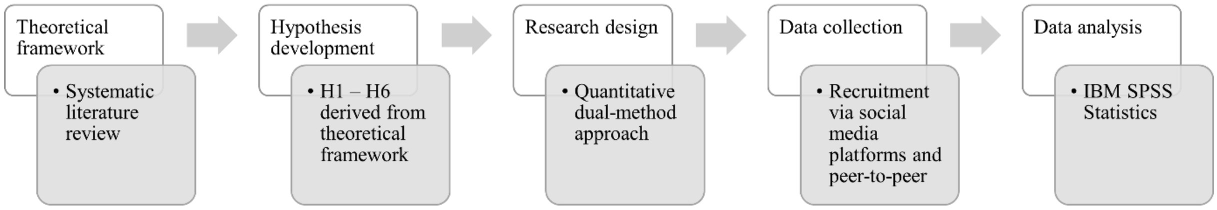


Figure 4 Research logic and methodological framework.

Note. Own illustration based on the methodological approach.

This methodological approach ensures a robust examination of how AI-generated product recommendations shape consumer decision-making across contexts, integrating experimental precision with survey-based generalisability.

4 Results of the Empirical Research

The results of the quantitative studies are presented below in accordance with hypotheses H1 to H6.

4.1 Sample Description

After data collection and data cleaning, excluding incomplete cases and respondents classified as so-called ‘speeders’ (completion time < 3 minutes), two data sets were available for analysis: an online survey with n = 103 fully evaluated cases and an online experiment with n = 30 participants. The average time taken to complete the survey was 340.62 seconds, which corresponds to approximately 5.7 minutes.

The online survey sample consisted predominantly of young adults. The majority of respondents were between 18 and 34 years old (93.2%), with a mean age of M = 29.3 years (SD = 4.2). 73.8% of respondents were identified as female, 26.2% male. In terms of the monthly net income, 35.9% of respondents reported an income of less than €1,000, while 29.1% reported a monthly income between €1,000 to €1,999. In regard to the educational level, it was noted that 36.9% of participants have a specialised high school diploma, 32.0% have a university degree and 17.5% have completed a technical college programme.

In addition to demographic data, as seen in Table 6, online shopping behaviour and the use of AI-generated product recommendations were assessed. More than half of the respondents (55.3%) stated that they shop online every month, a further 21.4% every two to six months, and 20.4% weekly. The present survey shows that smartphones were used most frequently (72.8%), followed by laptops (15.5%). The analysis revealed that the preferred shopping channels were large online marketplaces such as Amazon or Zalando (82.5%), shopping apps (52.4%) and individual retailers' own websites (42.7%). An analysis of shopping frequency by product group revealed that FMCG were purchased online the least frequently, while fashion and leisure & media categories showed the highest online purchase rates.

The online experiment sample showed a demographic structure similar to the survey sample. The majority of the sample consisted of mainly younger adults (M = 30.23 years), with 73.3% identified as female and 26.7% as male. 36.7% of the respondents reported a monthly net income below €1,000, while 33.3% of the respondents had a monthly net income between €2,000 to €2,999. With regard to educational attainment, 40% of respondents had obtained a general higher education entrance qualification, 26.7% a technical college degree and 16.7% a university degree. The shopping behaviour was also comparable to that of the survey sample. The majority of respondents (60%) indicated that they engage in online shopping on a monthly basis. This is followed by 26.7% purchasing weekly and 13.3% purchases made every two to six months. This study corroborates the findings of the online survey, which identified the smartphone as the predominant device, with a rate of 80%, while laptops played a minor role at 13.3%.

Overall, the descriptive data confirm that both samples are representative of digitally experienced, younger consumer groups typically engaged in online shopping activities. Table 6 summarises the demographic characteristics and online shopping behaviour of the survey and experimental samples, allowing a structured comparison between both datasets.

Table 6 Sample characteristics of the online survey and the online experiment.

Characteristic	***Survey (n = 103)***	***Experiment (n = 30)***
Age (years)	M = 29.3 (SD = 4.2)	M = 30.23
Gender	73.8% female, 26.2% male	73.3% female, 26.7% male
Monthly net income	< €1,000: 35.9% €1,000–1,999: 29.1%	< €1,000: 36.7% €2,000–2,999: 33.3%
Education	Specialised high school: 36.9% University degree: 32.0% Technical college: 17.5%	General high school: 40.0% Technical college: 26.7% University degree: 16.7%
Online shopping frequency	Monthly: 55.3% Weekly: 20.4% Every 2–6 months: 21.4%	Monthly: 60.0% Weekly: 26.7% Every 2–6 months: 13.3%
Device used most frequently	Smartphone: 72.8% Laptop: 15.5%	Smartphone: 80.0% Laptop: 13.3%
Preferred shopping channels	Marketplaces: 82.5% Shopping apps: 52.4% Retailer websites: 42.7%	— (not assessed)

Note. Own illustration based on results out of online survey and online experiment.

4.2 Perception of AI-Generated Product Recommendations

In the online experiment, consumers' perception and recognition of AI-generated product recommendations were recorded in addition to socio-demographic characteristics and shopping behaviour. Significant differences were found between the experimental conditions.

Across the full sample (n = 30), 18 participants (60.0%) reported that they had noticed a recommendation or at least expressed uncertainty about having seen one, whereas 12 participants (40.0%) stated that they had not noticed any recommendation. It is noteworthy that among those 18 respondents who reported noticing or being unsure, only 7 participants (23.3% of the total sample) were actually assigned to a recommendation condition. Conversely, 11 participants (36.7%) reported having seen a recommendation although no recommendation was displayed in their scenario. Only two participants (6.7%) correctly identified a displayed recommendation as AI-generated.

A differentiation according to scenarios revealed that in Option B (FMCG with recommendation), 3 out of 8 participants (37.5%) stated that they had noticed a recommendation, although all of them expressed uncertainty. In Option D (SMCG with recommendation), 4 out of 6 participants (66.7%) reported having seen a recommendation, of whom 2 correctly identified the recommendation as AI-generated. Overall, reported trust in the displayed recommendations was found to be generally low. In Option B, 3 of 8 participants (37.5%) trusted the recommendation, while in Option D, 1 of 6 participants (~16.7%) did so.

A closer look at the available data and facts reveals interesting differences in the reasons given for purchasing decisions. In Option B, 6 out of 8 participants stated that they made their decision based on perceived benefits or prior personal experience, while 2 referenced specific product characteristics, such as appearance. In both Option B and Option D, the majority of participants rated the recommendation as ‘neutral’ or ‘not influential’. As illustrated in Figure 5, in Option B, purchase decisions were classified as either neutral or spontaneous in 5 out of 8 cases (63%) and as analytical in 3 cases (38%). In Option D, all 6 decisions (100%) were classified as analytical. Across the range of conditions, recommendations were generally evaluated as being neutral or irrelevant for the purchase decision.

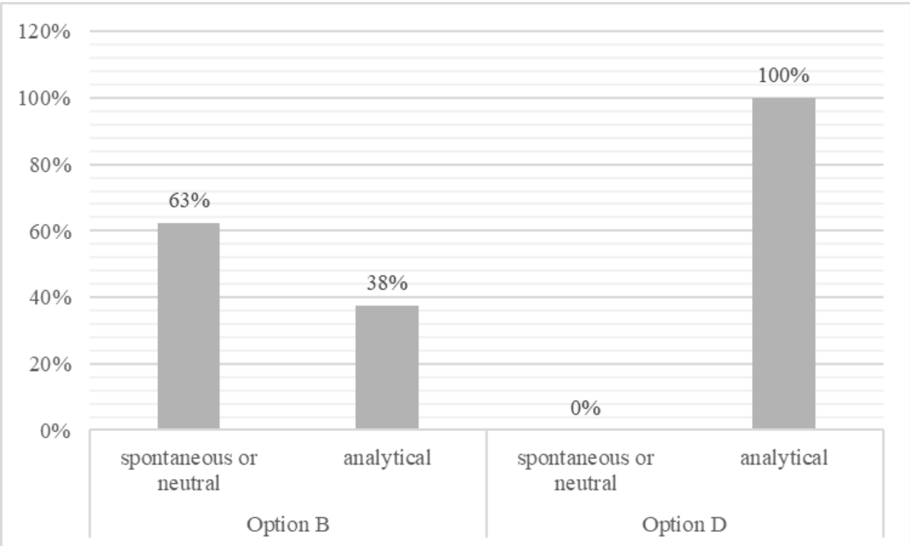


Figure 5 Classification of purchase decision per scenario.

Note. Own illustration based on results of empirical research.

4.3 Hypotheses Testing

The following subsections present the statistical results for the hypotheses H1 to H6. Each hypothesis is reported separately to maintain a clear connection between the research question and the empirical findings.

For each hypothesis, the statistical procedure applied (e.g., t-tests, ANOVA, regression analysis) is briefly stated. Subsequently, the relevant descriptive results (mean values, standard deviations) and inferential statistics (test statistics, significance levels and effect sizes) are reported.

Where circumstances permit, the results of the online survey and the online experiment are presented simultaneously in order to highlight the differences and similarities between general attitudinal data and situational decision behaviour.

As this chapter is dedicated solely to the empirical outcomes, no interpretation or theoretical contextualisation is provided at this point. These aspects are addressed separately in Chapter 5 (Discussion of Findings).

4.3.1 H1 – AI-generated product recommendations increase consumers' purchase intention, particularly for FMCG.

Hypothesis 1 examined whether AI-generated product recommendation systems increase the purchase intention for FMCG compared to a condition without recommendations. Only the data from the FMCG scenarios of the online experiment were included in this analysis. Participants were assigned either to a control group without recommendations or to an experimental group in which an AI-generated product recommendation was displayed. The dependent variable of the study was the purchase intention, which was measured on a 5-point Likert scale ('1 = very unlikely to 5 = very likely').

The descriptive results show significant differences between the groups. In the control group without recommendations ($n = 6$), an average purchase intention value of $M = 3.83$ ($SD = 1.17$) was determined. In the experimental group with AI-generated product recommendations ($n = 8$), on the other hand, all participants reported the minimum value of $M = 1.00$ ($SD = 0.00$). Thus, the raw data already indicate a substantial reduction in purchase intention when recommendations were presented.

For inferential statistical analysis, an independent-samples t-test was conducted. The Levene-Test indicated unequal variances ($F\ (1,12) = 15.54$, $p = .002$), therefore both variants (equal and unequal variances assumed) were reported. Under the assumption of equal variances, a highly significant difference was found ($t\ (12) = 6.95$, $p < .001$). Assuming unequal variances, the result could be classified as significant ($t\ (5) = 5.94$, $p = .002$). The mean difference between the two groups was 2.83 points, with a 95% confidence interval of [1.95; 3.72].

The effect sizes demonstrate the practical difference between the two methods. The value for Cohen's d is 3.76, while Hedges' g has a value of 3.51. Both effect sizes are significantly above the threshold for large effects and underline the strength of the observed difference.

In summary, purchase intention in the FMCG condition with AI-generated product recommendations was significantly lower than in the control condition without AI-generated product recommendations.

Therefore, Hypothesis 1, predicting an increase in purchase intention for everyday products, was not supported by the experimental data and therefore not confirmed in this study.

4.3.2 H2 – The effect of AI-generated product recommendations on consumers' purchase intention differs across the phases of the customer journey (inspiration, comparison, decision).

Hypothesis 2 examined whether the perceived helpfulness rating of AI-generated product recommendations varies between the different phases of the customer journey. For this purpose, the online survey included a repeated assessment of perceived helpfulness across five clearly defined phases, enabling a repeated-measures analysis of variance (RM-ANOVA).

The descriptive analysis demonstrates a continuous and significant decline in perceived helpfulness across the customer journey (see Table 7). AI-generated product recommendations were evaluated as most helpful in the inspiration and browsing phase (M = 3.59; SD = 0.98). Helpfulness ratings decreased across subsequent phases: product detail page (M = 3.24, SD = 1.10), product search phase (M = 2.90, SD = 1.16), and the shopping cart/checkout phase (M = 2.08, SD = 1.05). The lowest rating was reported for the post-purchase phase (M = 1.49; SD = 0.81).

Table 7 The descriptive statistics of the perceived helpfulness of AI-generated product recommendations across the customer journey phases.

Phase	***Mean value***	***Standard deviation***
Inspiration phase	3.59	0.975
Product search phase	2.90	1.159
Product detail page	3.24	1.102
Checkout phase	2.08	1.051
Post-purchase phase	1.49	0.810

Note. Own illustration based on results of empirical research.

Inferential statistical testing confirmed statistically significant differences between the phases ($F\ (4,96) = 86.724$, $p < .001$, $\eta^2 = .760$). Post hoc analyses with Bonferroni correction revealed that all phases showed significant differences from each other. In addition, within-subject contrasts indicated a significant linear trend ($F = 236.263$, $p < .001$), indicating that the perceived helpfulness rating decreases continuously from the beginning to the end of the customer journey.

In addition to the results of the previously conducted survey, the hypothesis was also tested using data from the online experiment. Since the helpfulness ratings were collected exclusively for the shopping cart phase, a complete comparison of all phases was not possible. Instead, the focus was placed on a direct comparison between FMCG and SMCG conditions.

The descriptive results indicate that participants in the FMCG scenarios tended to rate recommendations as more helpful than in the SMCG scenarios. The subsequent t-test for independent samples confirmed a statistically significant difference ($t(11.76) = 2.23$, $p = .046$). The mean difference between the two conditions amounted to 1.17 points, with the effect size Cohen's $d = 1.03$. This suggests a strong and practically significant effect.

In summary, the results for hypothesis 2 show that in the online survey, perceived helpfulness differs significantly across all phases of the customer journey with higher values in early phases and the lowest in the post-purchase phase. In the online experiment, AI-generated product recommendations in the shopping cart were rated as more helpful for FMCG than for SMCG. H2 is therefore fully supported. The perceived helpfulness of AI-generated product recommendations differs significantly across the phases of the customer journey.

4.3.3 H3 – The perceived necessity of a product moderates the effect of AI-generated product recommendations on purchase intention.

Hypothesis 3 examined whether the perceived necessity of a product moderates the effect of AI-generated product recommendations on purchase-related behaviour. The underlying assumption was that recommendations have a stronger effect when there is no acute pressure to buy.

In a first step, H3 was tested using the online survey data. Agreement with the statement *'When I have an urgent need, I ignore product recommendations'* (F17_statement03) was used as an indicator of perceived necessity. The dependent variable was defined by the self-reported purchase frequency based on product recommendations. In addition, the product type *'daily needs'* (F13) was included as a further predictor. A linear regression analysis was conducted with purchase frequency as the dependant variable and F17_statement03 and F13 as predictors.

The results show that the overall model was significant ($F(2,103) = 4.424$, $p = .014$) and explained 7.9% of the variance in purchase frequency ($R^2 = .079$). As presented in Table 8, within the model, agreement with F17_statement03 emerged as a significant negative predictor ($B = -1.165$, $p = .007$). The results show a clear correlation between agreement with the statement that recommendations are ignored in cases of urgent need and the rarity of purchases based on recommendations. The second predictor, *'daily need'* (F13), did not show a significant effect on purchase frequency ($B = 0.286$, $p = .185$).

Table 8 Influence of the in H3 used predictors.

Predictor	***Regression coefficient***	***p-value***
F13: daily needs	*0.286*	*.185*
F17: When I have an urgent need, I ignore product recommendations	*-1.165*	*.007*

Note. Own illustration based on results of empirical research.

In a second step, H3 was examined using the experiment data. In this analysis, perceived necessity was operationalised via relevance ratings in Options B and D. The dependent variable was the perceived helpfulness rating of the recommendations shown in the experiment. In addition, the product type (0 = FMCG, 1 = SMCG) was taken into account as an additional predictor. Only participants who were actually shown recommendations were included in the analysis, resulting in a sample size of $n = 14$. A linear regression analysis with helpfulness as the dependent variable and relevance ratings in Option B and Option D as well as product type as predictors was conducted.

The results of the regression analysis showed no significance for the overall model ($F(3,10) = 0.817$, $p = .513$), with an explained variance of 19.7% ($R^2 = .197$) and an adjusted $R^2 = -.044$. None of the predictors showed a significant effect. Neither the relevance assessment in Option B ($B = –0.227$, $p = .604$) nor the relevance assessment in Option D ($B = –1.000$, $p = .186$) nor the product type ($B = 1.697$, $p = .364$) had significant effects on the purchase intention.

Taken together, H3 was supported in the online survey data, where perceived necessity (urgency) showed a significant negative association with recommendation-based purchase frequency, but not supported in the experimental data, where no significant effects were observed. Accordingly, H3 can be considered partially confirmed.

4.3.4 H4 – Consumers evaluate AI-generated product recommendations for SMCG more critically than for FMCG.

Hypothesis 4 aimed to determine whether consumers evaluate the perceived helpfulness of AI-generated product recommendations differently between product categories, specifically whether recommendations for SMCG are rated more critically than those for FMCG.

In the online survey, respondents assessed the perceived helpfulness of AI-generated product recommendations across five product categories: FMCG, household & living, fashion, leisure & media, and technology (all SMCG). Since each participant provided information on all categories, a repeated measures analysis of variance (RM-ANOVA) was performed.

The results of the descriptive analysis presented in Table 9 demonstrate, that recommendations for FMCG received the lowest helpfulness rating ($M = 2.08$; $SD = 1.02$). The highest ratings were observed for all SMCG categories, including fashion ($M = 3.85$; $SD = 1.00$), leisure & media ($M = 3.51$; $SD = 1.09$), followed by household & living ($M = 3.48$; $SD = 1.01$) and technology ($M = 2.95$; $SD = 1.21$). The ANOVA revealed a highly significant overall effect ($F(4,101) = 59.531$, $p < .001$, $\eta^2 = .364$). Post-hoc analyses with Bonferroni correction further showed that the helpfulness of AI-generated product recommendations in the FMCG sector was significantly lower than in all SMCG categories. Based on the survey data, hypothesis 4 was therefore supported.

Table 9 Descriptive Statistic H4 Results of the RM-ANOVA.

Product categories	***FMCG or SMCG***	***Mean value***	***Standard deviation***
Everyday needs	FMCG	*2.08*	*1.02*
Household & living	SMCG	*3.48*	*1.01*
Fashion	SMCG	*3.85*	*1.00*
Leisure & media	SMCG	*3.51*	*1.09*
Technology	SMCG	*2.95*	*1.21*

Note. Own illustration based on results of empirical research.

In the online experiment, the perceived helpfulness of AI-generated product recommendations was assessed only in the shopping cart phase. For this purpose, two conditions were examined: FMCG with recommendation and SMCG with recommendation. The descriptive results indicate that the FMCG condition received higher helpfulness ratings (M = 4.00; SD = 1.20) than the SMCG condition (M = 2.83; SD = 0.75). An independent-samples t-test confirmed this difference as statistically significant (t (11.76) = 2.23, p = 0.046). The mean difference was 1.17 points, and Cohen's d was 1.03, indicating a large effect size. Thus, in contrast to the online survey findings, the online experiment results did not support hypothesis 4, as AI-generated product recommendations were rated as more helpful in the FMCG condition than in the SMCG condition.

In summary, the online survey results support hypothesis 4, showing that recommendations for SMCG, especially in the categories of fashion, leisure & media and home, were rated as more helpful than recommendations for FMCG. The experiment results, however, show the opposite pattern within the specific shopping-cart phase. Accordingly, hypothesis 4 can be considered partially supported, depending on the data source and situational context.

4.3.5 H5 – Trust mediates the relationship between AI-generated product recommendations and purchase intention.

Hypothesis 5 was designed to test whether trust in AI-generated product recommendation systems is correlated with the perceived helpfulness of AI-generated product recommendations. It was assumed that higher levels of trust would correspond to higher helpfulness ratings. The hypothesis was tested using data from the online experiment, as this dataset included measures of both general trust in recommendation systems (rec_trust_overall) and perceived helpfulness (rec_helpfulness). Only participants who were actually shown recommendations were included in the analysis, resulting in a sample size of n = 14.

The descriptive results indicate that perceived helpfulness ratings averaged M = 2.21 (SD = 0.98), while trust in recommendation systems showed comparatively low values, with M = 1.86 (SD = 0.54).

To test the relationship between trust and helpfulness, a bivariate Pearson correlation was first conducted. The correlation coefficient was $r = .211$, indicating a weak positive relationship. However, the results did not prove to be statistically significant (one-sided $p = 0.235$).

In a second step, a multiple linear regression analysis was performed, including the perceived helpfulness rating (rec_helpfulness) as the dependent variable and trust (rec_trust_overall) as the main predictor. In addition, the product type (0 = FMCG, 1 = SMCG) was included as a control variable. The regression model was not statistically significant ($F(2, 11) = 0.256$, $p = 0.779$) and explained only 4.4% of the variance ($R^2 = 0.044$, corrected $R^2 = -0.129$). Within the model, none of the predictors proved to be significant. Trust showed a regression coefficient of $B = 0.385$ ($p = .554$), while product type showed $B \approx 0.000$ ($p = 1.000$).

In summary, no significant relationship between trust and perceived helpfulness was found. Hypothesis 5 was therefore not confirmed, as neither the correlation nor the regression analysis yielded a statistically significant effect.

4.3.6 H6 – Greater openness towards AI-generated product recommendations is positively associated with trust in these systems.

Hypothesis 4 examined whether individuals who report greater openness towards AI-generated product recommendations also exhibit a higher level of trust in recommendation sources.

To test this assumption, data from the online survey was analysed. Openness towards AI-generated product recommendations was operationalised using item F15, while trust was measured using four trust ratings (F8) relating to different recommendation channels: large online marketplaces (e.g., Amazon, Zalando), specialised online shops, social media or influencers, and newsletters. Since all variables were interval-scaled, Pearson's correlation coefficients were calculated.

The results indicate that a high degree of openness correlates significantly positively with trust in two established e-commerce channels. For large online marketplaces, the correlation coefficient was $r = .269$ ($p = .005$), and for specialised online shops, it was $r = .240$ ($p = .017$). These results indicate that respondents who reported greater openness toward AI-generated product recommendations also reported higher trust in these two channels. However, no significant correlations were found for social media and influencer-based recommendations ($r = .099$, $p = .319$) or for newsletters ($r = .094$, $p = .334$). Thus, openness toward AI-generated product recommendations was not associated with trust in these more informal or less institution-alised channels.

Overall, hypothesis 6 was partially confirmed. While openness toward AI-generated recommenda-tions was significantly associated with trust in large marketplaces and specialised online shops, no such relationship was observed for social media or newsletters. The hypothesis could not be tested using the experiment data, as no measure of openness was collected in that dataset.

4.4 Summary of Hypothesis Tests

For clarity, the key empirical findings for the hypotheses H1 to H6 are summarised in Table 10. The table reports the status of each hypothesis (confirmed, partially confirmed or not confirmed), the statistical method used and the main findings.

Table 10 Summary of hypothesis testing results.

Hypothesis	***Content***	***Result***	***Method***	***Main Findings***
H1	AI-generated product recommendations increase purchase intention for FMCG (experiment)	**Not confirmed**	Independent-samples t-test (FMCG with vs. without recommendation)	Purchase intention was higher **without** recommendation (M = 3.83) than **with** recommendation (M = 1.00). Significant difference: t (12) = 6.95, p < .001, d = 3.76.
H2	Helpfulness ratings differ across customer-journey phases	**Confirmed**	RM-ANOVA (survey); t-test (experiment)	Survey: continuous decrease from inspiration (M = 3.59) to post-purchase (M = 1.49), F (4,96) = 86.72, p < .001. Experiment: FMCG recommendations rated as more helpful than SMCG in the shopping-cart phase.
H3	Perceived necessity moderates recommendation effects	**Partially confirmed**	Linear regression (survey & experiment)	Survey: higher urgency associated with fewer recommendation-based purchases (B = −1.165, p = .007). Experiment: no significant effects on helpfulness ratings.

H4	Consumers evaluate SMCG recommendations more critically than FMCG	**Confirmed, but context-dependent**	RM-ANOVA (survey); t-test (experiment)	Survey: SMCG perceived as more helpful than FMCG, $F(4,101) = 59.53$, $p < .001$. Experiment: in the shopping cart, FMCG recommendations rated as more helpful than SMCG.
H5	Trust predicts perceived helpfulness	**Not confirmed**	Pearson correlation & regression (experiment)	No significant correlation: $r = .211$, $p = .235$. Regression: trust not a significant predictor ($B = 0.385$, $p = .554$).
H6	Openness towards AI recommendations correlates with trust in recommendation sources	**Partially confirmed**	Pearson correlation (survey)	Significant correlations for marketplaces ($r = .269$, $p = .005$) and specialised shops ($r = .240$, $p = .017$). No correlations for social media ($r = .099$) or newsletters ($r = .094$).

Note. Own illustration based on results of empirical research.

The results of the study suggest that the effects of AI-generated product recommendation systems are highly dependent on the respective context of use. Hypothesis 2 was fully supported, demonstrating clear differences in perceived helpfulness across customer-journey phases, with a marked decline from early to late phases. In contrast, H1 could not be confirmed for FMCG products: in this category, recommendations resulted in lower purchase intention compared to no recommendation.

Hypothesis 3 received partial support. Survey data showed that higher perceived urgency reduces the likelihood of acting upon recommendations, whereas this effect did not appear in the experimental data. Hypothesis 4 was confirmed in both datasets but in opposite directions: while the survey indicated higher usefulness ratings for SMCG, the experiment found higher helpfulness ratings for FMCG in the shopping-cart phase.

Hypothesis 5 could not be confirmed, as trust in recommendation systems did not show a significant relationship with perceived helpfulness. Hypothesis 6 was partially supported: openness to AI-generated product recommendations correlated positively with trust in established e-commerce channels but not with social media or newsletters.

Overall, these findings suggest that the influence of AI-generated product recommendations is neither uniform nor universal. Instead, the effects vary according to product category, customer-journey phase, perceived urgency, and individual consumer dispositions. The following chapter discusses these findings in more detail and situates them within the theoretical framework and existing literature.

5 Discussion of Findings

This chapter interprets the empirical findings in light of the theoretical framework presented earlier. The discussion follows the order of the hypotheses (H1-H6) and integrates the decision-logic perspective (extensive, limited, habitual, impulsive), the phase logic of the customer journey and acceptance enablers and barriers (usefulness, relevance, trust, transparency, privacy) to explain how situational, product-related and individual factors jointly shape consumers' responses and decision-making to AI-generated product recommendations.

5.1 H1: AI-generated product recommendations increase consumer's purchase intention, particularly for FMCG.

The evaluation of the first hypothesis yielded a non-anticipated result. The present study sought to ascertain whether the display of AI-generated product recommendations would increase purchase intention for FMCG. However, the findings revealed the contrary. Instead of increasing the purchase intention for FMCG, the display of AI-generated product recommendations led to a significant decline in purchase intention. Participants in the control group, who did not receive any recommendations, reported considerably higher purchase intention values than those exposed to AI-generated product recommendations. Consequently, the effect occurred in a manner that was precisely contrary to the hypothesised outcome.

This outcome aligns with the habitual and low-involvement decision-making process characteristic of FMCG purchases, as evidenced in Table 1. The decisions made by consumers in relation to FMCG are frequently characterised by a high degree of routine and a low level of risk. In such contexts, external stimuli, such as AI-generated product recommendations, which impose a cognitive burden or appear misaligned with the immediate need, have the potential to disrupt the habitual flow and reduce the intention to purchase.

As previously mentioned in Section 2.2.3 of the consumer goods taxonomy, FMCG are closely associated with convenience goods and habitual/impulsive purchasing decisions. Conversely, SMCG, which include fashion, household and living goods, and technology, align more closely with shopping/specialty goods and limited/extensive purchasing logics. This mapping suggests that, at the point of decision, the marginal utility of additional information for FMCG is lower, but higher for SMCG, where search and evaluation are integral to the choice process. Consequently, the AI-generated product recommendations presented in the experiment might have been regarded as irrelevant.

It is plausible that the perception and acceptance of recommendation systems also played a role. It has been demonstrated that recommendations which are not perceived as credible or relevant by the recipients can trigger reactance rather than support. This finding aligns with the prevailing e-commerce perspective that digital touchpoints are effective when they reduce effort and are tailored to the micro-context.

A comparison with the extant literature highlights the category contingency of effects. AI-generated product recommendation systems have been shown to be particularly beneficial in information-intensive SMCG contexts, where consumers actively seek guidance. The present results complement this perspective by demonstrating that, in the context of FMCG, AI-generated product recommendations can be counterproductive.

5.2 H2: The effect of AI-generated product recommendations on consumers' purchase intention differs across the phase of the customer journey (inspiration, comparison, decision).

The results for hypothesis 2 revealed a clear and systematic pattern. The perceived helpfulness of AI-generated product recommendations declines linearly across the customer journey. It is asserted that these recommendations are most valuable in the early inspiration phase. However, as the process of comparison and decision-making, their significance gradually diminishes, reaching its nadir in the post-purchase phase. This finding is in close alignment with established customer journey models. These models posit that consumers are most receptive to external stimuli during the initial orientation and early search phases. In contrast, subsequent later phases prioritise certainty, completion, and the reduction of friction.

As delineated within the AICPURA model, the Awareness, Interest, Consideration phases are characterised by exploration, information search and the reduction of uncertainty. During these phases, recommendations offer value by structuring attention, enhancing visibility and supporting early evaluation. In contrast, the Purchase and Retention phases are characterised by cognitive narrowing and goal completion, making unsolicited suggestions more likely to be perceived as irrelevant or disruptive.

The survey results appear to support this theoretical expectation: Each phase exhibits significant disparities from all others, thereby indicating that consumers deliberately differentiate between situations in which recommendations offer added value (e.g., inspiration and the initial search) and situations in which they are no longer contribute meaningfully to their decision-making process (e.g., during or after a purchase).

This trend is also consistent with the decision logics typology (see Table 1). In early phases, consumers often engage in extensive or limited evaluation, states in which additional cues can reduce cognitive effort. As the journey progresses, the process of decision-making becomes more habitualised or confirmation-oriented, meaning that additional external inputs no longer add value.

The experiment data provide a valuable addition to these findings by isolating a specific micro-moment: the checkout phase. In this instance, FMCG recommendations were perceived as being more beneficial than SMCG recommendations. This is a theoretically plausible proposition: the checkout phase is structurally compatible with impulsive or add-on decisions for low-involvement FMCG, but not with high-involvement SMCG, where last-minute prompts more easily provoke scepticism or reactance. This differentiation mirrors the consumer-goods typology (Section 2.2.3). FMCG, are characterised by their tendency to be added to shopping baskets in a spontaneous manner. SMCG has been observed to demonstrate a tendency to align with the domains of shopping and specialty goods. The approach employed by SMCG characterised by a reliance on deliberative evaluation, a method that has been shown to render late-phase recommendations inconsistent with the anticipated decision logic.

In comparison with extant studies, the results demonstrate that the effectiveness of AI-generated product recommendations is contingent on the specific circumstances, as opposed to being universally applicable. It is evident from previous research that acceptance is contingent upon alignment between recommendation timing, task structure, and cognitive load. The present findings provide empirical confirmation by demonstrating that both the phase of the customer journey and the product type jointly shape perceived usefulness.

5.3 H3: The perceived necessity of a product moderates the effect of AI-generated product recommendations on purchase intention.

The results for hypothesis 3 demonstrate a differentiated pattern across methods. The survey data reveal a clear negative relationship between the urgency with which consumers respond to AI-generated product recommendations and their responsiveness to these recommendations. It has been demonstrated that the higher the perceived necessity of a purchase, the lower the openness to additional suggestions. This finding is consistent with established consumer decision-making logics. In circumstances where there is an acute need or time pressure, consumers have been observed to make decisions in a more efficient manner. They have been found to rely on habitual choices and to reduce exploratory behaviour. In such situations, external stimuli, such as AI-generated product recommendations, are less likely to be perceived as helpful and more likely to be ignored or bypassed.

This pattern is consistent with e-commerce research highlighting consumers' inclination to prioritise effort reduction and expediency under pressure. If recommendation systems fail to offer a demonstrable acceleration in the process or clearly match the immediate requirements, they offer no incremental value in this decision-making process. In fact, their implementation may even result in an increase in perceived friction.

However, this effect was not replicated in the online experiment. A number of plausible explanations require consideration. Firstly, it is important to note that the reduced sample size of the experiment may limit statistical power and increase the likelihood of non-detection. Secondly, the operationalisation differs in that the survey asked participants explicitly about perceived necessity in general purchasing situations, whereas the experiment embedded urgency implicitly within specific scenario-based stimuli. The findings indicate that perceived necessity exerts a more significant influence on general purchasing orientations than on moment-specific decisions in controlled experimental settings.

The discrepancy between survey and experimental findings is theoretically significant. Research on involvement demonstrates that high-urgency or high-pressure decisions trigger routine behaviour and reduce openness to additional information cues, while low-pressure situations preserve cognitive resources for exploring alternative options. The survey captures these general behavioural patterns, whereas the experiment, focused on a constrained decision moment, may not elicit the same cognitive dynamics.

The findings, when considered as a whole, suggest that necessity functions as a situational moderator rather than a universal determinant of recommendation acceptance. The concept of high urgency has been demonstrated to have a significant impact on consumers' willingness to engage with or consider recommendations. However, this tendency is only observed in instances where the recommendations are perceived as being highly relevant, extremely quick to process or entirely unobtrusive.

5.4 H4: Consumers evaluate AI-generated product recommendations for SMCG more critically than for FMCG.

The results for H4 demonstrate a pattern that is both differentiated and method-dependent. Whilst the survey evaluated recommendations for SMCG as more beneficial, the experiment, which concentrated on a concrete checkout decision, identified higher levels of helpfulness for FMCG. Despite their initial divergence, these results demonstrate a strong alignment with the theoretical distinctions between product types, decision logics, and situational versus generalised evaluations.

From a theoretical standpoint, SMCG correspond to shopping goods and specialty goods (Homburg, 2020), which are characterised by high involvement, extended information search, and deliberate comparison. In such contexts, consumers have been shown to place significant value on supplementary stimuli and informational support. This observation is supported by the survey's findings, which identified SMCG recommendations as being perceived as more beneficial. This finding is consistent with the principles of decision-making: SMCG decisions are often informed by extensive or limited information processing, both of which are enhanced by structured guidance, transparency and informational enrichment.

Conversely, FMCG purchases are characterised by habitual or impulsive decision-making processes, characterised by low involvement, minimal comparison, and high routine. The experiment captured a late-phase, situational micro-moment (checkout), at which point such products are often added spontaneously. In this particular context, AI-generated product recommendations may function as low-effort, complementary stimuli, thus aligning with the anticipated behavioural pattern. This finding is consistent with the anticipated behavioural pattern. This finding is consistent with the extant literature, which demonstrates that recommendations are most effective when they minimise effort, align with the timing of the consumers' actions, are congruent with the characteristics of the device and phase context.

The divergent findings thus reflect the difference between two distinct concepts. Firstly, there is the generalised belief about usefulness (survey), which is dominated by perceived information need (higher for SMCG). Secondly, there is the immediate situational reaction (experiment) which is dominated by impulse-fit and effort reduction (higher for FMCG).

The theoretical coherence of this distinction is evident in the manner in which SMCG benefits from early-phase, information-rich recommendations. These recommendations are consistent with the AICPURA phases of Awareness, Interest and Consideration. Conversely, FMCG have been shown to be influenced by incentives in the late-phase of the purchase cycle, which correspond to impulsive or habitual purchasing patterns.

Overall, the findings of this study serve to reinforce the broader theoretical insight that the effectiveness of a recommendation is not universal but rather dependent upon the interplay between product type, decision logic, and purchase context. The extant literature on AI-generated product recommendations similarly emphasises the importance of context-aware personalisation. For instance, personalisation that is sensitive to timing, product characteristics, device and user state, is superior to one-size-fits-all approaches.

5.5 H5: Trust mediates the relationship between AI-generated product recommendations and purchase intention.

The analyses for H5 did not confirm the expected relationship between trust in recommendation systems and the perceived helpfulness of AI-generated product recommendations. Both the bivariate correlations and the regression model (controlling for product type) revealed no significant association between the two constructs. The minimal explained variance indicates that trust did not play a central role in shaping the perceived usefulness of recommendations in this experimental setting.

At first sight, this contradicts established research emphasising trust as a key driver of acceptance in digital environments. In the theoretical framework, trust is emphasised as a crucial prerequisite for e-commerce, given the lack of physical interaction. Similarly, studies on AI-generated product recommendations emphasise that trust, perceived fairness and transparency strongly influence system acceptance (McKnight et al., 2011; Gefen et al., 2003). However, closer examination of the specific context of the present experiment and the nature of the stimuli provides a theoretically plausible explanation as to why trust did not have a measurable effect.

A key factor lies in the simplicity and non-personalised character of the recommendations used in the experiment. Contemporary models of AI acceptance highlight that trust becomes most influential when systems are perceived as operating in a complex, obscure or data-driven way - particularly for high-involvement products. In the present experiment, the recommendations were generic rather than deeply personalised. This may have reduced the psychological relevance of “trust” as a criterion, because participants could not meaningfully evaluate whether the system relied on their data, matched their preferences or demonstrated algorithmic competence.

Additionally, perceived helpfulness is shaped by multiple situational factors, such as product relevance, timing, purchasing phase, and cognitive load. These factors may have overridden the trust effect. As demonstrated by H2 and H4, participants responded strongly to the alignment of the recommendation with the product type and the decision-making context. In such circumstances, trust acts more as a background condition rather than as an active predictor of helpfulness.

From a decision-making perspective, this is consistent with the idea that trust is more important for extensive or high-involvement evaluations (e.g., SMCG), whereas its relevance diminishes in habitual or impulsive contexts (e.g., FMCG). As the experimental task was framed as an individual purchase scenario, it may not have activated trust-based deliberation to a degree that could be detected in statistical analyses.

The findings also relate to the transparency challenge in AI-generated systems. Trust tends to matter more when consumers explicitly recognise a recommendation as AI-generated. In this study, however, only a small proportion of participants correctly identified the AI-generated nature of the recommendations (see Section 4.2). If users do not consciously attribute the suggestion to an AI system, their trust in AI cannot influence their assessment of its helpfulness.

Overall, the findings suggest that trust is a context-dependent acceptance factor rather than a universal predictor of perceived usefulness. In this dataset, perceived relevance and situational fit appear to be more important determinants than general trust dispositions.

5.6 H6: Greater openness towards AI-generated product recommendations to positively associated with trust in these systems.

The analyses for H6 revealed partially significant relationships. Openness towards AI-generated product recommendations exhibited a positive correlation with trust in two established e-commerce channels, namely online marketplaces and specialised online shops. Conversely, no significant associations emerged for social media or newsletter-based shopping channels. Thus, hypothesis 6 is only partly substantiated.

This pattern is consistent with the theoretical foundations introduced in Chapter 2. In the digital context, trust is of particular significance due to the absence of physical interaction and the reliance on technology-mediated product evaluation. Consumers develop a sense of trust in systems primarily through repeated positive experiences, transparency, and reliability. These mechanisms are more characteristic of established and structured shopping environments, such as large marketplaces or specialised retailers. These platforms characteristically provide standardised interfaces, robust filtering mechanisms, review systems, and predictable recommendation logics, thereby facilitating cognitive processing and reducing perceived risk.

The present findings are in alignment with the outlined reasoning: participants who exhibit a higher degree of receptivity to AI-generated product recommendations demonstrated a greater propensity to place trust in platforms where recommendation systems have become an integral and well-established component of the purchase experience. In these environments, AI-generated product recommendations are integrated into the decision-making process in a seamless manner. This integration occurs during the initial orientation, comparison and evaluation phases of the decision-making process, as outlined in the AICPURA model. This compatibility is likely to strengthen the perceived credibility and acceptance of algorithmic assistance.

The absence of a significant relationship for social media and newsletter-based channels further reinforces this interpretation. Social media platforms function as external touchpoints, characterised by high content heterogeneity, fluctuating credibility signals and strong commercial persuasion cues. Theoretical models of decision-making logic suggest that such environments tend to elicit emotional or impulsive decision-making patterns, as opposed to structured evaluation. Consequently, a propensity towards AI is inadequate in itself to generate trust in platforms where algorithmic recommendations are less transparent, more commercialised or less embedded in recognised shopping routines.

Similarly, newsletters constitute a low-interaction, low-control environment, characterised by a deficit of transparency and the absence of an inherent recommendation feedback loop. Since consumers are not able to observe the generation of recommender systems by algorithms or the tailoring of content, trust formation mechanisms are weaker in comparison to those observed in AI-generated shop environments. The former provides no visible stimuli of personalisation or system competence, in contrast to the latter.

The findings, when considered as a whole, indicate that a universal predictor of trust across all digital context is not necessarily associated with a positive stance towards AI. Conversely, the effect is contingent on the structural characteristics of the respective touchpoint. In environments characterised by high informational clarity, stable interface logic and established trust norms (e.g., marketplaces and specialised shops), openness towards AI is more readily translated into trust. In environments where there is less structure or more promotion (e.g., social media), it has been demonstrated that openness alone is insufficient to outweigh scepticism.

Overall, the results of the study demonstrate that AI openness is a relevant, but context-dependent, determinant of trust in e-commerce environments. The acceptance of algorithmically assisted decision-making appears strongest in stable, functionally oriented digital ecosystems. In more dynamic or entertainment-driven contexts, additional trust signals are required to achieve similar effects.

5.7 Overall Discussion Summary

Across the full range of hypotheses, the findings provide a differentiated and context-dependent account of how consumers respond to AI-generated product recommendations in e-commerce. The findings, when considered collectively, underscore the notion that the effectiveness and perception of such systems are influenced by a combination of product-related, situational, and individual factors. These findings are consistent with the theoretical foundations outlined in Chapter 2, particularly the decision-making logic typology (extensive, limited, habitual, impulsive), the structural logic of the customer journey, and the acceptance determinants of digital systems (usefulness, relevance, trust, transparency, privacy).

Firstly, the results for H1 demonstrate that product type exerts a fundamental moderating influence on consumers' reactions. Contrary to the prevailing hypothesis, the utilisation of AI-generated product recommendations has been observed to exert a negative influence on the intention to purchase in the FMCG context. This finding aligns with the established decision-making processes associated with convenience goods: routine, low-involvement purchases offer minimal cognitive engagement and require minimal additional input, thereby rendering external stimuli potentially interruptive or misaligned. The findings highlight that the value of recommendation systems is not uniform and is contingent upon their ability to meaningfully support or disrupt the prevailing decision logic of the designated product category.

Secondly, H2 shows a clear, systematic decline in perceived helpfulness across the customer journey. Recommendations are most appreciated in early phases, where consumers seek inspiration and structure. However, as decisions become more solidified, the need for recommendations diminishes. The journey phase interacts with product type, as evidenced by the experiment: in contrast to the tendency exhibited by FMCG, SMCG do not benefit from late-phase, impulse-compatible suggestions. These results lend further support to the theoretical proposition that AI-generated product recommendations must align with both cognitive needs and momentary task structures if they are to be effective.

Thirdly, H3 indicates that the urgency and perceived necessity of a recommendation have a negative impact on its overall receptiveness, at least in the context of general purchase behaviour. However, this relationship does not appear to hold true in controlled experimental settings. This pattern aligns with the theoretical framework of involvement and effort reduction, whereby consumers, under pressure, prioritise efficiency, familiarity and heuristics, thereby diminishing the efficacy of exploratory stimuli. The importance of contextual relevance is therefore critical, with recommendations must either accelerate the process or operate with minimal perceptibility.

Fourthly, the mixed evidence for H4 underscores the notion that product type exerts a divergent influence on acceptance, contingent on whether responses are indicative of general attitudes (survey) or immediate behaviour (experiment). The presence of SMCG engenders elevated information needs, consequently giving rise to higher general helpfulness evaluations. Conversely, FMCG has been observed to elicit more positive responses in fast checkout contexts. This divergence is consistent with theoretical distinctions between shopping goods and convenience goods. Furthermore, it reinforces the notion that interactions at the phase of production shape perceived usefulness.

Fifthly, the results of H5 indicate that trust alone is not a decisive predictor of perceived helpfulness in particular decision-making scenarios. Given that the experimental recommendations were neither personalised nor highly transparent, trust may function as a precondition for system use rather than a direct driver of situational evaluations. This finding aligns with theoretical perspectives that place greater emphasis on relevance, fit, and cognitive benefit as more immediate determinants than generalised trust, particularly in low-complexity tasks.

Finally, H6 demonstrated that openness towards AI is associated with trust exclusively in stable, structured e-commerce environments (marketplaces, specialised shops). However, this association is not observed in more fluid or promotional environments (social media, newsletters). This finding indicated that acceptance is contingent upon the structural characteristics of touchpoints. Openness, in itself, is inadequate when there is a paucity of transparency, credibility or informational clarity.

Overall, the findings underscore that AI-generated product recommendations are highly context-dependent systems, whose effectiveness emerges from the interplay between consumer needs, decision phases, product types and touchpoint characteristics. Rather than functioning as a universally beneficial instrument, recommendation systems must be aligned with the micro-context of decision-making to add value. The results have enriched theoretical perspectives on digital decision-making by providing empirical evidence that AI-generated support is contingent, situational and sensitive to both cognitive and behavioural dynamics.

6 Limitations

While this study provides valuable insights into the impact of AI-generated product recommendations, several limitations must be considered when interpreting the findings. These limitations concern the composition of the sample, the methodological approaches, the ecological validity of the experimental setting, the nature of the recommendation stimuli and behavioural data, as well as the measurement of key constructs.

1. *Small and homogeneous samples*

A central limitation concerns the size and composition of the samples. The online experiment included only n = 30 participants, primarily young, female and digitally experienced consumers. The survey sample (n = 103) showed a similar demographic profile. This homogeneity limits the generalisability of the findings and raises the possibility that gender-specific or age-specific patterns, for example in trust, AI openness or online shopping behaviour, may have influenced the results. A more balanced gender distribution, or a separate gender-based analyses, would have been desirable but could not be realised within the scope of the study. Accordingly, the findings should be interpreted primarily with regard to the overrepresented demographic group, and caution is advised when extending the conclusions to broader consumer populations.

2. *Divergent and partly non-standardised measurement approaches*

A second limitation concerns the operationalisation of key constructs. The survey relied on validated self-report measures of necessity, trust and openness, whereas the experiment assessed situational perceptions such as helpfulness and relevance. Moreover, the two designs did not employ fully standardised scales across both datasets, which restricts the comparability of results and complicates the integration of findings. Future studies would benefit from unified measurement instruments that allow for more coherent cross-method interpretations.

3. *Limited ecological validity due to simulated, non-personalised scenarios*

Although the experiment simulated an online shopping environment with realistic phases (homepage, product page, shopping cart), the setting remained hypothetical, generic and non-personalised. Participants did not engage in real purchases, which limits ecological validity. Real-world online shopping involves stronger emotional, financial and temporal involvement, which may influence responsiveness to recommendations. Furthermore, the recommendations used were generic, whereas real AI-generated systems rely on algorithmic personalisation based on consumer data. This reduces authenticity and may have attenuated perceived relevance, trust and overall impact. It is highly plausible that AI-generated product recommendations would have elicited different perceptions and outcomes. Consequently, the transferability of the findings to authentic purchasing behaviour is constrained.

4. Reliance on self-reported intentions rather than behavioural data

The study primarily measured self-reported purchase intentions and perceived helpfulness rather than actual purchase behaviour. While these indicators are widely used in consumer behaviour research, they do not always translate directly into real-world decisions. The absence of behavioural data, such as clickstream behaviour, actual conversions or dwell time, limits the ability to draw conclusions about genuine consumer responses.

5. *Differences in methodological focus and operationalisation across designs*

A further limitation arises from the different methodological focus of the two empirical components. The survey captured general attitudes and retrospective evaluations, while the experiment assessed immediate, situational decision behaviour. These differences introduce heterogeneity that complicates direct comparisons between the two datasets. Harmonising methodological approaches or integrating mixed methods more systematically would enhance interpretability.

6. *Limited scope of individual-difference variables*

Finally, the study considered individual differences such as AI attitudes, shopping frequency and trust in selected channels only to a limited extent. Relevant psychological and contextual variables—such as personality traits, cognitive styles, cultural norms or socio-economic factors—were not included but may play a significant role in determining responsiveness to AI-generated product recommendations. A more comprehensive inclusion of such variables could deepen the explanatory power of future models.

In summary, these limitations constrain the generalisability and ecological validity of the findings but also indicate productive directions for future research. Addressing them—through larger and more diverse samples, personalised recommendation stimuli, behavioural data collection and more comprehensive theoretical modelling—will be essential for developing a more complete understanding of how AI-generated product recommendation systems influence online consumer decision-making.

7 Implications and Future Research

This study makes a significant contribution to the field of AI-generated product recommendation systems by offering a more nuanced understanding of the context-dependence of such recommendation systems. The findings demonstrate that both research and managerial practice must adopt diversified strategies to ensure that AI-generated product recommendation systems unfold their potential in a targeted, effective and consumer-centred manner. The subsequent section outlines the theoretical contributions, the practical implications for e-commerce, and the directions for future research.

7.1 Theoretical Implications

From a theoretical perspective, this study advances the growing body of literature that emphasises the situational and multidimensional nature of AI-generated product recommendations. The findings demonstrate that the effectiveness of such systems varies considerably across product categories (FMCG vs. SMCG), customer journey phases, decision-making logics (extensive, habitual, impulsive), situational urgency, and individual consumer dispositions such as openness, perceived necessity and trust. This variability supports theoretical arguments that recommendation systems cannot be treated as universally effective mechanisms. Instead, their impact depends upon the alignment between recommendation stimuli, cognitive involvement, and contextual features of the purchasing situation. The observed backfiring effects in the FMCG domain illustrate this particularly clearly, showing that recommendations can be counterproductive in habitual and low-involvement context where consumers prefer cognitive simplicity.

The results also advance theoretical discussions by showing that contextual and individual factors interact rather than operate in isolation. Consumers respond differently depending on their cognitive state (urgent vs. non-urgent need), the underlying decision logic (routine behaviour vs. extensive search), and the situational value of external stimuli. This confirms the need for theoretical frameworks that integrate situational context, product characteristics, cognitive involvement and individual traits, rather than analysing recommendation effects through single isolated variables. The study therefore contributes to a more holistic understanding in which recommendation systems are embedded within broader consumer decision-making architectures, not treated as isolated technological artefacts.

Furthermore, the findings reinforce theoretical work suggesting that psychological constructs such as trust, perceived control and transparency do not exert uniform effects across all touchpoints or product categories. Trust-building alone is insufficient if recommendations lack relevance, appropriate timing or cognitive convenience. This highlights the need for theoretical models that combine psychological aspects with structural elements of digital decision environments, acknowledging that acceptance emerges from the interplay between consumer dispositions and the micro-context of the recommendation.

7.2 Practical Implications

From a managerial perspective, the findings of this study provide several actionable insights for the strategic design, placement and communication of AI-generated product recommendation systems in e-commerce. The results underline that recommendation systems must be differentiated, context-sensitive and aligned with consumer decision-making logics to be effective.

1. *Avoid undifferentiated, one-size-fits-all recommendation strategies*

The findings clearly show that recommendation systems cannot be applied uniformly across all product categories or purchasing contexts. In the FMCG sector, characterised by habitual, time-efficient, low-involvement decisions, recommendations carry the risk of being perceived as irrelevant or intrusive and may even reduce purchase intention. In contrast, SMCG categories benefit more consistently from additional information stimuli, provided they are offered at the appropriate moment in the customer journey.

2. *Prioritise context-sensitive, phase-aligned recommendation design*

Recommendation effectiveness depends strongly on where and when recommendations appear. For SMCG, AI-generated product recommendations should be implemented early in the customer journey (inspiration, search, comparison), when consumers actively seek guidance and engage in extensive or limited evaluation. In contrast, FMCG recommendations are more effective in checkout micro-moments, where low effort, impulse-fit and basket relevance are decisive.

Misaligned timing like too early, too late, or at unsuitable touchpoints, reduces perceived relevance and increases the likelihood of rejection.

3. *Reduce cognitive load and align with dominant decision logic*

Recommendations should be designed to enhance, rather than interrupt, the dominant decision-making logic. Habitual FMCG decisions require subtle, non-intrusive stimuli that do not increase cognitive effort. Extensive SMCG decisions benefit from detailed, informative suggestions early in the journey. In both cases, a mismatch between cognitive involvement and recommendation design (e.g., a complex suggestion during a fast FMCG purchase) increases reactance and undermines effectiveness.

4. *Incorporate individual differences and segment-specific responsiveness*

The study highlights that perceived necessity, urgency, openness to AI and trust levels shape how consumers evaluate recommendations. Retailers should therefore adopt user-sensitive and behaviourally adaptive systems, incorporating differences in openness to personalisation, sensitivity to timing and relevance, individual thresholds for cognitive effort and behavioural indicators of urgency or routine behaviour. Personalised and adaptive systems are more likely to be accepted than static, uniform models.

5. *Recognise that timing, relevance and cognitive fit outweigh algorithmic sophistication*

The findings underscore that structural and perceptual factors are more influential than the underlying algorithmic complexity. Effective recommendation systems require precise timing aligns with micro-moments, high relevance to the purchasing task, minimal perceived effort and seamless integration into the interface. Without these elements, even technically advanced systems underperform or provoke negative reactions.

6. *Ensure transparency, simplicity and user control to support trust*

Trust building remains important but must be supported by system design that enhances credibility and perceived fairness. Effective systems therefore communicate personalisation clearly (e.g., “why this recommendation?” explanations), ensure consistent and trustworthy interface design and provide user control over personalisation settings. Such measures reduce uncertainty and foster long-term acceptance.

7. *Account for situational urgency and cognitive pressure*

Recommendations are most effective when the decision context allows for reflection or exploration. Under conditions of high urgency or acute necessity, consumers revert to habitual shortcuts and tolerate minimal cognitive load. In these moments recommendations may disrupt rather than support, relevance thresholds increase, and intrusion risks rise significantly.

Retailers should therefore detect urgency signals (e.g., repeated past purchases, time-sensitive categories) and adjust recommendation presence accordingly.

8. *Transition from standardised to personalised and adaptive recommendation strategies*

This study reinforces the need for dynamic, personalised and context-aware recommendation systems. Retailers should invest in models that leverage behavioural, contextual and historical data to deliver tailored suggestions, micro-moment targeting and product-specific calibration. Static, generic recommendation systems—uniformly applied across all touchpoints—are likely to deliver suboptimal performance or even elicit negative reactions.

7.3 Future Research

The limitations and findings of this study point to several promising avenues for future research that can be deepen the understanding of how AI-generated product recommendations operate across contexts, consumer groups and technological configurations.

1. *Broaden sample diversity and increase sample size*

Future studies should employ larger and more heterogeneous samples to enhance external validity and reduce demographic biases related to age, gender or digital literacy. This would allow for more robust generalisations and enable finer-grained analyses of demographic or generational differences in recommendation acceptance.

2. *Deepen the contextual analysis of product type and customer-journey phase*

Given the strong situational variation observed in this study, future research should investigate more precisely how recommendation effectiveness depends on specific product categories beyond FMCG and SMCG (including B2B or industrial goods), micro-moments within the customer journey, and shifts in decision logic (habitual, extensive, impulsive).

More granular experimental manipulation would help disentangle how product complexity and customer journey phase jointly shape perceived usefulness.

3. *Examine personalised versus generic recommendation systems*

A key direction for future work is the study of personalised, dynamic, real-time recommender systems. Unlike the generic recommendations used in this study, personalised systems may produce stronger behavioural effects and higher acceptance. Research should therefore investigate how personalisation interacts with psychological constructs such as trust, openness, reactance and perceived control.

4. *Conduct field experiments in real e-commerce environments*

To strengthen ecological validity, future research should implement field studies or A/B tests in authentic online shopping environments. These should include real personalised recommendations, real products and transactional decisions, and dynamic consumer paths through actual digital interfaces.

Such studies would allow the observation of naturally occurring behaviour rather than hypothetical or scenario-based responses.

5. *Integrate behavioural and psychological data*

Future work should combine self-reported measures with objective behavioural indicators, including clickstream and browsing behaviour, eye-tracking and attention metrics, dwell time and interaction patterns, and conversion and abandonment behaviour.

This multimethod approach would provide deeper insights into how consumers process, ignore or engage with AI-generated product recommendations.

6. *Investigate underlying psychological mechanisms*

Several psychological mechanisms warrant further exploration, including reactance (why and when recommendations cause resistance), trust calibration (how trust fluctuates after positive or negative experiences), and cognitive load and perceived intrusiveness, perceived control and autonomy.

Understanding these mechanisms can clarify why recommendations sometimes decrease purchase intention instead of increasing it.

7. *Study transparency and explainability effects*

A central unresolved question concerns the optimal visibility of AI in recommendation systems. Future research should examine when transparency enhances trust and acceptance, when invisibility reduces cognitive load or avoids reactance, and how "why this recommendation?" explanations affect perceived relevance across product types and journey phases.

This line of inquiry can inform guidelines for explainable AI in commerce.

8. *Extend research to cross-cultural and gender differences*

Given that technology acceptance varies across cultures and social groups, future studies should investigate whether openness to AI, trust levels and perceived helpfulness differ across markets and demographic segments. This would help tailor AI-generated product recommendation strategies to culturally and socially diverse consumer groups.

7.4 Conclusion of the Implications

In conclusion, this study provides valuable insights into the context-dependence of AI-generated product recommendation systems. The findings demonstrate that their effectiveness is shaped by an interplay of product type, customer-journey phase and individual consumer characteristics. Rather than exerting uniform effects, AI-generated product recommendations influence purchasing decisions in ways that depend on situational relevance, cognitive involvement and the degree to which they align with consumers' needs and expectations.

The results show that AI-generated product recommendations may not only support decision-making but can also hinder it, particularly in habitual, low-involvement FMCG contexts where irrelevant or poorly timed stimuli trigger reactance or disrupt established routines. Conversely, recommendations for more complex and information-intensive SMCG tend to be more effective in early journey phases, when consumers seek orientation, inspiration and additional information. These findings highlight the importance of context-sensitive, phase-appropriate and user-aligned system design.

Moreover, the study underscores the relevance of individual dispositions such as trust, openness and perceived necessity. While these factors do not exert uniform effects across all touchpoints, they shape consumers' responsiveness to AI-generated stimuli and reinforce the need for personalised, adaptive recommender systems that respect cognitive boundaries and decision logic.

Overall, the findings contribute to theoretical discussions by emphasising the multidimensional nature of recommendation effects and support practical efforts to design systems that are not only technologically sophisticated but also consumer-centred. Future research should further explore psychological mechanisms, real-world behavioural patterns and the role of personalisation to build a more comprehensive understanding of how AI-generated product recommendations function in diverse and dynamic e-commerce environments.

8 Conclusion

This study examined how consumers respond to AI-generated product recommendations across different product categories, phases of the customer journey and individual characteristics. By combining an online survey with a scenario-based online experiment, the research provides an empirically grounded and theory-informed assessment of when and how AI-generated product recommendations support or hinder decision-making in e-commerce.

The findings demonstrate that the effectiveness of AI-generated product recommendations is not universal but highly context-dependent. Across all analyses, three determinants consistently shaped consumers' responses: product type, customer journey phase, and individual dispositions. These factors jointly shape whether recommendations are perceived as helpful, relevant or disruptive.

First, the results highlight the central role of the product category. While recommendations for more complex SMCG tended to receive higher usefulness ratings in general evaluations, recommendations for FMCG were not effective in increasing purchase intention and even reduced it in the experimental condition. This contrast underscores the importance of aligning recommendation design with the cognitive effort and information needs associated with different product types.

Second, the findings show that the phase of the customer journey strongly influences perceived usefulness. Recommendations were evaluated most positively in early, exploration-oriented phases and progressively less so in later phases, especially after the purchase. This pattern confirms theoretical models of decision-making that emphasise declining openness to external stimuli as consumers approach goal completion.

Third, the results indicate that individual factors, such as perceived necessity, openness towards AI and trust in digital channels, play a selective but meaningful role in shaping acceptance. While urgency reduced openness to recommendations in the online survey, trust did not significantly predict helpfulness in the online experiment. Openness towards AI correlated with trust only in established e-commerce environments, highlighting that personal dispositions interact with contextual features rather than exerting universal influence.

Overall, the study shows that AI-generated product recommendations influence purchasing decisions in ways determined by situational relevance, decision logic and cognitive involvement. Their impact cannot be assumed to be positive by default. Instead, AI-generated product recommendation systems must be context-sensitive, phase-appropriate and aligned with consumer needs to unfold their potential.

By integrating theoretical insights with empirical evidence, the study contributes to a more nuanced understanding of AI-supported decision-making in e-commerce. While the insights advance academic knowledge on contextual and cognitive determinants of recommendation acceptance, they also provide actionable guidance for practitioners seeking to implement AI-generated product recommendation systems in a consumer-centred and effective manner.

Future research should extend these findings by employing larger and more diverse samples, personalised recommendation stimuli and real-world behavioural data in authentic e-commerce environments. Such research will be essential for building a more comprehensive understanding of how AI-generated product recommendations operate across different consumer groups, touchpoints and technological conditions.

The fundamental take-home message is that the full potential of AI-generated product recommendation systems is not realised in their indiscriminate application. However, this potential is realised through their context-sensitive deployment, which achieves a balance between technological complexity and consumer relevance.

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Appendix

Appendix A – Online-Survey

A1. Online-Survey Structure

The online survey consisted of the following sections:

1. Introduction and consent
2. Online shopping behaviour
3. Evaluation of AI-generated product recommendations
4. Customer journey phases (five-step model)
5. Product categories (FMCG/SMCG)
6. Purchase behaviour regarding recommendations
7. Demographic information

Participants progressed linearly through all survey blocks without branching logics.

A2. Full Online-Survey

Titel: KI-gestützte Produktempfehlungen im Online-Handel – Ihre Meinung ist gefragt!

Einleitungstext
Vielen Dank, dass Sie sich Zeit für diese Umfrage nehmen. Ziel dieser Befragung ist es, besser zu verstehen, wie Konsument*innen auf **KI-gestützte Produktempfehlungen** im **Online-Handel** reagieren – insbesondere in den **verschiedenen Phasen des Online-Einkaufsprozesses** (Customer Journey) und je **nach Produkttyp**.

Produktempfehlungen im E-Commerce können auf unterschiedliche Weise generiert werden:
Einfachere, nicht KI-gestützte Systeme basieren meist auf festen Regeln, z. B. Empfehlungen wie „Kund:innen kauften auch …“. Im Gegensatz dazu analysieren **KI-basierte Empfehlungssysteme** individuelle Verhaltensmuster, Klicks, Käufe oder Kontexte in Echtzeit und generieren **personalisierte Vorschläge**, die sich **dynamisch anpassen** können.

Die Teilnahme an der Umfrage ist **anonym** und dauert etwa **5 Minuten**. Es gibt keine „richtigen“ oder „falschen“ Antworten – wir sind an Ihrer persönlichen Einschätzung interessiert. Alle erhobenen Daten werden ausschließlich zu wissenschaftlichen Zwecken verwendet. Es werden keine personenbezogenen Daten wie Name oder E-Mail-Adresse erfasst, sodass keine Rückschlüsse auf Einzelpersonen möglich sind.

Bitte führen Sie die Umfrage bis zum Ende durch, da nur vollständige Datensätze in die Auswertung einbezogen werden können.

Vielen Dank für Ihre Unterstützung!

Figure A 1 Introduction of the online survey.

1. allgemeines Einkaufsverhalten

Wie häufig kaufen Sie online ein?
- täglich
- wöchentlich
- monatlich
- seltener
- nie

Über welches Gerät kaufen Sie hauptsächlich online ein?
- Smartphone
- Laptop
- Desktop-PC
- Tablet
- Sprachassistent (z.B. Alexa)
- Anderes Gerät: _____

Wie häufig kaufen Sie folgende Produktgruppen online ein?
(1 = nie, 2= selten, 3= gelegentlich, 4= oft, 5 = sehr häufig)
- Täglicher Bedarf *(FMCG)*: Lebensmittel, Kosmetik etc.
- Haushalt & Wohnen *(SMCG)*: Einrichtung, Garten etc.
- Mode & persönliche Ausstattung *(SMCG)*: Kleidung, Schmuck etc.
- Freizeit & Medien *(SMCG)*: Bücher, Hobbys etc.
- Technik & Unterhaltung *(SMCG)*: Elektrogeräte etc.

Figure A 2 Online-Shopping behaviour section.

2. Wahrnehmung von Produktempfehlungen

An welchen Kontaktpunkten begegnen Sie Online-Shops oder Produktempfehlungen typischerweise?
(Mehrfachantwort möglich)
- beim Stöbern auf Online-Marktplätzen (z.B. Amazon, Zalando)
- in spezialisierten Online-Shops (z.B. für Möbel, Technik oder Kosmetik)
- über Social Media (z.B. Instagram, TikTok, Facebook)
- beim Lesen von Blogs, Magazinen oder Produktvergleichen
- in E-Mails oder Newslettern
- durch Werbung auf externen Webseiten oder Apps (z.B. Banner, Pop-ups)
- über Sprachassistenten (z.B. Alexa, Google Assistant)

Figure A 3 AI-generated product recommendation evaluation section 1.

<u>In welcher Form sind Ihnen KI-gestützte Produktempfehlungen im Online-Shopping bereits begegnet?</u>
(Mehrfachantwort möglich)
- Produktempfehlungen basierend auf meinem bisherigen Such- oder Kaufverhalten
(z. B. „Für Sie empfohlen“, „Das könnte Ihnen gefallen“)
- Empfehlungen, die auf dem Verhalten anderer Kunden basieren
(z. B. „Kunden kauften auch …“)
- Vorschläge auf der Startseite, Produktseite oder im Warenkorb
- Produktempfehlungen außerhalb des Shops
(z. B. in Newslettern, Social Media oder Werbeanzeigen)
- Mir sind keine Produktempfehlungen aufgefallen / Ich bin mir nicht sicher

<u>Wie hilfreich empfinden Sie diese Produktempfehlungen beim Online-Shopping insgesamt?</u>
(Bitte bewerten Sie auf einer Skala von 1 bis 5)
- 1 = überhaupt nicht hilfreich
- 2 = eher nicht hilfreich
- 3 = teils/neutral
- 4 = eher hilfreich
- 5 = sehr hilfreich

<u>Wie personalisiert erscheinen Ihnen KI-Empfehlungen im Online-Shopping allgemein?</u>
(Bitte bewerten Sie auf einer Skala von 1 bis 5)
- 1 = gar nicht
- 2 = ein wenig
- 3 = teils/neutral
- 4 = stark
- 5 = sehr stark

<u>Wie stark vertrauen Sie Produktempfehlungen aus folgenden Quellen?</u>
(1 = gar nicht, 5 = sehr stark)

- Große Marktplätze (Amazon, Zalando)
- Spezialisierte Webshops (Westwing etc.)
- Empfehlungen auf Social Media/ Influencer-Links
- Newsletter-Empfehlungen

Figure A 4 AI-generated product recommendation evaluation section 2.

3. Customer Journey – Einfluss von Empfehlungen

<u>In welcher Phase des Kaufprozesses begegnen Ihnen KI-gestützte Produktempfehlungen?</u>
(Mehrfachauswahl möglich)

Phasen:
- beim Browsen/Inspiration (z. B. Startseite) – Ich bin noch unentschlossen
- während der Produktsuche – Ich informiere mich
- auf der Produktdetailseite – Ich vergleiche aktiv Produkte
- im Warenkorb/beim Check-out - Ich stehe kurz vor dem Kauf
- nach dem Kauf (z.B. E-Mail-Empfehlungen etc.)

<u>Bitte bewerten Sie den Einfluss KI-gestützter Empfehlungen in folgenden Phasen auf Ihre Kaufentscheidung. (noch mehr spezifizieren: EINFLUSS)</u>
(1 = gar nicht, 2 = eher nicht, 3 = neutral, 4 = eher hilfreich, 5 = sehr hilfreich)

Phasen:
- beim Browsen/Inspiration (z. B. Startseite)
- während der Produktsuche
- auf der Produktdetailseite
- im Warenkorb/beim Check-out
- nach dem Kauf (z.B. E-Mail-Empfehlungen etc.)

Figure A 5 Customer journey evaluation items.

<u>Wie hilfreich empfinden Sie KI-gestützte Empfehlungen in den folgenden Produktbereichen?</u>
| Produkttyp | gar nicht | eher nicht | neutral | eher hilfreich | sehr hilfreich |

- Täglicher Bedarf *(FMCG)*: Lebensmittel, Kosmetik etc.
- Haushalt & Wohnen *(SMCG)*: Einrichtung, Garten etc.
- Mode & persönliche Ausstattung *(SMCG)*: Kleidung, Schmuck etc.
- Freizeit & Medien *(SMCG)*: Bücher, Hobbys etc.
- Technik & Unterhaltung *(SMCG)*: Elektrogeräte etc.

Figure A 6 Product categories (FMCG/SMCG).

5. Kaufverhalten & Wirkung
<u>Wie häufig haben Sie ein Produkt gekauft, das ausschließlich durch eine KI-Empfehlung auf Sie aufmerksam gemacht wurde?</u>
- nie
- selten
- manchmal
- häufig
- sehr häufig

<u>Bei welchen Produktgruppen passiert das am ehesten?</u>
- Täglicher Bedarf *(FMCG)*: Lebensmittel, Kosmetik etc.
- Haushalt & Wohnen *(SMCG)*: Einrichtung, Garten etc.
- Mode & persönliche Ausstattung *(SMCG)*: Kleidung, Schmuck etc.
- Freizeit & Medien *(SMCG)*: Bücher, Hobbys etc.
- Technik & Unterhaltung *(SMCG)*: Elektrogeräte etc.

<u>Ab welchem Warenkorbwert beeinflussen Empfehlungen Ihre Entscheidung?</u>
- unter 20 €
- 20–50 €
- 51–100 €
- über 100 €
- Keine Angabe

4. Vertrauen und Akzeptanz
<u>Wie sehr stimmen Sie der folgenden Aussage zu?</u>
<u>„Ich bin grundsätzlich offen für KI-gestützte Produktempfehlungen im Online-Handel.“</u>
(1 = stimme gar nicht zu, 5 = stimme voll zu)

<u>Erkennen Sie, ob eine Produktempfehlung durch künstliche Intelligenz erstellt wurde?</u>
- Ja, meistens
- Manchmal
- Selten
- Nie
- Ist mir egal

<u>Wie sehr stimmen Sie den folgenden Aussagen zu?</u>
(1 = stimme gar nicht zu, 5 = stimme voll zu)

- Ich weiß meist genau, was ich kaufen möchte.
- Ich entdecke häufig neue Produkte durch Produktempfehlungen.
- Wenn ich ein Produkt dringend benötige, beeinflussen mich Produktempfehlungen weniger.
- Wenn ich unentschlossen bin, helfen mir Empfehlungen bei der Entscheidung.
- Bei spontanen Käufen orientiere ich mich häufiger an Produktempfehlungen.
- Je wichtiger mir ein Produkt ist, desto kritischer prüfe ich Produktempfehlungen.
- Ich vertraue Produktempfehlungen, wenn sie auf mein bisheriges Verhalten abgestimmt sind.
- Ich vertraue Produktempfehlungen, wenn sie zu meiner Suche passen, auch wenn ich das Unternehmen nicht kenne.
- Ich finde es wichtig zu wissen, ob eine Empfehlung von einer KI stammt.
- Ich empfinde manche Produktempfehlungen als aufdringlich oder datenschutzrechtlich bedenklich.

Figure A 7 Purchase behaviour regarding product recommendations.

<u>Was müsste passieren, damit Sie KI-Empfehlungen im Online-Shop als vertrauenswürdiger oder relevanter empfinden würden?</u>

[Freitextfeld]

Soziodemografische Daten

<u>Alter:</u>

☐ unter 18 ☐ 18–24 ☐ 25–34 ☐ 35–44 ☐ 45–54 ☐ 55+

<u>Geschlecht:</u>

☐ weiblich ☐ männlich ☐ divers ☐ keine Angabe

<u>Über welche Kanäle kaufen Sie hauptsächlich ein?</u> (Mehrfachauswahl möglich)

☐ Desktop-Webshop ☐ Mobile Website ☐ App ☐ Social Media ☐ Sprachassistenten (Alexa etc.)

Schluss

Herzlichen Dank für Ihre Teilnahme!

Mit Ihren Antworten leisten Sie einen wertvollen Beitrag zum besseren Verständnis der Wirkung KI-gestützter Produktempfehlungen im Online-Handel.

Die Befragung wurde vollständig anonym durchgeführt – personenbezogene Daten wurden nicht erhoben.

Gerne können Sie den Umfragelink an Kolleginnen und Kollegen, Freundinnen und Freunde oder Familienmitglieder weiterleiten.
Jede Rückmeldung ist wichtig und unterstützt die Forschung.

Bei Fragen zur Umfrage oder zum Datenschutz kontaktieren Sie mich gerne unter:
[Ihre E-Mail-Adresse]

Sie können das Browserfenster nun schließen.
Vielen Dank für Ihre Unterstützung!

Figure A 8 Demographic information.

Appendix B – Online-Experiment

B1. Online-Experimental Design

The experiment was based on a **2 × 2 between-subjects design**:

- FMCG vs. SMCG
- AI-generated product recommendation vs. no product recommendation

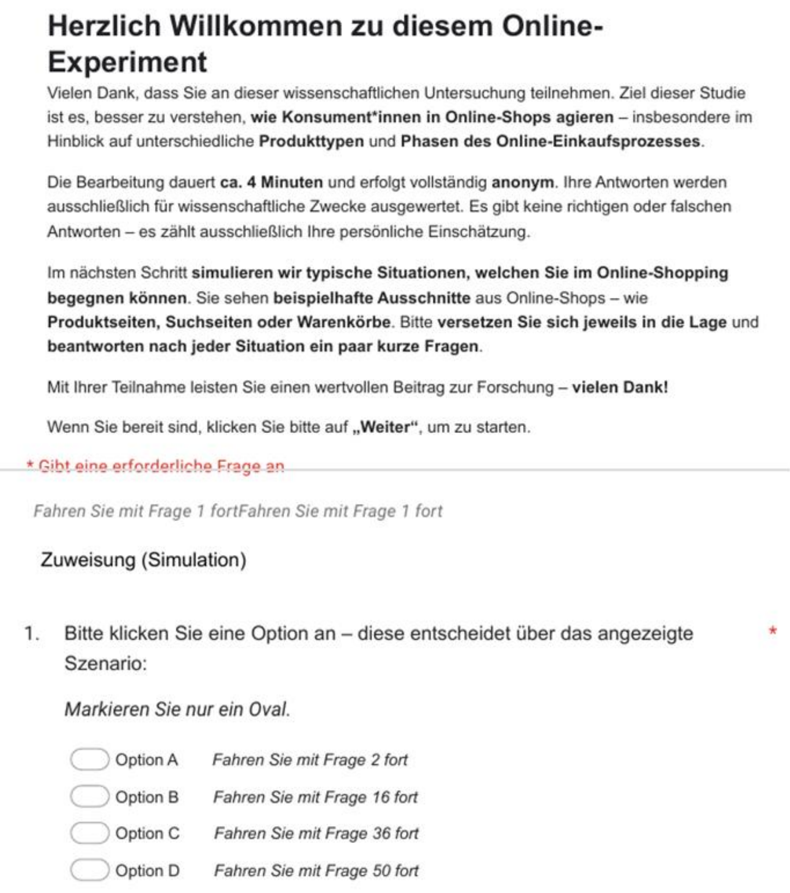
Participants were randomly assigned to one of the four conditions.

B2. Online-Experimental Structure

The online-experiment consisted of four phases:

1. Introduction and assignment
2. Inspiration phase (homepage)
3. Information & evaluation phase (product detail page)
4. Decision phase (shopping cart)
5. Demographic information and purchase behaviour

B3. Example Screenshots


Herzlich Willkommen zu diesem Online-Experiment

Vielen Dank, dass Sie an dieser wissenschaftlichen Untersuchung teilnehmen. Ziel dieser Studie ist es, besser zu verstehen, **wie Konsument*innen in Online-Shops agieren** – insbesondere im Hinblick auf unterschiedliche **Produkttypen** und **Phasen des Online-Einkaufsprozesses**.

Die Bearbeitung dauert **ca. 4 Minuten** und erfolgt vollständig **anonym**. Ihre Antworten werden ausschließlich für wissenschaftliche Zwecke ausgewertet. Es gibt keine richtigen oder falschen Antworten – es zählt ausschließlich Ihre persönliche Einschätzung.

Im nächsten Schritt **simulieren wir typische Situationen, welchen Sie im Online-Shopping begegnen können**. Sie sehen **beispielhafte Ausschnitte** aus Online-Shops – wie **Produktseiten, Suchseiten oder Warenkörbe**. Bitte **versetzen Sie sich jeweils in die Lage** und **beantworten nach jeder Situation ein paar kurze Fragen**.

Mit Ihrer Teilnahme leisten Sie einen wertvollen Beitrag zur Forschung – **vielen Dank!**

Wenn Sie bereit sind, klicken Sie bitte auf **„Weiter“**, um zu starten.

* Gibt eine erforderliche Frage an

Fahren Sie mit Frage 1 fortFahren Sie mit Frage 1 fort

Zuweisung (Simulation)

1. Bitte klicken Sie eine Option an – diese entscheidet über das angezeigte Szenario: *

Markieren Sie nur ein Oval.

- Option A *Fahren Sie mit Frage 2 fort*
- Option B *Fahren Sie mit Frage 16 fort*
- Option C *Fahren Sie mit Frage 36 fort*
- Option D *Fahren Sie mit Frage 50 fort*

Figure B 1 Introduction and assignment item.

Abschnitt für Option A

Bitte stellen Sie sich folgendes vor:

Sie besuchen zum ersten Mal einen neuen Online-Shop. Der Shop wirkt auf den ersten Blick seriös, gut strukturiert und ansprechend gestaltet. Obwohl Sie dort noch nie zuvor eingekauft haben, sind Sie bereit, diesem Anbieter einen gewissen **Vertrauensvorschuss** zu geben.

Im Folgenden werden Ihnen **verschiedene Phasen eines typischen Online-Kaufprozesses** gezeigt. Versetzen Sie sich dabei bitte gedanklich in die jeweilige Situation – so, als würden Sie sich **real** gerade in diesem Online-Shop befinden.

Startseite des Online-Shops ***ShopItNow***

Sie befinden sich auf der Startseite des Online-Shops und beginnen, sich über verschiedene Produkte zu informieren. Sie stöbern durch das Sortiment und verschaffen sich einen ersten Überblick über das Angebot, ohne ein konkretes Produkt im Blick zu haben.

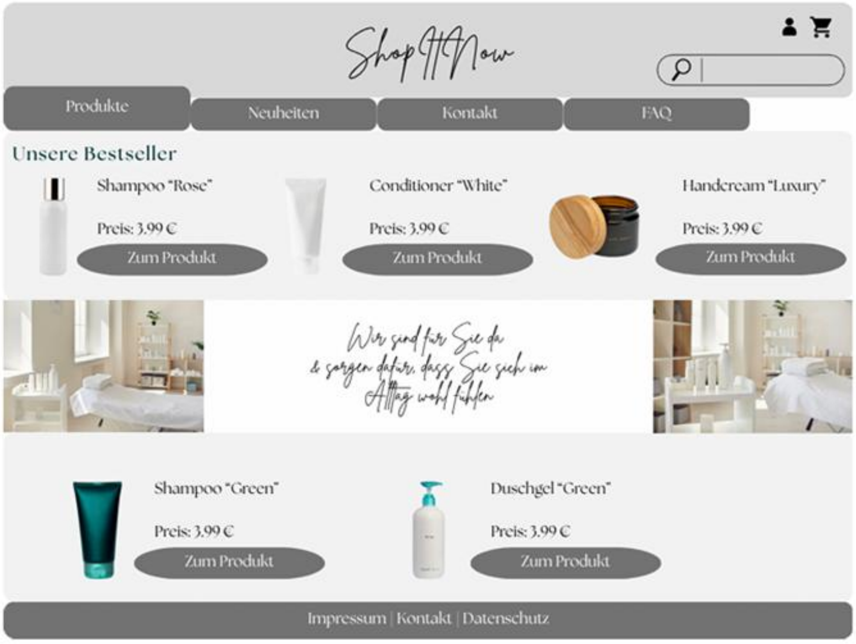


Figure B 2 FMCG introduction example before every phase.

Figure B 3 FMCG homepage (example with AI-generated product recommendation).

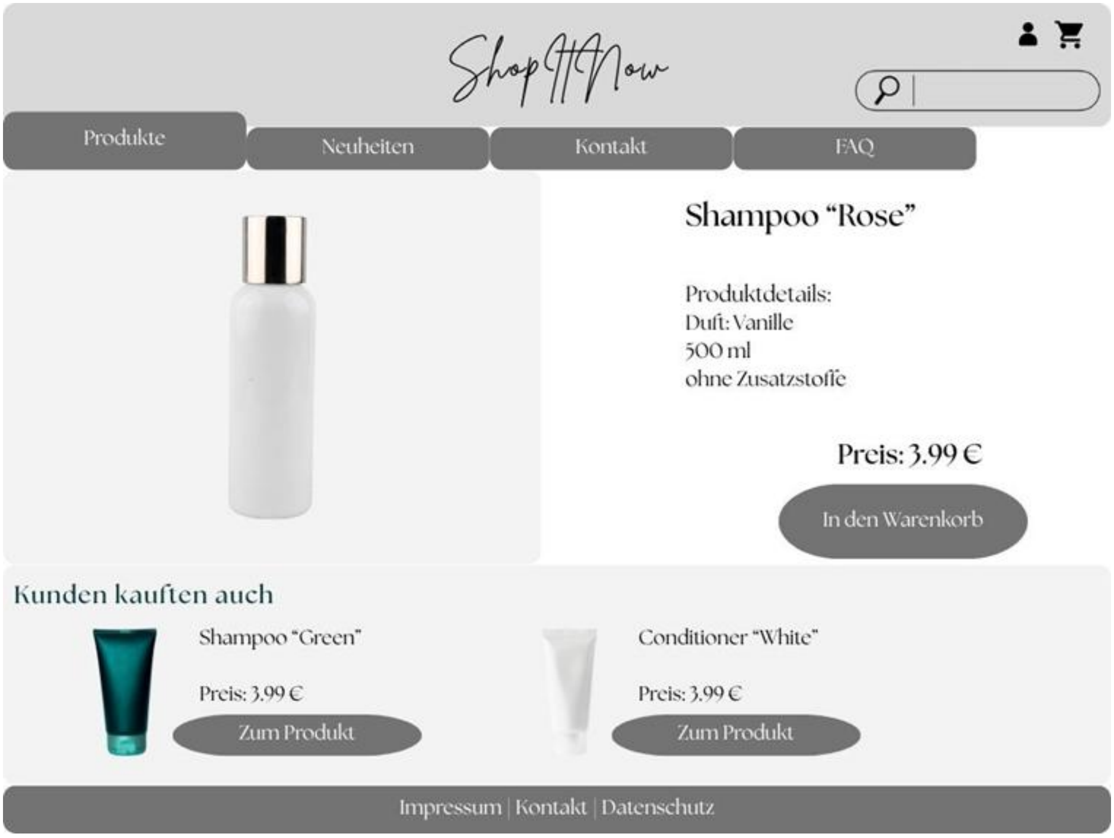


Figure B 4 FMCG product detail page (example without AI-generated product recommendation).

Figure B 5 SMCG product detail page (example with AI-generated product recommendation).

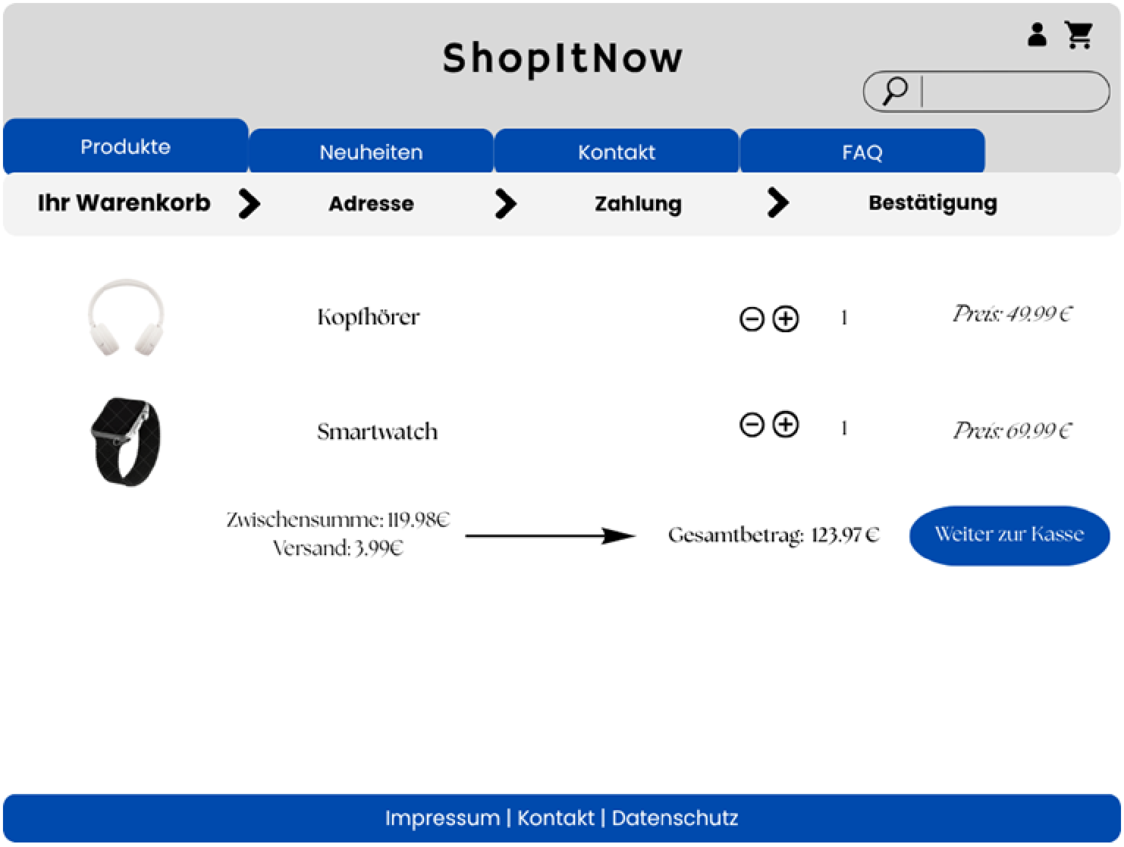


Figure B 6 Shopping cart SMCG (example without AI-generated product recommendation).

2. Was war Ihr erster Eindruck vom gezeigten Produktangebot? *

Markieren Sie nur ein Oval.

- unattraktiv
- neutral
- attraktiv

3. Wie relevant erschienen Ihnen die Produkte für Ihren Bedarf? *

Markieren Sie nur ein Oval.

- sehr unrelevant
- unrelevant
- neutral
- relevant
- sehr relevant

4. Haben Sie sich spontan für ein Produkt interessiert? *

Markieren Sie nur ein Oval.

- Ja
- Nein

5. Falls **Ja** für welches?

Markieren Sie nur ein Oval.

- Shampoo "Rose"
- Conditioner "White"
- Handcream "Luxury"
- Shampoo "Green"
- Duschgel "Green"

24. Würden Sie das Produkt in den Warenkorb legen? *

Markieren Sie nur ein Oval.

- Ja
- Nein

25. Würden Sie sich ein anderes dargestelltes Produkt näher ansehen wollen? *

Markieren Sie nur ein Oval.

- Shampoo "Green"
- Conditioner "White"
- Nein

26. Würden Sie den Kauf auf dieser Seite abschließen? *

Markieren Sie nur ein Oval.

- Ja
- Nein

27. Wirkt die Empfehlung auf Sie personalisiert? *

Markieren Sie nur ein Oval.

- Ja
- Nein

28. Würden Sie diesem Vorschlag tendenziell folgen? *

Markieren Sie nur ein Oval.

- Ja
- Nein

Figure B 7 Online-Experiment Option A questions as an outlook and example.

Fragen zu Kaufszenarien

70. Haben Sie in der gezeigten Kaufsituation eine Produktempfehlung wahrgenommen? *

Markieren Sie nur ein Oval.

- Ja
- Nein
- Ich bin mir nicht sicher

71. Falls Sie eine Produktempfehlung gesehen haben: Hatten Sie den Eindruck, dass diese durch eine Künstliche Intelligenz (KI) erstellt wurde? *

Markieren Sie nur ein Oval.

- Ja, eindeutig
- Vielleicht/Ich vermute es
- Nein
- Ich bin mir nicht sicher

72. Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl? *

Markieren Sie nur ein Oval.

- überhaupt nicht hilfreich
- eher nicht hilfreich
- neutral
- eher hilfreich
- sehr hilfreich

73. Wie sehr hat die Empfehlung Ihre Auswahl oder Bewertung beeinflusst? *

Markieren Sie nur ein Oval.

- überhaupt nicht beeinflusst
- nicht beeinflusst
- neutral
- beeinflusst
- sehr beeinflusst

Figure B 8 Purchase behaviour and AI-generated product recommendation items as an outlook and example.

74. Worauf basierte Ihre Entscheidung hauptsächlich? *

Markieren Sie nur ein Oval.

- Preis
- Nutzen
- Ästhetik
- Empfehlung
- Intuition
- Erfahrung mit ähnlichen Produkten
- Spontanität

75. Wie würden Sie Ihren Entscheidungsstil in dieser Situation beschreiben? *

Markieren Sie nur ein Oval.

- sehr analytisch
- analytisch
- neutral
- spontan
- sehr spontan

76. Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf? *

Markieren Sie nur ein Oval.

- Ja
- Nein
- Sonstiges: ______________________

77. Was ist Ihnen bei der Kaufsituation besonders aufgefallen? Gab es etwas, das Sie überrascht, gestört oder überzeugt hat? *

____

Figure B 9 Purchase behaviour and AI-generated product recommendation items as an outlook and example 2.

78. Wie alt sind Sie? *

79. Welchem Geschlecht fühlen Sie sich zugehörig? *

Markieren Sie nur ein Oval.

- weiblich
- männlich
- divers
- keine Angabe

80. Wie hoch ist ihr monatliches Nettoeinkommen? *

Markieren Sie nur ein Oval.

- unter 1.000€
- 1.000 - 1.999€
- 2.000 - 2.999€
- 3.000 - 3.999€
- 4.000 - 4.999€
- 5.000 - 5.999€
- 6.000 - 7.000€
- über 7.000€

81. Was ist Ihr höchster abgeschlossener Bildungsabschluss? *

Markieren Sie nur ein Oval.

- kein Schulabschluss
- Hauptschulabschluss
- Realschulabschluss/Mittlere Reife
- (Fach-)Abitur/Allgemeine Hochschulreife
- Berufsausbildung (z.B. IHK-/HWK-Abschluss)
- Fachhochschulabschluss (z.B. Bachelor FH)
- Universitätsabschluss (z.B. Bachelor, Master, Diplom, Staatsexamen)
- Promotion oder Habilitation

82. Wie häufig kaufen Sie online ein? *

Markieren Sie nur ein Oval.

- täglich
- wöchentlich
- monatlich
- alle 2-6 Monate
- einmal im Jahr oder seltener
- nie

83. Über welches Endgerät kaufen Sie am häufigsten online ein? *

Markieren Sie nur ein Oval.

- Smartphone
- Laptop
- Desktop-PC
- Tablet
- Sonstiges:

Figure B 10 Demographic information items.

Appendix C – Data Tables & Coding

C1. Overview of Variables used in the Online-Survey and Online-Experiment

Table C 1 Overview of Variables in the Online-Survey Dataset.

Variable	*Description*	*Scale*	*Notes*
Häufigkeit	Frequency of online shopping	1–5 Likert	Self-reported
Endgerät	Main device used	categorical	Smartphone/Laptop/etc.
Produktgruppen_01–03	Product categories purchased	categorical	FMCG/SMCG clustering
F1–F20	Perception of AI-generated product recommendations	1–5 Likert	Used in H2, H4, H6
F13	Perceived necessity	1–5 Likert	Moderator for H3
Kauf_freq	Purchase frequency due to recommendations	1–5 Likert	Dependent variable
age, gender, income	Demographics	various	Controls

Table C 2 Overview of Variables in the Online-Experiment Dataset.

Variable	*Description*	*Scale*	*Notes*
phase1_first_impression	First impression of product	1–5 Likert	Phase 1 (Inspiration)
phase1_relevance	Relevance of recommended item	1–5 Likert	A/B-test relevant
phase1_purchase_intent	Purchase intention	1–5 Likert	DV in H1
…	…	…	…
rec_seen	Recommendation noticed?	0/1	Manipulation check
rec_ai_perceived	Recognised as AI?	0/1	Manipulation check

rec_helpfulness	Helpfulness rating	1–5 Likert	Hypothesis tests
decision_basis	Reason for decision	categorical	qualitative coding
age, gender	Demographics	various	Controls

C2. Coding Scheme

C2.1 Online-Survey Coding Scheme

Table C 3 Demographics Coding.

Variable	***Coding***
ender	1 = Female, 2 = Male
income	1 = <1000€, 2 = 1000–1999€, 3 = 2000–2999€, …
education	1 = specialized high school, 2 = university degree, …

Table C 4 Online-Shopping Behaviour Coding.

Variable	***Coding***
Häufigkeit	1 = weekly, 2 = monthly, 3 = 2–6 months, 4 = rarely
Endgerät	1 = smartphone, 2 = laptop, 3 = tablet

Variable: AI-related Variables (F1-F20)

Coding: 1=strongly disagree, 5=strongly agree

C2.2 Online-Experiment Coding Scheme

Table C 5 AI-generated Product Recommendation Coding.

Variable	***Coding***
rec_seen	0 = no, 1 = yes
rec_ai_perceived	0 = no, 1 = yes
rec_personalized	1 = felt personalized, 0 = not personalized

Table C 6 Decision Variables Coding.

Variable	***Coding***
decision_style	1 = analytical, 2 = spontaneous, 3 = neutral
add_to_cart	1 = yes, 0 = no
real_purchase	1 = yes, 0 = no

C3. Data Cleaning & Exclusion Criteria

Table C 7 Data Cleaning Procedures.

Step	***Description***
Removal of speeders	Cases with survey completion time < 3 minutes were removed (n = X).
Removal of incomplete cases	Entries with missing > 20% of key variables excluded.
Validity check	Records without valid demographic entries removed.
Experiment condition check	Participants who did not finish all four phases were excluded.
Recoding	Textual answers recoded to numerical values (see Appendix C2).
Outlier check	No extreme outliers requiring deletion.

Appendix D - Statistical Output

Hypothesis Testing Output

H1 (t-test):

Deskriptive Statistiken

	0=FMCG, 1=SMCG	0=ohne, 1=mit	Mittelwert	Standardabweichung	N
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	,00	,00	3,83	1,169	6
		1,00	1,00	,000	8
		Gesamt	2,21	1,626	14
	1,00	,00	1,00	,000	10
		1,00	1,00	,000	6
		Gesamt	1,00	,000	16
	Gesamt	,00	2,06	1,569	16
		1,00	1,00	,000	14
		Gesamt	1,57	1,251	30
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	,00	,00	1,00	,000	6
		1,00	3,75	1,488	8
		Gesamt	2,57	1,785	14
	1,00	,00	1,00	,000	10
		1,00	1,00	,000	6
		Gesamt	1,00	,000	16
	Gesamt	,00	1,00	,000	16
		1,00	2,57	1,785	14
		Gesamt	1,73	1,437	30
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	,00	,00	1,00	,000	6
		1,00	1,00	,000	8
		Gesamt	1,00	,000	14
	1,00	,00	3,50	1,179	10
		1,00	1,00	,000	6
		Gesamt	2,56	1,548	16
	Gesamt	,00	2,56	1,548	16
		1,00	1,00	,000	14
		Gesamt	1,83	1,367	30
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	,00	,00	1,00	,000	6
		1,00	1,00	,000	8
		Gesamt	1,00	,000	14
	1,00	,00	1,00	,000	10
		1,00	3,50	,837	6
		Gesamt	1,94	1,340	16
	Gesamt	,00	1,00	,000	16
		1,00	2,07	1,385	14
		Gesamt	1,50	1,075	30

Bartlett-Test auf Sphärizität[a]

Likelihood-Quotient	,000
Ungefähres Chi-Quadrat	14,625
df	9
Sig.	,102

Prüft die Nullhypothese, dass sich die Residuen-Kovarianzmatrix proportional zur Einheitsmatrix verhält.

a. Design: Konstanter Term + Produkttyp + empfehlung + Produkttyp * empfehlung
Innersubjektdesign: Phase

Multivariate Tests[a]

Effekt		Wert	F	Hypothese df	Fehler df	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[c]
Phase	Pillai-Spur	,023	,186[b]	3,000	24,000	,905	,023	,558	,080
	Wilks-Lambda	,977	,186[b]	3,000	24,000	,905	,023	,558	,080
	Hotelling-Spur	,023	,186[b]	3,000	24,000	,905	,023	,558	,080
	Größte charakteristische Wurzel nach Roy	,023	,186[b]	3,000	24,000	,905	,023	,558	,080
Phase * Produkttyp	Pillai-Spur	,871	53,994[b]	3,000	24,000	<,001	,871	161,982	1,000
	Wilks-Lambda	,129	53,994[b]	3,000	24,000	<,001	,871	161,982	1,000
	Hotelling-Spur	6,749	53,994[b]	3,000	24,000	<,001	,871	161,982	1,000
	Größte charakteristische Wurzel nach Roy	6,749	53,994[b]	3,000	24,000	<,001	,871	161,982	1,000
Phase * empfehlung	Pillai-Spur	,872	54,667[b]	3,000	24,000	<,001	,872	164,000	1,000
	Wilks-Lambda	,128	54,667[b]	3,000	24,000	<,001	,872	164,000	1,000
	Hotelling-Spur	6,833	54,667[b]	3,000	24,000	<,001	,872	164,000	1,000
	Größte charakteristische Wurzel nach Roy	6,833	54,667[b]	3,000	24,000	<,001	,872	164,000	1,000
Phase * Produkttyp * empfehlung	Pillai-Spur	,842	42,540[b]	3,000	24,000	<,001	,842	127,619	1,000
	Wilks-Lambda	,158	42,540[b]	3,000	24,000	<,001	,842	127,619	1,000
	Hotelling-Spur	5,317	42,540[b]	3,000	24,000	<,001	,842	127,619	1,000
	Größte charakteristische Wurzel nach Roy	5,317	42,540[b]	3,000	24,000	<,001	,842	127,619	1,000

a. Design: Konstanter Term + Produkttyp + empfehlung + Produkttyp * empfehlung
Innersubjektdesign: Phase

b. Exakte Statistik

c. Unter Verwendung von Alpha = ,05 berechnet

Mauchly-Test auf Sphärizität[a]

Maß: MASS_1

Innersubjekteffekt	Mauchly-W	Ungefähres Chi-Quadrat	df	Sig.	Epsilon[b] Greenhouse-Geisser	Epsilon[b] Huynh-Feldt (HF)	Epsilon[b] Untergrenze
Phase	,759	6,820	5	,235	,862	1,000	,333

Prüft die Nullhypothese, dass sich die Fehlerkovarianz-Matrix der orthonormalisierten transformierten abhängigen Variablen proportional zur Einheitsmatrix verhält.

a. Design: Konstanter Term + Produkttyp + empfehlung + Produkttyp * empfehlung
Innersubjektdesign: Phase

b. Kann zum Korrigieren der Freiheitsgrade für die gemittelten Signifikanztests verwendet werden. In der Tabelle mit den Tests der Effekte innerhalb der Subjekte werden korrigierte Tests angezeigt.

Tests der Innersubjekteffekte

Maß: MASS_1

Quelle		Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
Phase	Sphärizität angenommen	,159	3	,053	,143	,934	,005	,430	,075
	Greenhouse-Geisser	,159	2,587	,061	,143	,912	,005	,371	,074
	Huynh-Feldt (HF)	,159	3,000	,053	,143	,934	,005	,430	,075
	Untergrenze	,159	1,000	,159	,143	,708	,005	,143	,065
Phase * Produkttyp	Sphärizität angenommen	50,159	3	16,720	45,361	<,001	,636	136,082	1,000
	Greenhouse-Geisser	50,159	2,587	19,392	45,361	<,001	,636	117,328	1,000
	Huynh-Feldt (HF)	50,159	3,000	16,720	45,361	<,001	,636	136,082	1,000
	Untergrenze	50,159	1,000	50,159	45,361	<,001	,636	45,361	1,000
Phase * empfehlung	Sphärizität angenommen	50,308	3	16,769	45,496	<,001	,636	136,487	1,000
	Greenhouse-Geisser	50,308	2,587	19,450	45,496	<,001	,636	117,677	1,000
	Huynh-Feldt (HF)	50,308	3,000	16,769	45,496	<,001	,636	136,487	1,000
	Untergrenze	50,308	1,000	50,308	45,496	<,001	,636	45,496	1,000
Phase * Produkttyp * empfehlung	Sphärizität angenommen	50,308	3	16,769	45,496	<,001	,636	136,487	1,000
	Greenhouse-Geisser	50,308	2,587	19,450	45,496	<,001	,636	117,677	1,000
	Huynh-Feldt (HF)	50,308	3,000	16,769	45,496	<,001	,636	136,487	1,000
	Untergrenze	50,308	1,000	50,308	45,496	<,001	,636	45,496	1,000

Fehler(Phase)	Sphärizität angenommen	28,750	78	,369					
	Greenhouse-Geisser	28,750	67,250	,428					
	Huynh-Feldt (HF)	28,750	78,000	,369					
	Untergrenze	28,750	26,000	1,106					

a. Unter Verwendung von Alpha = ,05 berechnet

Tests der Innersubjektkontraste

Maß: MASS_1

Quelle	Phase	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
Phase	Linear	,140	1	,140	,601	,445	,023	,601	,116
	Quadratisch	,003	1	,003	,008	,928	,000	,008	,051
	Kubisch	,016	1	,016	,031	,862	,001	,031	,053
Phase * Produkttyp	Linear	40,438	1	40,438	173,785	<,001	,870	173,785	1,000
	Quadratisch	,003	1	,003	,008	,928	,000	,008	,051
	Kubisch	9,717	1	9,717	19,261	<,001	,426	19,261	,988
Phase * empfehlung	Linear	10,349	1	10,349	44,475	<,001	,631	44,475	1,000
	Quadratisch	,152	1	,152	,413	,526	,016	,413	,095
	Kubisch	39,807	1	39,807	78,905	<,001	,752	78,905	1,000
Phase * Produkttyp * empfehlung	Linear	,050	1	,050	,216	,646	,008	,216	,073
	Quadratisch	50,152	1	50,152	136,066	<,001	,840	136,066	1,000
	Kubisch	,105	1	,105	,208	,652	,008	,208	,072
Fehler(Phase)	Linear	6,050	26	,233					
	Quadratisch	9,583	26	,369					
	Kubisch	13,117	26	,504					

a. Unter Verwendung von Alpha = ,05 berechnet

Levene-Test auf Gleichheit der Fehlervarianzen[a]

		Levene-Statistik	df1	df2	Sig.
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	Basiert auf dem Mittelwert	15,707	3	26	<,001
	Basiert auf dem Median	10,196	3	26	<,001
	Basierend auf dem Median und mit angepaßten df	10,196	3	5,000	,014
	Basiert auf dem getrimmten Mittel	14,323	3	26	<,001
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	Basiert auf dem Mittelwert	26,481	3	26	<,001
	Basiert auf dem Median	22,698	3	26	<,001
	Basierend auf dem Median und mit angepaßten df	22,698	3	7,000	<,001
	Basiert auf dem getrimmten Mittel	26,427	3	26	<,001
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	Basiert auf dem Mittelwert	23,111	3	26	<,001
	Basiert auf dem Median	6,783	3	26	,002
	Basierend auf dem Median und mit angepaßten df	6,783	3	9,000	,011
	Basiert auf dem getrimmten Mittel	23,111	3	26	<,001
Wie wahrscheinlich ist es, dass Sie dieses Produkt kaufen würden?	Basiert auf dem Mittelwert	22,187	3	26	<,001
	Basiert auf dem Median	2,971	3	26	,050
	Basierend auf dem Median und mit angepaßten df	2,971	3	5,000	,136
	Basiert auf dem getrimmten Mittel	17,512	3	26	<,001

Prüft die Nullhypothese, dass die Fehlervarianz der abhängigen Variablen über Gruppen hinweg gleich ist.

a. Design: Konstanter Term + Produkttyp + empfehlung + Produkttyp * empfehlung
Innersubjektdesign: Phase

Tests der Zwischensubjekteffekte

Maß: MASS_1
Transformierte Variable: Mittel

Quelle	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
Konstanter Term	316,421	1	316,421	858,464	<,001	,971	858,464	1,000
Produkttyp	,152	1	,152	,413	,526	,016	,413	,095
empfehlung	,003	1	,003	,008	,928	,000	,008	,051
Produkttyp * empfehlung	,003	1	,003	,008	,928	,000	,008	,051
Fehler	9,583	26	,369					

a. Unter Verwendung von Alpha = ,05 berechnet

Allgemeine schätzbare Funktion[a]

Parameter	Kontrast L1	L2	L4	L6
Konstanter Term	1	0	0	0
[Produkttyp=,00]	0	1	0	0
[Produkttyp=1,00]	1	-1	0	0
[empfehlung=,00]	0	0	1	0
[empfehlung=1,00]	1	0	-1	0
[Produkttyp=,00] * [empfehlung=,00]	0	0	0	1
[Produkttyp=,00] * [empfehlung=1,00]	0	1	0	-1
[Produkttyp=1,00] * [empfehlung=,00]	0	0	1	-1
[Produkttyp=1,00] * [empfehlung=1,00]	1	-1	-1	1

a. Design: Konstanter Term + Produkttyp + empfehlung + Produkttyp * empfehlung
Innersubjektdesign: Phase

Matrix mit Quadratsummen und Kreuzprodukten innerhalb der Subjekte

Phase

		Phase : Zeile	Phase : Spalte Linear	Quadratisch	Kubisch
Hypothese	Konstanter Term	Linear	,140	-,021	-,047
		Quadratisch	-,021	,003	,007
		Kubisch	-,047	,007	,016
	Produkttyp	Linear	40,438	-,355	-19,823
		Quadratisch	-,355	,003	,174
		Kubisch	-19,823	,174	9,717
	empfehlung	Linear	10,349	-1,256	20,297
		Quadratisch	-1,256	,152	-2,463
		Kubisch	20,297	-2,463	39,807
	Produkttyp * empfehlung	Linear	,050	-1,589	,073
		Quadratisch	-1,589	50,152	-2,296
		Kubisch	,073	-2,296	,105
Fehler		Linear	6,050	-,783	-2,650
		Quadratisch	-,783	9,583	-1,379
		Kubisch	-2,650	-1,379	13,117

Basierend auf Typ III Quadratsumme

H1 (Podhoc-test):

Paarweise Vergleiche

Maß: MASS_1

0=ohne, 1=mit	Phase	(I) 0=FMCG, 1=SMCG	(J) 0=FMCG, 1=SMCG	Mittelwertdifferenz (I-J)	Std.-Fehler	Sig.[b]	95% Konfidenzintervall für Differenz[b] Untergrenze	Obergrenze
,00	1	,00	1,00	2,833*	,265	<,001	2,289	3,378
		1,00	,00	-2,833*	,265	<,001	-3,378	-2,289
	2	,00	1,00	-4,441E-16	,399	1,000	-,820	,820
		1,00	,00	4,441E-16	,399	1,000	-,820	,820
	3	,00	1,00	-2,500*	,358	<,001	-3,236	-1,764
		1,00	,00	2,500*	,358	<,001	1,764	3,236
	4	,00	1,00	,000	,189	1,000	-,389	,389
		1,00	,00	,000	,189	1,000	-,389	,389
1,00	1	,00	1,00	-4,441E-16	,277	1,000	-,569	,569
		1,00	,00	4,441E-16	,277	1,000	-,569	,569
	2	,00	1,00	2,750*	,417	<,001	1,893	3,607
		1,00	,00	-2,750*	,417	<,001	-3,607	-1,893
	3	,00	1,00	4,441E-16	,374	1,000	-,770	,770
		1,00	,00	-4,441E-16	,374	1,000	-,770	,770
	4	,00	1,00	-2,500*	,198	<,001	-2,907	-2,093
		1,00	,00	2,500*	,198	<,001	2,093	2,907

Basiert auf geschätzten Randmitteln
*. Die Mittelwertdifferenz ist in Stufe ,05 signifikant.
b. Anpassung für Mehrfachvergleiche: Geringste signifikante Differenz (entspricht keiner Korrektur).

Paarweise Vergleiche

Maß: MASS_1

0=FMCG, 1=SMCG	Phase	(I) 0=ohne, 1=mit	(J) 0=ohne, 1=mit	Mittelwertdifferenz (I-J)	Std.-Fehler	Sig.[b]	95% Konfidenzintervall für Differenz[b] Untergrenze	Obergrenze
,00	1	,00	1,00	2,833*	,277	<,001	2,264	3,402
		1,00	,00	-2,833*	,277	<,001	-3,402	-2,264
	2	,00	1,00	-2,750*	,417	<,001	-3,607	-1,893
		1,00	,00	2,750*	,417	<,001	1,893	3,607
	3	,00	1,00	-4,441E-16	,374	1,000	-,770	,770
		1,00	,00	4,441E-16	,374	1,000	-,770	,770
	4	,00	1,00	4,441E-16	,198	1,000	-,407	,407
		1,00	,00	-4,441E-16	,198	1,000	-,407	,407
1,00	1	,00	1,00	,000	,265	1,000	-,544	,544
		1,00	,00	,000	,265	1,000	-,544	,544
	2	,00	1,00	1,110E-15	,399	1,000	-,820	,820
		1,00	,00	-1,110E-15	,399	1,000	-,820	,820
	3	,00	1,00	2,500*	,358	<,001	1,764	3,236
		1,00	,00	-2,500*	,358	<,001	-3,236	-1,764
	4	,00	1,00	-2,500*	,189	<,001	-2,889	-2,111
		1,00	,00	2,500*	,189	<,001	2,111	2,889

Basiert auf geschätzten Randmitteln

*. Die Mittelwertdifferenz ist in Stufe ,05 signifikant.

b. Anpassung für Mehrfachvergleiche: Geringste signifikante Differenz (entspricht keiner Korrektur).

Paarweise Vergleiche

Maß: MASS_1

0=FMCG, 1=SMCG	0=ohne, 1=mit	(I) Phase	(J) Phase	Mittelwertdifferenz (I-J)	Std.-Fehler	Sig.[b]	95% Konfidenzintervall für Differenz[b] Untergrenze	Obergrenze
,00	,00	1	2	2,833*	,378	<,001	2,056	3,611
			3	2,833*	,352	<,001	2,110	3,557
			4	2,833*	,257	<,001	2,304	3,362
		2	1	-2,833*	,378	<,001	-3,611	-2,056
			3	-1,110E-16	,424	1,000	-,871	,871
			4	1,110E-16	,349	1,000	-,717	,717
		3	1	-2,833*	,352	<,001	-3,557	-2,110
			2	1,110E-16	,424	1,000	-,871	,871
			4	2,220E-16	,320	1,000	-,658	,658
		4	1	-2,833*	,257	<,001	-3,362	-2,304
			2	-1,110E-16	,349	1,000	-,717	,717
			3	-2,220E-16	,320	1,000	-,658	,658
	1,00	1	2	-2,750*	,328	<,001	-3,424	-2,076
			3	-6,661E-16	,305	1,000	-,627	,627
			4	,000	,223	1,000	-,458	,458
		2	1	2,750*	,328	<,001	2,076	3,424
			3	2,750*	,367	<,001	1,996	3,504
			4	2,750*	,302	<,001	2,129	3,371
		3	1	6,661E-16	,305	1,000	-,627	,627
			2	-2,750*	,367	<,001	-3,504	-1,996
			4	6,661E-16	,277	1,000	-,570	,570
		4	1	,000	,223	1,000	-,458	,458
			2	-2,750*	,302	<,001	-3,371	-2,129
			3	-6,661E-16	,277	1,000	-,570	,570
1,00	,00	1	2	-4,441E-16	,293	1,000	-,602	,602
			3	-2,500*	,273	<,001	-3,061	-1,939
			4	,000	,199	1,000	-,410	,410
		2	1	4,441E-16	,293	1,000	-,602	,602
			3	-2,500*	,328	<,001	-3,175	-1,825
			4	4,441E-16	,270	1,000	-,556	,556
		3	1	2,500*	,273	<,001	1,939	3,061
			2	2,500*	,328	<,001	1,825	3,175
			4	2,500*	,248	<,001	1,990	3,010
		4	1	,000	,199	1,000	-,410	,410
			2	-4,441E-16	,270	1,000	-,556	,556
			3	-2,500*	,248	<,001	-3,010	-1,990
	1,00	1	2	7,772E-16	,378	1,000	-,778	,778
			3	2,220E-16	,352	1,000	-,724	,724
			4	-2,500*	,257	<,001	-3,029	-1,971
		2	1	-7,772E-16	,378	1,000	-,778	,778
			3	-5,551E-16	,424	1,000	-,871	,871
			4	-2,500*	,349	<,001	-3,217	-1,783
		3	1	-2,220E-16	,352	1,000	-,724	,724
			2	5,551E-16	,424	1,000	-,871	,871
			4	-2,500*	,320	<,001	-3,158	-1,842
		4	1	2,500*	,257	<,001	1,971	3,029
			2	2,500*	,349	<,001	1,783	3,217
			3	2,500*	,320	<,001	1,842	3,158

Basiert auf geschätzten Randmitteln

*. Die Mittelwertdifferenz ist in Stufe ,05 signifikant.

b. Anpassung für Mehrfachvergleiche: Geringste signifikante Differenz (entspricht keiner Korrektur).

H2 (RM-ANOVA):

Deskriptive Statistiken

	Mittelwert	Standardabweichung	N
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	3,59	,975	100
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	2,90	1,159	100
F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	3,24	1,102	100
F10: Warenkorb / Check-Out	2,08	1,051	100
F10: Nach dem Kauf (z.B. per E-Mail)	1,49	,810	100

Multivariate Tests[a]

Effekt		Wert	F	Hypothese df	Fehler df	Sig.
Phase	Pillai-Spur	,760	75,855[b]	4,000	96,000	<,001
	Wilks-Lambda	,240	75,855[b]	4,000	96,000	<,001
	Hotelling-Spur	3,161	75,855[b]	4,000	96,000	<,001
	Größte charakteristische Wurzel nach Roy	3,161	75,855[b]	4,000	96,000	<,001

a. Design: Konstanter Term
Innersubjektdesign: Phase

b. Exakte Statistik

Mauchly-Test auf Sphärizität[a]

Maß: MASS_1

Innersubjekteffekt	Mauchly-W	Ungefähres Chi-Quadrat	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt (HF)	Untergrenze
Phase	,799	21,859	9	,009	,911	,950	,250

Prüft die Nullhypothese, dass sich die Fehlerkovarianz-Matrix der orthonormalisierten transformierten abhängigen Variablen proportional zur Einheitsmatrix verhält.

a. Design: Konstanter Term
Innersubjektdesign: Phase

b. Kann zum Korrigieren der Freiheitsgrade für die gemittelten Signifikanztests verwendet werden. In der Tabelle mit den Tests der Effekte innerhalb der Subjekte werden korrigierte Tests angezeigt.

Tests der Innersubjekteffekte

Maß: MASS_1

Quelle		Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.
Phase	Sphärizität angenommen	296,420	4	74,105	86,724	<,001
	Greenhouse-Geisser	296,420	3,642	81,382	86,724	<,001
	Huynh-Feldt (HF)	296,420	3,799	78,033	86,724	<,001
	Untergrenze	296,420	1,000	296,420	86,724	<,001
Fehler(Phase)	Sphärizität angenommen	338,380	396	,854		
	Greenhouse-Geisser	338,380	360,589	,938		
	Huynh-Feldt (HF)	338,380	376,067	,900		
	Untergrenze	338,380	99,000	3,418		

Tests der Innersubjektkontraste

Maß: MASS_1

Quelle	Phase	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.
Phase	Linear	252,004	1	252,004	236,263	<,001
	Quadratisch	12,071	1	12,071	15,980	<,001
	Kubisch	2,116	1	2,116	3,113	,081
	Ordnung 4	30,229	1	30,229	32,990	<,001
Fehler(Phase)	Linear	105,596	99	1,067		
	Quadratisch	74,786	99	,755		
	Kubisch	67,284	99	,680		
	Ordnung 4	90,714	99	,916		

Tests der Zwischensubjekteffekte

Maß: MASS_1
Transformierte Variable: Mittel

Quelle	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.
Konstanter Term	3537,800	1	3537,800	1909,718	<,001
Fehler	183,400	99	1,853		

Appendix

t-Test

Gruppenstatistiken

	0=FMCG, 1=SMCG	N	Mittelwert	Std.-Abweichung	Standardfehler des Mittelwertes
helpfulnesrec_Warenkorb	,00	8	4,0000	1,19523	,42258
	1,00	6	2,8333	,75277	,30732

Test bei unabhängigen Stichproben

		Levene-Test der Varianzgleichheit		t-Test für die Mittelwertgleichheit							
						Signifikanz				95% Konfidenzintervall der Differenz	
		F	Sig.	T	df	Einseitiges p	Zweiseitiges p	Mittlere Differenz	Differenz für Standardfehler	Unterer Wert	Oberer Wert
helpfulnesrec_Warenkorb	Varianzen sind gleich	2,726	,125	2,089	12	,029	,059	1,16667	,55850	-,05020	2,38353
	Varianzen sind nicht gleich			2,233	11,758	,023	,046	1,16667	,52251	,02561	2,30772

Effektgrößen bei unabhängigen Stichproben

		Standardisierer[a]	Punktschätzung	95% Konfidenzintervall	
				Unterer Wert	Oberer Wert
helpfulnesrec_Warenkorb	Cohen's d	1,03414	1,128	-,040	2,257
	Hedges' Korrektur	1,10492	1,056	-,038	2,113
	Glass' Delta	,75277	1,550	,099	2,921

a. Der bei der Schätzung der Effektgrößen verwendete Nenner.
Für 'Cohen d' wird die zusammengefasste Standardabweichung verwendet.
Für die Hedges-Korrektur wird die zusammengefasste Standardabweichung mit einem Korrekturfaktor verwendet.
Für das Glass-Delta wird die Standardabweichung der Stichprobe der Kontrollgruppe (d. h. der zweiten Gruppe) verwendet.

Univariate Varianzanalyse

Zwischensubjektfaktoren

		N
0=FMCG, 1=SMCG	,00	8
	1,00	6

Tests der Zwischensubjekteffekte

Abhängige Variable: helpfulnesrec_Warenkorb

Quelle	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.
Korrigiertes Modell	8,063[a]	4	2,016	1,923	,191
Konstanter Term	1,769	1	1,769	1,687	,226
recseen_num	1,223	1	1,223	1,167	,308
rectrust_num	1,987	1	1,987	1,895	,202
recperceived_num	,587	1	,587	,560	,473
Produkttyp	4,847	1	4,847	4,623	,060
Fehler	9,437	9	1,049		
Gesamt	189,000	14			
Korrigierte Gesamtvariation	17,500	13			

a. R-Quadrat = ,461 (korrigiertes R-Quadrat = ,221)

t-Test

Statistik bei einer Stichprobe

	N	Mittelwert	Std.-Abweichung	Standardfehler des Mittelwertes
Wie sehr hat die Empfehlung Ihre Entscheidung beeinflusst?	8	4,00	1,195	,423

Test bei einer Stichprobe

	Testwert = 3						
			Signifikanz			95% Konfidenzintervall der Differenz	
	T	df	Einseitiges p	Zweiseitiges p	Mittlere Differenz	Unterer Wert	Oberer Wert
Wie sehr hat die Empfehlung Ihre Entscheidung beeinflusst?	2,366	7	,025	,050	1,000	,00	2,00

Effektgrößen bei einer Stichprobe

		Standardisierer[a]	Punktschätzung	95% Konfidenzintervall	
				Unterer Wert	Oberer Wert
Wie sehr hat die Empfehlung Ihre Entscheidung beeinflusst?	Cohen's d	1,195	,837	,000	1,631
	Hedges' Korrektur	1,346	,743	,000	1,449

a. Der bei der Schätzung der Effektgrößen verwendete Nenner.
Cohen's d verwendet die Standardabweichung einer Stichprobe.
Hedges' Korrektur verwendet die Standardabweichung einer Stichprobe und einen Korrekturfaktor.

Appendix

t-Test

Statistik bei einer Stichprobe

	N	Mittelwert	Std.-Abweichung	Standardfehler des Mittelwertes
Wie sehr hat die Empfehlung Ihre Entscheidung beeinflusst?	6	2,83	,753	,307

Test bei einer Stichprobe

	Testwert = 3						
			Signifikanz			95% Konfidenzintervall der Differenz	
	T	df	Einseitiges p	Zweiseitiges p	Mittlere Differenz	Unterer Wert	Oberer Wert
Wie sehr hat die Empfehlung Ihre Entscheidung beeinflusst?	-,542	5	,305	,611	-,167	-,96	,62

Effektgrößen bei einer Stichprobe

		Standardisierer[a]	Punktschätzung	95% Konfidenzintervall	
				Unterer Wert	Oberer Wert
Wie sehr hat die Empfehlung Ihre Entscheidung beeinflusst?	Cohen's d	,753	-,221	-1,022	,600
	Hedges' Korrektur	,895	-,186	-,859	,505

a. Der bei der Schätzung der Effektgrößen verwendete Nenner.
Cohen's d verwendet die Standardabweichung einer Stichprobe.
Hedges' Korrektur verwendet die Standardabweichung einer Stichprobe und einen Korrekturfaktor.

H2 (Posthoc test):

Parameterschätzungen

Abhängige Variable	Parameter	RegressionskoeffizientB	Std.-Fehler	T	Sig.	95% Konfidenzintervall Untergrenze	95% Konfidenzintervall Obergrenze	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	Konstanter Term	3,590	,098	36,805	<,001	3,396	3,784	,932	36,805	1,000
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	Konstanter Term	2,900	,116	25,020	<,001	2,670	3,130	,863	25,020	1,000
F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	Konstanter Term	3,240	,110	29,399	<,001	3,021	3,459	,897	29,399	1,000
F10: Warenkorb / Check-Out	Konstanter Term	2,080	,105	19,790	<,001	1,871	2,289	,798	19,790	1,000
F10: Nach dem Kauf (z.B. per E-Mail)	Konstanter Term	1,490	,081	18,390	<,001	1,329	1,651	,774	18,390	1,000

a. Unter Verwendung von Alpha = ,05 berechnet

Allgemeine schätzbare Funktion[a]

Parameter	Kontrast L1
Konstanter Term	1

a. Design: Konstanter Term
Innersubjektdesign: Phase

Matrix mit Quadratsummen und Kreuzprodukten innerhalb der Subjekte

Phase			Phase : Spalte			
		Phase : Zeile	Niveau 2 vs. Niveau 1	Niveau 3 vs. Niveau 1	Niveau 4 vs. Niveau 1	Niveau 5 vs. Niveau 1
Hypothese	Konstanter Term	Niveau 2 vs. Niveau 1	47,610	24,150	104,190	144,900
		Niveau 3 vs. Niveau 1	24,150	12,250	52,850	73,500
		Niveau 4 vs. Niveau 1	104,190	52,850	228,010	317,100
		Niveau 5 vs. Niveau 1	144,900	73,500	317,100	441,000
Fehler		Niveau 2 vs. Niveau 1	175,390	74,850	106,810	87,100
		Niveau 3 vs. Niveau 1	74,850	162,750	104,150	84,500
		Niveau 4 vs. Niveau 1	106,810	104,150	218,990	140,900
		Niveau 5 vs. Niveau 1	87,100	84,500	140,900	165,000

Basierend auf Typ III Quadratsumme

Matrix mit Quadratsummen und Kreuzprodukten zwischen den Subjekten

			MASS_1
Hypothese	Konstanter Term	MASS_1	707,560
Fehler		MASS_1	36,680

Basierend auf Typ III Quadratsumme

Appendix

		StÃ¶bern: Nutzer ist unentschlossen	Produktsuche: Nutzer hat ein Kaufziel im Kopf	eines ausgewÃ¤hlten Produkts	F10: Warenkorb / Check-Out	F10: Nach dem Kauf (z.B. per E-Mail)
Quadratsumme und Kreuzprodukte	F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	94,190	25,900	25,840	-7,720	-2,910
	F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	25,900	133,000	32,400	30,800	15,900
	F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	25,840	32,400	120,240	28,080	13,240
	F10: Warenkorb / Check-Out	-7,720	30,800	28,080	109,360	36,080
	F10: Nach dem Kauf (z.B. per E-Mail)	-2,910	15,900	13,240	36,080	64,990
Kovarianz	F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	,951	,262	,261	-,078	-,029
	F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	,262	1,343	,327	,311	,161
	F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	,261	,327	1,215	,284	,134
	F10: Warenkorb / Check-Out	-,078	,311	,284	1,105	,364
	F10: Nach dem Kauf (z.B. per E-Mail)	-,029	,161	,134	,364	,656
Korrelation	F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	1,000	,231	,243	-,076	-,037
	F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	,231	1,000	,256	,255	,171
	F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	,243	,256	1,000	,245	,150
	F10: Warenkorb / Check-Out	-,076	,255	,245	1,000	,428
	F10: Nach dem Kauf (z.B. per E-Mail)	-,037	,171	,150	,428	1,000

Basierend auf Typ III Quadratsumme

Multivariate Tests

Abhängige Variablen		Wert	F	Hypothese df	Fehler df	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[b]
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	97,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	5,000	94,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	97,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	4,000	95,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	97,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	4,000	95,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	97,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	4,000	95,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	97,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	4,000	95,000	1,000	,000	,000	,050

F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	97,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	4,000	95,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Warenkorb / Check-Out	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050

F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts, F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	3,000	96,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen, F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	2,000	97,000	1,000	,000	,000	,050
F10: Warenkorb / Check-Out, F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	98,500	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	2,000	97,000	1,000	,000	,000	,050
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	99,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	1,000	98,000	1,000	,000	,000	,050
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	99,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	1,000	98,000	1,000	,000	,000	,050
F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	99,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	1,000	98,000	1,000	,000	,000	,050
F10: Warenkorb / Check-Out	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	99,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	1,000	98,000	1,000	,000	,000	,050
F10: Nach dem Kauf (z.B. per E-Mail)	Pillai-Spur	,000	.	,000	,000	.	.	.	.
	Wilks-Lambda	1,000	.	,000	99,000	.	.	.	.
	Hotelling-Spur	,000	.	,000	2,000	.	.	.	.
	Größte charakteristische Wurzel nach Roy	,000	,000[a]	1,000	98,000	1,000	,000	,000	,050

a. Exakte Statistik

b. Unter Verwendung von Alpha = ,05 berechnet

Tests auf Univariate

Abhängige Variable	Quelle	Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	unzureichende Anpassung	,000	0	.	.	.	,000	,000	.
	Reiner Fehler	94,190	99	,951					
F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	unzureichende Anpassung	,000	0	.	.	.	,000	,000	.
	Reiner Fehler	133,000	99	1,343					
F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	unzureichende Anpassung	,000	0	.	.	.	,000	,000	.
	Reiner Fehler	120,240	99	1,215					
F10: Warenkorb / Check-Out	unzureichende Anpassung	,000	0	.	.	.	,000	,000	.
	Reiner Fehler	109,360	99	1,105					
F10: Nach dem Kauf (z.B. per E-Mail)	unzureichende Anpassung	,000	0	.	.	.	,000	,000	.
	Reiner Fehler	64,990	99	,656					

a. Unter Verwendung von Alpha = ,05 berechnet

SSCP-Matrix

		F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	F10: Warenkorb / Check-Out	F10: Nach dem Kauf (z.B. per E-Mail)
unzureichende Anpassung	F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	,000	,000	,000	,000	,000
	F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	,000	,000	,000	,000	,000
	F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	,000	,000	,000	,000	,000
	F10: Warenkorb / Check-Out	,000	,000	,000	,000	,000
	F10: Nach dem Kauf (z.B. per E-Mail)	,000	,000	,000	,000	,000
Reiner Fehler	F10: Inspiration / StÃ¶bern: Nutzer ist unentschlossen	94,190	25,900	25,840	-7,720	-2,910
	F10: Produktsuche: Nutzer hat ein Kaufziel im Kopf	25,900	133,000	32,400	30,800	15,900
	F10: Produktdetailseite: Seite eines ausgewÃ¤hlten Produkts	25,840	32,400	120,240	28,080	13,240
	F10: Warenkorb / Check-Out	-7,720	30,800	28,080	109,360	36,080
	F10: Nach dem Kauf (z.B. per E-Mail)	-2,910	15,900	13,240	36,080	64,990

H3 (Regression Analysis):

Regression

Aufgenommene/Entfernte Variablen[a]

Modell	Aufgenommene Variablen	Entfernte Variablen	Methode
1	F17: Bei dringendem Bedarf ignoriere ich Empfehlungen., F13: TÃ¤glicher Bedarf: Lebensmittel, Hygieneartikel etc.[b]	.	Einschluß

a. Abhängige Variable: F12

b. Alle gewünschten Variablen wurden eingegeben.

Modellzusammenfassung

Modell	R	R-Quadrat	Korrigiertes R-Quadrat	Standardfehler des Schätzers
1	,281[a]	,079	,061	,672

a. Einflußvariablen : (Konstante), F17: Bei dringendem Bedarf ignoriere ich Empfehlungen., F13: TÃ¤glicher Bedarf: Lebensmittel, Hygieneartikel etc.

H4 (RM-ANOVA):

Deskriptive Statistiken

	Mittelwert	Standardabweichung	N
F11: TÃ¤glicher Bedarf: Lebensmittel, Hygieneartikel etc.	2,08	1,016	105
F11: Haushalt & Wohnen: Einrichtung, Garten etc.	3,48	1,010	105
F11: Mode: Kleidung, Schmuck etc.	3,85	,998	105
F11: Freizeit & Medien: BÃ¼cher, Sportartikel etc.	3,51	1,093	105
F11: Technik: ElektrogerÃ¤te etc.	2,95	1,212	105

Multivariate Tests[a]

Effekt		Wert	F	Hypothese df	Fehler df	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[c]
Produktgruppe	Pillai-Spur	,659	48,765[b]	4,000	101,000	<,001	,659	195,060	1,000
	Wilks-Lambda	,341	48,765[b]	4,000	101,000	<,001	,659	195,060	1,000
	Hotelling-Spur	1,931	48,765[b]	4,000	101,000	<,001	,659	195,060	1,000
	Größte charakteristische Wurzel nach Roy	1,931	48,765[b]	4,000	101,000	<,001	,659	195,060	1,000

a. Design: Konstanter Term
Innersubjektdesign: Produktgruppe

b. Exakte Statistik

c. Unter Verwendung von Alpha = ,05 berechnet

Appendix

t-Test

[DataSet1] D:\Denise Laptop\02.08.2025\Masterarbeit\SPSS Dateien\Datensatz Online-Experiment.sav

Gruppenstatistiken

	0=FMCG, 1=SMCG	N	Mittelwert	Std.-Abweichung	Standardfehler des Mittelwertes
helpfulnesrec_Warenkorb	,00	8	4,0000	1,19523	,42258
	1,00	6	2,8333	,75277	,30732

Test bei unabhängigen Stichproben

		Levene-Test der Varianzgleichheit		t-Test für die Mittelwertgleichheit							
						Signifikanz				95% Konfidenzintervall der Differenz	
		F	Sig.	T	df	Einseitiges p	Zweiseitiges p	Mittlere Differenz	Differenz für Standardfehler	Unterer Wert	Oberer Wert
helpfulnesrec_Warenkorb	Varianzen sind gleich	2,726	,125	2,089	12	,029	,059	1,16667	,55850	-,05020	2,38353
	Varianzen sind nicht gleich			2,233	11,758	,023	,046	1,16667	,52251	,02561	2,30772

Effektgrößen bei unabhängigen Stichproben

		Standardisierer[a]	Punktschätzung	95% Konfidenzintervall	
				Unterer Wert	Oberer Wert
helpfulnesrec_Warenkorb	Cohen's d	1,03414	1,128	-,040	2,257
	Hedges' Korrektur	1,10492	1,056	-,038	2,113
	Glass' Delta	,75277	1,550	,099	2,921

a. Der bei der Schätzung der Effektgrößen verwendete Nenner.
Für 'Cohen d' wird die zusammengefasste Standardabweichung verwendet.
Für die Hedges-Korrektur wird die zusammengefasste Standardabweichung mit einem Korrekturfaktor verwendet.
Für das Glass-Delta wird die Standardabweichung der Stichprobe der Kontrollgruppe (d. h. der zweiten Gruppe) verwendet.

Parameterschätzungen

Abhängige Variable	Parameter	RegressionskoeffizientB	Std.-Fehler	T	Sig.	95% Konfidenzintervall Untergrenze	95% Konfidenzintervall Obergrenze	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
F11: TÃ¤glicher Bedarf: Lebensmittel, Hygieneartikel etc.	Konstanter Term	2,076	,099	20,936	<,001	1,880	2,273	,808	20,936	1,000
F11: Haushalt & Wohnen: Einrichtung, Garten etc.	Konstanter Term	3,476	,099	35,251	<,001	3,281	3,672	,923	35,251	1,000
F11: Mode: Kleidung, Schmuck etc.	Konstanter Term	3,848	,097	39,510	<,001	3,655	4,041	,938	39,510	1,000
F11: Freizeit & Medien: BÃ¼cher, Sportartikel etc.	Konstanter Term	3,514	,107	32,949	<,001	3,303	3,726	,913	32,949	1,000
F11: Technik: ElektrogerÃ¤te etc.	Konstanter Term	2,952	,118	24,962	<,001	2,718	3,187	,857	24,962	1,000

a. Unter Verwendung von Alpha = ,05 berechnet

Mauchly-Test auf Sphärizität[a]

Maß: MASS_1

Innersubjekteffekt	Mauchly-W	Ungefähres Chi-Quadrat	df	Sig.	Epsilon[b] Greenhouse-Geisser	Epsilon[b] Huynh-Feldt (HF)	Epsilon[b] Untergrenze
Produktgruppe	,725	33,001	9	<,001	,883	,918	,250

Prüft die Nullhypothese, dass sich die Fehlerkovarianz-Matrix der orthonormalisierten transformierten abhängigen Variablen proportional zur Einheitsmatrix verhält.

a. Design: Konstanter Term
Innersubjektdesign: Produktgruppe

b. Kann zum Korrigieren der Freiheitsgrade für die gemittelten Signifikanztests verwendet werden. In der Tabelle mit den Tests der Effekte innerhalb der Subjekte werden korrigierte Tests angezeigt.

Tests der Innersubjekteffekte

Maß: MASS_1

Quelle		Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
Produktgruppe	Sphärizität angenommen	201,093	4	50,273	59,531	<,001	,364	238,125	1,000
	Greenhouse-Geisser	201,093	3,532	56,934	59,531	<,001	,364	210,268	1,000
	Huynh-Feldt (HF)	201,093	3,671	54,772	59,531	<,001	,364	218,568	1,000
	Untergrenze	201,093	1,000	201,093	59,531	<,001	,364	59,531	1,000
Fehler(Produktgruppe)	Sphärizität angenommen	351,307	416	,844					
	Greenhouse-Geisser	351,307	367,334	,956					
	Huynh-Feldt (HF)	351,307	381,834	,920					
	Untergrenze	351,307	104,000	3,378					

a. Unter Verwendung von Alpha = ,05 berechnet

Tests der Innersubjektkontraste

Maß: MASS_1

Quelle	Produktgruppe	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
Produktgruppe	Linear	33,661	1	33,661	28,662	<,001	,216	28,662	1,000
	Quadratisch	160,678	1	160,678	150,689	<,001	,592	150,689	1,000
	Kubisch	6,720	1	6,720	9,259	,003	,082	9,259	,854
	Ordnung 4	,035	1	,035	,085	,772	,001	,085	,060
Fehler(Produktgruppe)	Linear	122,139	104	1,174					
	Quadratisch	110,894	104	1,066					
	Kubisch	75,480	104	,726					
	Ordnung 4	42,794	104	,411					

a. Unter Verwendung von Alpha = ,05 berechnet

Tests der Zwischensubjekteffekte

Maß: MASS_1
Transformierte Variable: Mittel

Quelle	Typ III Quadratsumme	df	Mittel der Quadrate	F	Sig.	Partielles Eta-Quadrat	Dezentr. Parameter	Beobachtete Trennschärfe[a]
Konstanter Term	5286,773	1	5286,773	2264,267	<,001	,956	2264,267	1,000
Fehler	242,827	104	2,335					

a. Unter Verwendung von Alpha = ,05 berechnet

H5 (Regression Analysis):

Regression

Warnungen

Bei Modellen mit der abhängigen Variablen Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl? sind die folgenden Variablen Konstanten oder weisen fehlende Korrelationen auf: 0=ohne, 1=mit. Sie werden aus der Analyse gelöscht.

Deskriptive Statistiken

	Mittelwert	Std.-Abweichung	N
Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?	2,21	,975	14
Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	1,86	,535	14
0=FMCG, 1=SMCG	,4286	,51355	14
0=ohne, 1=mit	1,0000	,00000	14

Korrelationen

		Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?	Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	0=FMCG, 1=SMCG	0=ohne, 1=mit
Korrelation nach Pearson	Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?	1,000	,211	,110	.
	Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	,211	1,000	,520	.
	0=FMCG, 1=SMCG	,110	,520	1,000	.
	0=ohne, 1=mit	.	.	.	1,000
Sig. (1-seitig)	Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?	.	,235	,354	<,001
	Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	,235	.	,028	,000
	0=FMCG, 1=SMCG	,354	,028	.	,000
	0=ohne, 1=mit	,000	,000	,000	.
N	Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?	14	14	14	14
	Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	14	14	14	14
	0=FMCG, 1=SMCG	14	14	14	14
	0=ohne, 1=mit	14	14	14	14

Aufgenommene/Entfernte Variablen[a]

Modell	Aufgenommene Variablen	Entfernte Variablen	Methode
1	0=FMCG, 1=SMCG, Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?[b]	.	Einschluß

a. Abhängige Variable: Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?

b. Alle gewünschten Variablen wurden eingegeben.

Modellzusammenfassung

Modell	R	R-Quadrat	Korrigiertes R-Quadrat	Standardfehler des Schätzers
1	,211[a]	,044	-,129	1,036

a. Einflußvariablen : (Konstante), 0=FMCG, 1=SMCG, Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?

ANOVA[a]

Modell		Quadratsumme	df	Mittel der Quadrate	F	Sig.
1	Regression	,549	2	,275	,256	,779[b]
	Nicht standardisierte Residuen	11,808	11	1,073		
	Gesamt	12,357	13			

a. Abhängige Variable: Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?

Koeffizienten[a]

Modell		Nicht standardisierte Koeffizienten: Regressionskoeffizient B	Std.-Fehler	Standardisierte Koeffizienten: Beta	T	Sig.	95,0% Konfidenzintervalle für B: Untergrenze	Obergrenze	Korrelationen: Nullter Ordnung	Partiell	Teil
1	(Konstante)	1,500	1,087		1,380	,195	-,892	3,892			
	Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	,385	,630	,211	,611	,554	-1,001	1,770	,211	,181	,180
	0=FMCG, 1=SMCG	-1,581E-16	,655	,000	,000	1,000	-1,442	1,442	,110	,000	,000

a. Abhängige Variable: Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?

Korrelation der Koeffizienten[a]

Modell			0=FMCG, 1=SMCG	Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?
1	Korrelationen	0=FMCG, 1=SMCG	1,000	-,520
		Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	-,520	1,000
	Kovarianzen	0=FMCG, 1=SMCG	,429	-,215
		Vertrauen Sie solchen Empfehlungssystemen beim Online-Einkauf?	-,215	,396

a. Abhängige Variable: Wie hilfreich empfanden Sie die dargestellten Empfehlungen bei Ihrer Produktauswahl?

H6 (Correlation Matrix):

Korrelationen

		F8: MarktplÃ¤tze (z.B. Amazon)	F8: Spezialisierte Online-Shops (z.B. Douglas)	F8: Social Media / Influencer	F8: Newsletter	F15
F8: MarktplÃ¤tze (z.B. Amazon)	Pearson-Korrelation	1	,355**	,235*	,274**	,269**
	Sig. (2-seitig)		<,001	,017	,005	,005
	N	106	99	103	102	106
F8: Spezialisierte Online-Shops (z.B. Douglas)	Pearson-Korrelation	,355**	1	,119	,274**	,240*
	Sig. (2-seitig)	<,001		,243	,007	,017
	N	99	99	98	97	99
F8: Social Media / Influencer	Pearson-Korrelation	,235*	,119	1	,347**	,099
	Sig. (2-seitig)	,017	,243		<,001	,319
	N	103	98	103	101	103
F8: Newsletter	Pearson-Korrelation	,274**	,274**	,347**	1	,167
	Sig. (2-seitig)	,005	,007	<,001		,094
	N	102	97	101	102	102
F15	Pearson-Korrelation	,269**	,240*	,099	,167	1
	Sig. (2-seitig)	,005	,017	,319	,094	
	N	106	99	103	102	106

**. Die Korrelation ist auf dem Niveau von 0,01 (2-seitig) signifikant.

*. Die Korrelation ist auf dem Niveau von 0,05 (2-seitig) signifikant.