

# AI-Generated Review Summaries on E-Commerce Platforms: Drivers of Consumers' Usage Intentions

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## Keywords

E-Commerce Platforms, Artificial Intelligence, AI-generated Summaries, Online Consumer Reviews, Trust Dimensions

## Abstract

E-Commerce platforms increasingly rely on consumer reviews to support decision-making and enhance the overall shopping experience. Yet, the abundance and heterogeneity of reviews often hinder consumers from extracting relevant information. AI-generated summaries can help by structuring and presenting key review content more accessibly. This study examines factors influencing consumers' intentions to use such AI-powered tools. Drawing on survey data and structural equation modelling, results show that perceived utilitarian value, ease of use, trust in AI, and trust in other reviewers significantly shape consumers' intentions to use AI-generated review summaries. These findings contribute to research by identifying key factors that drive consumers' intentions to use AI-powered tools and by highlighting their potential to foster informed decision-making in e-commerce. They further offer guidance for platform providers and AI developers on how to design user-centered, trustworthy AI-powered tools that encourage adoption and improve the overall shopping experience.

## 1. Introduction

E-commerce platforms such as Amazon or eBay have transformed online shopping by offering vast product selections, yet the abundance of options can be overwhelming. Consumers therefore rely on online consumer reviews (OCR) as informational resources that reduce cognitive effort and simplify decision-making (Chen et al. 2022; Chevalier and Mayzlin 2006). However, the sheer volume and inconsistent quality of OCR makes it difficult to extract valuable insights from reviews, leading to cognitive overload, which ultimately reduces decision efficiency and the overall shopping experience (Hu and Krishen 2019; Mudambi and Schuff 2010; Park and Lee 2008). These challenges underscore the need for tools that can help consumers aggregate, condense, and process review information efficiently.

Artificial intelligence (AI) provides such support. Through personalization and content generation based on user behavior and preferences, AI tools enhance consumers' decision-making efficiency and satisfaction (Davenport et al. 2020; Vaid et al. 2023). Generative AI models, such as the Generative Pre-trained Transformer (GPT), further expand these capabilities by helping consumers navigate complex decisions (Hollebeek et al. 2024). Major e-commerce platforms such as Amazon (Schermerhorn 2023) and Target (Target 2024), as well as review service providers such as Yelp (Saldanha 2024), now offer automated summaries that aggregate large numbers of consumer reviews. These tools aim to condense dispersed OCR information and make it more accessible during online shopping. However, existing implementations typically provide standardized summaries with limited flexibility for individual information needs (Trowbridge 2024).

Against this background, the use of AI to summarize OCR raises concerns regarding consumer acceptance, trust, and perceived utility (Choung et al. 2023; Kelly et al. 2023). Issues related to personalization, privacy, and the impersonal nature of algorithmic interactions (Davenport et al. 2020; Longoni and Cian

2020) create adoption barriers for AI-generated review summaries. Whereas consumers previously relied on human-generated reviews, they must now decide whether to trust algorithm-generated content, making an understanding of acceptance factors and trust particularly important.

While prior research has examined the role of consumer reviews in e-commerce (Chen et al. 2022; Mudambi and Schuff 2010) and the integration of AI into marketing activities (Davenport et al. 2020), limited insights have been provided regarding how generative AI can be effectively integrated to support consumers shopping online. Accordingly, the impact of AI-generated review summaries on consumer behavior and factors driving usage intentions remains underexplored. Moreover, prior research has often treated trust as a unidimensional construct (e.g., Singh et al. 2024), yet recent literature emphasizes its multidimensional nature (Foehr and Germelmann 2020; Yang and Wibowo 2022). Moreover, trust in AI-generated information differs from trust in human reviewers or platforms: while AI may be accepted for creative or low-stakes tasks, trusting AI to accurately summarize others' opinions has direct implications for purchase decisions (Jia et al. 2025; Klingbeil et al. 2024). This distinction becomes particularly relevant given the prevalence of fake reviews and declining interpersonal trust in online environments. Accordingly, the interplay between trust in the AI system, trust in the platform provider, and trust in other consumers remains insufficiently understood.

To address these gaps, this study focuses on AI-generated review summaries embedded directly into e-commerce platforms and the shopping interface. Unlike most existing solutions, the AI tool examined here allows consumers to specify product attributes that guide the summarization process. This study seeks to understand which factors influence consumers' intentions to use AI-generated review summaries. Accordingly, we address the following research questions: *RQ1: What factors influence consumers' intentions to use AI-generated review summaries on e-commerce*

*platforms? RQ2: How do different dimensions of trust—specifically trust in AI, trust in provider, trust in others—jointly shape consumers’ usage intentions of AI-generated review summaries?*

This study makes several contributions. First, it provides initial insights into consumers’ perceptions of AI-generated review summaries as a novel way of aggregating OCR in e-commerce, focussing explicitly on usage intentions rather than downstream outcomes. Second, it advances trust research by conceptualizing trust as a multidimensional construct, distinguishing between trust in AI, trust in the platform provider, and trust in other reviewers. This approach provides a deeper understanding of how different forms of trust play distinct—and in some cases opposing—roles in shaping consumers’ intentions to use AI-generated review summaries. Third, this study offers actionable recommendations for platform managers on how to design and implement trustworthy, user-centered AI tools that support adoption in e-commerce contexts.

## 2. Theoretical Background

### 2.1. Consumer Reviews and Decision-Making in E-Commerce

OCR, as a form of electronic word of mouth (eWOM), play a crucial role in e-commerce by enabling consumers to share and access product experiences across geographical and temporal boundaries (Chen and Xie 2008; Chevalier and Mayzlin 2006). By minimizing search costs and serving as a trusted information source, OCR significantly influence consumers’ decision-making (Hennig-Thurau et al. 2004; Mudambi and Schuff 2010). E-commerce platforms increasingly leverage OCR to enhance credibility, as consumers perceive OCR as more reliable than traditional advertising (Chen and Xie 2008; Mudambi and Schuff 2010; Picazo-Vela et al. 2010). As such, OCR have become a key mechanism through which consumers

reduce uncertainty associated with decision-making, build trust, and evaluate products during online shopping (Hennig-Thurau et al. 2004; Mudambi and Schuff 2010).

At the same time, the rapid growth of e-commerce has led to an unprecedented volume of review information. Popular products often accumulate thousands of reviews, which can overwhelm consumers rather than support their decisions (Park and Lee 2008). Prior research documents this ambivalence: while OCR can increase perceived informativeness and decision confidence (e.g., Chevalier and Mayzlin 2006; Mudambi and Schuff 2010), they can also generate information overload, inconsistent quality signals, biased opinions, or strategic manipulation, ultimately impairing decision efficiency and the overall shopping experience (e.g., Hu and Krishen 2019; Mudambi and Schuff 2010). These challenges highlight that more information does not necessarily translate into better decisions.

To cope with large volumes of review content, consumers rely on cues that signal review credibility and usefulness, such as balanced arguments, concrete product-related information, and consistency across reviews (e.g., Jensen et al. 2013; Moran and Muzellec 2014). In contrast, extreme emotions, contradictory evaluations, or excessive amounts of information can reduce perceived credibility and usefulness (e.g., Cheung et al. 2009; Furner and Zinko 2016; Kim and Gupta 2012). Evaluating and integrating these cues, however, requires cognitive effort and may impair decision-efficiency in review-rich settings.

In parallel, e-commerce platforms implement mechanisms to increase review quantity and quality, such as helpfulness votes, expert reviews, or ranking systems (Mathwick and Mosteller 2017; Mishra et al. 2022). While these measures can support review generation and selection, they do not fully resolve the underlying challenge of information overload. Against this background, AI-generated review summaries have gained increasing attention as a means of aggregating and condensing review information, thereby supporting more efficient navigation of OCR during online shopping.

## 2.2. Integration of AI-Powered Tools into E-Commerce Platforms

To address information overload on e-commerce platforms, AI-powered tools are increasingly used to support consumers in processing large amounts of content and streamline decision-making through personalized recommendations, enhanced search, and real-time support (Hollebeek et al. 2024; Longoni and Cian 2020). Among these tools, AI-generated review summaries provide a promising solution to filter, organize, and present relevant review content efficiently. By aggregating OCR and highlighting frequently mentioned product features or sentiments, such summaries seek to reduce information overload and facilitate information processing during online shopping.

AI-generated review summaries have recently been implemented in various forms in online retailing, differing substantially in design and granularity. Many currently available AI tools, such as for Amazon, Yelp, or Target, generate general summaries that aggregate all available reviews, often accompanied by a list of frequently mentioned aspects (Saldanha 2024; Schermerhorn 2023; Target 2024). Other designs provide simple pro-and-con lists to provide quick overviews of positive and negative evaluations (e.g., Newegg; Wein 2023). In some cases, summaries are restricted to selected subsets of reviews, such as verified purchases (Trowbridge 2024), or fail to distinguish between product- and platform-related features (Peterson 2023), which may exclude relevant user experiences. Review aggregation is also offered via browser-based tools (e.g., Google Chrome; Diaz 2025) or third-party providers (e.g., Bazaarvoice or Reviewcap). While these approaches reduce information overload at an aggregate level, they typically provide standardized outputs and offer limited room for consumers to actively shape the summarized information.

Against this background, this study conceptualizes AI-generated review summaries as platform-integrated tools that aggregate OCR and generate concise summaries during on-

line shopping. Extending existing approaches, the focus lies on summaries that allow consumers to specify which product attributes or dimensions should be emphasized. Rather than replacing existing review systems, such summaries are designed to complement them by enabling a more attribute-specific and user-configurable form of information reduction.

Existing research on AI-generated review summaries has primarily examined their technical characteristics, behavioral effects, and user perceptions (for an overview, see Jia et al. 2026). Prior studies comparing AI-generated and human-generated summaries highlight differences in trust, credibility, and information processing and show that AI-generated summaries can reduce information overload and support more efficient decision-making (Cheng et al. 2025; Su et al., 2024; Jia et al. 2026). Other work documents behavioral consequences of AI-generated summaries, including changes in review volume, engagement, rating distributions, and subsequent review content (Su et al., 2024; Kim et al., 2024). For instance, exposure to AI-generated summaries has been shown to increase user engagement and interaction while shaping the content of subsequently written reviews (Koo et al., 2025).

At the same time, prior findings point to ambivalent consumer responses. While AI-generated summaries provide standardized and seemingly objective review aggregations, consumers may question their authenticity, transparency, and fairness compared to human-generated content (Su et al., 2024; Wang et al., 2025). Research further indicates that perceptions of credibility and helpfulness depend on system affordances such as transparency, understandability, and convenience (Jia et al., 2026), and that consumers often rely on AI-generated summaries alongside, rather than instead of, original reviews (Su et al., 2024).

Despite these advances, existing research offers limited insight into consumers' intentions to use AI-generated review summaries that are fully integrated into e-commerce interfaces. Moreover, trust has predominantly been examined as a general perception, while distinct sources of trust have rarely been considered

jointly. Addressing these gaps, the present study focuses on consumers' intentions to use platform-integrated, attribute-configurable AI-generated review summaries and examines key drivers underlying their adoption in e-commerce.

### 3. Conceptual Framework and Hypotheses Development

#### 3.1. Main Effects on Usage Intention

To examine the factors that drive consumer intentions to use AI-generated review summaries, we build on the Technology Acceptance Model (TAM; Davis 1989), which has been widely extended but consistently emphasizes perceived ease of use and perceived usefulness as key adoption drivers. Therefore, we used it as the basic framework for our research model. However, instead of perceived usefulness, we decided for a more context-fitting construct, utilitarian value, and incorporated additional constructs, namely pleasure and trust (see *Figure 1*).

##### Utilitarian Value

In the original TAM, Davis (1989) identified perceived usefulness as central to technology adoption and emphasized its role in fostering a positive relationship between system use and improved outcomes. However, in consumer decision environments such as AI-generated review summaries, the usefulness of a technology is less about enhancing performance and more about facilitating decision-making and providing valuable information. Accordingly, utilitarian value, as the extent to which a technology is believed to enhance task performance or efficiency, better captures the functional, task-oriented benefits consumers perceive when using the technology (e.g., decision facilitation, efficiency, informativeness). It thus captures the instrumental aspects of the

user experience more appropriately than the traditional notion of perceived usefulness.

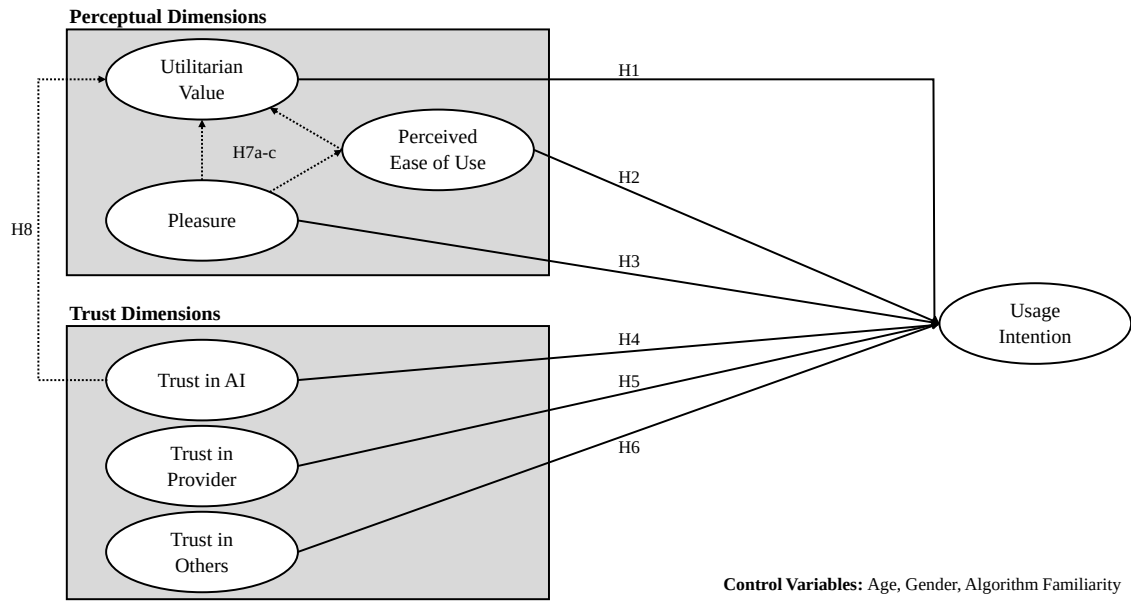
Research shows that consumers are more likely to adopt technologies that offer clear functional benefits (Hollebeek et al. 2024; Venkatesh et al. 2003). In e-commerce, the significance of utilitarian value is amplified by the vast amount of information consumers must navigate. Technologies that reduce effort and streamline decision-making are highly valued (Hollebeek et al. 2024; Longoni and Cian 2020). AI-generated review summaries embody these advantages by enhancing efficiency and simplifying product comparisons. Thus, we propose:

*H1: Utilitarian value positively influences consumer usage intentions for AI-generated review summaries.*

##### Perceived Ease of Use

Perceived ease of use refers to the extent to which consumers perceive a technology as simple and straightforward to use (Davis 1989). Numerous studies highlight its critical role in shaping consumer attitudes and adoption intentions across various contexts (Childers et al. 2001; Hollebeek et al. 2024; Venkatesh et al. 2003). For AI-generated review summaries, perceived ease of use is particularly important because consumers favor technologies that integrate seamlessly into their shopping experiences. Tools with intuitive, user-friendly interfaces that allow for easy navigation are accessible to a broader audience. Since online shoppers rely heavily on reviews for purchase decisions (Chen and Xie 2008; Chevalier and Mayzlin 2006), AI-generated review summaries should provide effortless functionality to encourage adoption. Complex or unintuitive interfaces may deter consumers, while accessible tools are more likely to foster regular use (Childers et al. 2001). Thus, perceived ease of use is essential to ensure that AI-generated review summaries simplify rather than hinder the shopping process. We therefore hypothesize:

*H2: Perceived ease of use positively influences consumer usage intentions for AI-generated review summaries.*



**Fig. 1** Conceptual research framework. Solid arrows indicate main effects on usage intention. Dotted arrows represent theory-consistent interrelationships among antecedent constructs. (Source: Own illustration)

erated review summaries.

## Pleasure

Beyond utilitarian benefits, hedonic factors play a crucial role in influencing technology adoption. Pleasure, often referred to as perceived enjoyment, describes the intrinsic satisfaction derived from technology use and significantly impacts adoption across various contexts (Venkatesh et al. 2003). This is especially true for AI-powered tools, where enjoyable and engaging experiences enhance user engagement and usage intention (Childers et al. 2001; Longoni and Cian 2020). In e-commerce, consumers may be motivated to use AI-generated review summaries, since pleasure can stem from the novel and exciting interactions with technologies (Childers et al. 2001; Longoni and Cian 2020). Empirical studies confirm that technologies perceived as enjoyable are more likely to be adopted (Davis 1989; Hollebeek et al. 2024). Based on these findings, we hypothesize:

*H3: Pleasure positively influences consumer usage intentions for AI-generated review summaries.*

## Trust

Trust reflects consumers' beliefs in an entity's integrity, benevolence, and competence to protect their interests (Mayer et al. 1995). It arises in a dyadic scenario where the consumer relies on another entity to create an outcome that may be beneficial but is associated with uncertainty and risk (Castelfranchi and Falcone 2010; Foehr and Germelmann 2020; Shi et al. 2021). In e-commerce, the varying extent and quality of OCR heighten uncertainty, making it difficult for consumers to assess credibility. As a result, trust becomes essential for navigating such complexities.

Prior research has identified trust as a key determinant of consumers' perceptions and the inherent goodwill of AI (e.g., Singh et al. 2024) and/or its technical competence (e.g., Shin 2021). More recent studies, however, argue that trust is more complex, often involving multiple dimensions and reference points (Foehr and Germelmann 2020; Yang and Wibowo 2022). These studies emphasize the need to account for the specific characteristics of trust by exploring different trust dimensions and components—thus, considering trust not only in terms of technical competence, but also in

terms of ethical considerations, data security, social interactions, or the credibility of the data source. In response to these calls, we argue that on e-commerce platforms, multiple reference points for trust exist and therefore differentiate between trust in AI, trust in provider, and trust in others.

Trust in AI refers to the consumer's belief that the AI will perform as intended without error. When using such AI-tools, consumers must trust that the algorithms will process all relevant reviews and not omit important feedback, such as negative ratings. Prior research has identified trust in AI as a key factor driving usage intentions (e.g., Kaplan et al. 2021; Singh et al. 2024). Accordingly, we hypothesize:

*H4: Trust in AI positively influences consumer usage intentions for AI-generated review summaries.*

Trust in provider refers to the degree to which consumers believe that the e-commerce platform provider has implemented the AI-powered tool with good intentions and without a hidden agenda. Importantly, the provider must not have developed the AI tool itself, as this would conflate different trust reference points. While trust in AI and trust in provider can be closely related, prior research has demonstrated that they are conceptually distinct dimensions of trust that act independently of each other (Kuen et al. 2023). Moreover, studies on smart home services or mobile payments have emphasized the role of trust in provider regarding usage intentions (e.g., Slade et al. 2014; Yang et al. 2017). Thus, we hypothesize:

*H5: Trust in provider positively influences consumer usage intentions for AI-generated review summaries.*

Trust in others refers to the degree to which consumers perceive other reviewers on e-commerce platforms as trustworthy. This includes reviewing products they have actually used, sharing genuine experiences, and avoiding the spread of misinformation, all of which are essential for the AI-powered tool to generate reliable summaries. Prior research shows that trust in other consumers facilitates reliance

on consumer-generated information and promotes the adoption of technologies that depend on third-party data, such as sharing-based platforms, digital contact tracing apps, and online health communities (Cha and Lee 2022; Heimann et al. 2023; Zhou 2019). However, in the context of AI-generated review summaries, competing mechanisms are conceivable. While higher trust in other reviewers may reduce perceived need for algorithmic aggregation, lower trust may increase reliance on AI-based summaries as a compensatory information source. Acknowledging this potential tension, we formulate the following hypothesis based on the predominant trust—adoption logic:

*H6: Trust in others positively influences consumer usage intentions for AI-generated review summaries.*

### 3.2. Relationships Among Key Drivers of Usage Intention

While the primary objective of this study is to identify key antecedents of consumers' intentions to use AI-generated review summaries, the conceptual model also incorporates theory-consistent interrelationships among these antecedents as suggested by prior technology adoption research (e.g., Wang et al. 2023). These relationships are included to reflect established mechanisms in the literature and to provide a coherent structure of the model.

Consistent with prior TAM research, perceived ease of use has been shown to shape users' evaluations of a technology's functional value (Alalwan et al. 2017; Wu et al. 2011). Technologies that are experienced as intuitive and effortless are more likely to be perceived as useful and efficient. In addition, research on hedonic motivation indicates that pleasure shapes users' evaluations of technologies, including perceptions of usefulness and ease of use (Agarwal and Karahanna 2000; Koenig-Lewis et al. 2015). Enjoyable interactions can make technologies appear less effortful and more beneficial, as positive affect is often incorporated into performance-related judgments

(Babin and Attaway 2000; Schwarz and Clore 2003). In line with these established findings, we account for the following relationships in our model:

*H7a: Perceived ease of use positively influences utilitarian value.*

*H7b: Pleasure positively influences utilitarian value.*

*H7c: Pleasure positively influences perceived ease of use.*

Prior research on technology adoption highlights trust as a key determinant of users' evaluations of technologies, particularly regarding perceived usefulness and functional value (Gefen et al. 2003; Wu et al. 2011). Trust in technological systems reduces uncertainty and increases the likelihood that system outputs are perceived as reliable, efficient, and valuable (Alagarsamy and Mehroliia 2023; Pavlou 2003). In the context of AI-generated review summaries, trust in AI reflects consumers' confidence in the accurate aggregation of review information, which may lead to more favorable evaluations of their functional benefits, as consumers are more likely to regard AI-generated outputs as reliable and efficient. Accordingly, we account for the following relationship in our model:

*H8: Trust in AI positively influences utilitarian value.*

## 4. Methodology

### 4.1. Study Design and Participants

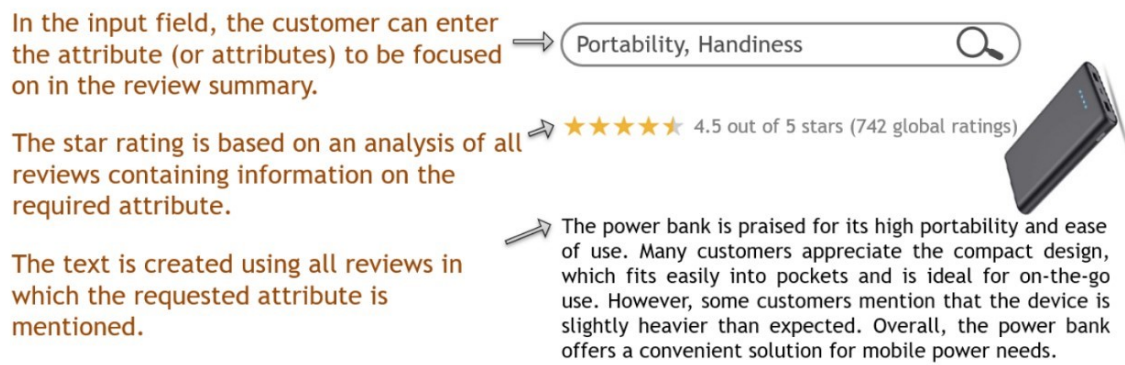
We employed a cross-sectional online survey to examine factors influencing consumers' intentions to use AI-generated review summaries on an e-commerce platform. Participants were recruited via the online panel provider Prolific. The survey was conducted from July 11 to July 12, 2024 in Great Britain and resulted in a final sample of 300 participants ( $M_{\text{age}} = 37.69$  years,  $SD_{\text{age}} = 12.63$  years, 56.7 % female).

To ensure comprehension, participants received a detailed explanation of AI-generated review summaries and their functionality. A comprehension check was included immediately after the description, asking participants to identify how the review summaries were generated (i.e., by an artificial intelligence, by consumers themselves, by service employees, or not generated at all). Only participants who correctly answered proceeded with the survey. Participants were then presented with a self-designed visual simulating a realistic example of an AI-generated review summary with brief descriptions (see *Figure 2*). The example served as a standardized reference to ensure a common understanding of the AI tool and was not intended to elicit recall of a specific prior shopping experience. It illustrated an attribute-specific, on-demand review summary, reflecting the user-configurable design of the AI tool conceptualized in this study. The visual was designed to closely resemble real-world e-commerce environments, using a realistic product example, text length, and layout. For the full descriptions and instructions, see *Appendix A*. Participants then evaluated their general intentions to use AI-generated review summaries and related constructs.

### 4.2. Measures

All constructs were measured using validated scales adapted for AI-generated review summaries. Participants rated their agreement on seven-point Likert scales (1 = “strongly disagree” to 7 = “strongly agree”). A pretest was conducted to assess the suitability and dimensionality of the measures prior to data collection<sup>1</sup>.

<sup>1</sup> As the present study adapts the Technology Acceptance Model (TAM) to the context of AI-generated review summaries, perceived usefulness was operationalized as the broader construct of utilitarian value reflecting both efficiency-related (e.g., time saving) and decision-related benefits (e.g., improved informedness). Moreover, pleasure was included as an additional perceptual driver. Because both constructs extend the orig-



**Fig. 2** Self-Designed Visual Example of an AI-Generated Review Summary (Source: Own illustration)

Behavioral intention to use AI-generated review summaries was measured as the dependent variable using established scales (Fishbein and Ajzen 2011; Picazo-Vela et al. 2010). The independent variables included utilitarian value (drawing on perceived usefulness and related functional value measures; e.g., Davis 1989), pleasure (drawing on established hedonic motivation scales; e.g., Childers et al. 2001), three trust dimensions (Chandra et al. 2010; Heimann et al. 2023), and perceived ease of use (Davis 1989). Familiarity with algorithms served as a control variable (Mahmud et al. 2024). Detailed descriptions and reliability statistics of all the measures are provided in Tab. 1.

### 4.3. Data Analysis and Results

To evaluate the measurement quality of our model, we ran a confirmatory factor analysis with a MLM estimator using Mplus 8.5 (Muthén and Muthén 2017). The overall fit met commonly accepted standards ( $\chi^2(469) =$

876.303,  $p < .001$ ; CFI = .951 TLI = .945; RMSEA = .054; SRMR = .044). We tested the robustness of all constructs (see Tab. 1). The measures for each construct exceeded the cut-off values for factor loadings, internal consistency (Cronbach's  $\alpha$ ), and composite reliability, confirming model reliability. Average variance extracted values exceeded recommended thresholds, confirming convergent validity (Hair et al. 2019). Lastly, the heterotrait-monotrait criterion (Henseler et al. 2015) was applied, confirming discriminant validity (see Appendix B). Additionally, we used Harman's single factor test (Craighead et al. 2011) to rule out common method bias.

To test our hypotheses, we analyzed the structural model using structural equation modeling (SEM) within Mplus 8.5. The model fit was adequate ( $\chi^2(473) = 932.689$ ,  $p < .001$ ; CFI = .946; TLI = .940; RMSEA = .057; SRMR = .064). Algorithm familiarity, age, and gender were included as covariates. For a summary of hypotheses testing, see Tab. 2, and for results of the structural model, including direct and indirect effects, see Appendix C. Consistent with the study's primary focus, we first examined the direct effects on consumers' intention to use AI-generated review summaries. Utilitarian value ( $\beta = .562$ ,  $p < .001$ ), perceived ease of use ( $\beta = .120$ ,  $p < .05$ ), and trust in AI ( $\beta = .336$ ,  $p < .05$ ) all showed significant positive effects on usage intention, supporting hypotheses H1, H2, and H4. Contradictory to our assumptions, trust in others had a significant negative effect on usage intention ( $\beta = -.134$ ,

inal TAM specification and because established, context-specific scales for AI-generated review summaries are still limited, a pretest was conducted. Initial item pools for utilitarian value and pleasure were compiled from multiple established sources in the literature and evaluated using exploratory and confirmatory factor analyses. This procedure ensured that the final item sets adequately captured the relevant facets of these constructs in the specific context of AI-generated review summaries.

**Tab. 1** Measurement Items, Factor Loadings, and Reliability Statistics for Constructs

| Constructs                                                                                                       | Factor loadings <sup>1</sup> | AVE  | $\alpha$ | CR   |
|------------------------------------------------------------------------------------------------------------------|------------------------------|------|----------|------|
| <i>Usage Intention</i> (adapted from Fishbein and Ajzen 2011 and Picazo-Vela et al. 2010)                        |                              | .858 | .960     | .960 |
| I intend to use AI-generated review summaries in the future.                                                     | .951                         |      |          |      |
| I expect to use AI-generated review summaries in the future.                                                     | .901                         |      |          |      |
| I plan to use AI-generated review summaries in the future.                                                       | .916                         |      |          |      |
| I am likely to use AI-generated review summaries in the future.                                                  | .936                         |      |          |      |
| <i>Utilitarian Value</i> (drawing on perceived usefulness and related functional value scales; e.g., Davis 1989) |                              | .763 | .948     | .950 |
| Using AI-generated review summaries allows me to save time.                                                      | .817                         |      |          |      |
| Using AI-generated review summaries saves me effort in comparing products.                                       | .794                         |      |          |      |
| AI-generated review summaries help me to make informed decisions.                                                | .861                         |      |          |      |
| I find AI-generated review summaries to be a useful tool for online shopping.                                    | .917                         |      |          |      |
| Using AI-generated review summaries is convenient to me.                                                         | .903                         |      |          |      |
| AI-generated review summaries improve my online shopping experience.                                             | .912                         |      |          |      |
| <i>Perceived Ease of Use</i> (adapted from Davis 1989)                                                           |                              | .770 | .930     | .930 |
| It is easy for me to learn how to use AI-generated review summaries for online shopping.                         | .875                         |      |          |      |
| I find it easy to use AI to generate review summaries in the format I need.                                      | .843                         |      |          |      |
| I find it easy to use AI-generated review summaries for online shopping.                                         | .906                         |      |          |      |
| I find it easy and straightforward to interact with the AI that generates review summaries for online shopping.  | .885                         |      |          |      |
| <i>Pleasure</i> (drawing on established hedonic motivation scales; e.g., Childers et al. 2001)                   |                              | .826 | .959     | .960 |
| Using AI-generated review summaries is a joy.                                                                    | .936                         |      |          |      |
| Using AI-generated review summaries is exciting.                                                                 | .922                         |      |          |      |
| Using AI-generated review summaries makes me feel good.                                                          | .908                         |      |          |      |
| Overall, I enjoy using AI-generated review summaries while shopping online.                                      | .878                         |      |          |      |
| Overall, I find using AI-generated review summaries to be fun.                                                   | .898                         |      |          |      |
| <i>Trust in AI</i> (adopted from Chandra et al. 2010 and Heimann et al. 2023)                                    |                              | .822 | .929     | .932 |
| I trust that the AI generating the review summaries is reliable.                                                 | .914                         |      |          |      |
| I trust that the AI generating the review summaries is safe.                                                     | .852                         |      |          |      |
| I have confidence in the AI generating the review summaries.                                                     | .945                         |      |          |      |

**Tab. 1** Measurement Items, Factor Loadings, and Reliability Statistics for Constructs (continued)

|                                                                                                                                         |      |      |      |      |
|-----------------------------------------------------------------------------------------------------------------------------------------|------|------|------|------|
| <i>Trust in Provider</i> (adopted from Chandra et al. 2010 and Heimann et al. 2023)                                                     |      | .793 | .935 | .936 |
| I believe the e-commerce platform offering AI-generated review summaries keeps its promise.                                             | .898 |      |      |      |
| I believe the e-commerce platform offering AI-generated review summaries keeps customers' interests in mind.                            | .883 |      |      |      |
| I believe the e-commerce platform offering AI-generated review summaries is trustworthy.                                                | .926 |      |      |      |
| I believe the e-commerce platform offering AI-generated review summaries will do everything to secure the request entries of customers. | .835 |      |      |      |
| <i>Trust in Others</i> (adopted from Chandra et al. 2010 and Heimann et al. 2023)                                                       |      | .767 | .906 | .908 |
| I trust other people who wrote reviews that the AI uses to generate the review summaries.                                               | .887 |      |      |      |
| I believe that other people write reliable reviews that can be used by the AI to generate review summaries.                             | .858 |      |      |      |
| I trust other people to behave correctly when writing reviews that can be used by AI to generate review summaries.                      | .882 |      |      |      |
| <i>Algorithm Familiarity</i> (adopted from Mahmud et al. 2024)                                                                          |      | .586 | .728 | .736 |
| I am familiar with the way recommendation algorithms work.                                                                              | .854 |      |      |      |
| I frequently use apps or services that contain algorithm-based recommendations.                                                         | .670 |      |      |      |

**Notes:** AI = Artificial Intelligence;  $\alpha$  = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted, SE = standard error.

<sup>1</sup>Factor loading scores from CFA are significant at  $p < .001$ .

$p < .05$ ), leading us to reject *H6*. No significant direct effects emerged for pleasure and trust in provider, thus rejecting *H3* and *H5*. Next, we examined the theory-consistent interrelationships among the key drivers. Perceived ease of use had a significant positive effect on utilitarian value ( $\beta = .157, p < .001$ ), supporting *H7a*. Pleasure showed significant positive effects on utilitarian value ( $\beta = .431, p < .001$ ) and perceived ease of use ( $\beta = .482, p < .001$ ), thus supporting *H7b* and *H7c*. In addition, trust in AI also had a significant positive effect on utilitarian value ( $\beta = .403, p < .001$ ), thus accepting *H8*. These findings support the internal coherence of the conceptual model but are not interpreted as primary contributions of the study.

For completeness, we additionally examined indirect effects within our research model. All specific indirect effects were significant and positive (see *Appendix C*). Given the study's

focus on direct effects, these indirect effects are reported as supplementary findings.

The model depicted satisfactory  $R^2$  values for usage intention ( $R^2 = .782$ ) and utilitarian value ( $R^2 = .762$ ) and moderate but acceptable value for perceived ease of use ( $R^2 = .232$ ). Age ( $\beta = .119, p < .001$ ) and algorithm familiarity ( $\beta = .072, p < .05$ ) showed small but significant effects. All supported hypothesized relationships remained significant when controlling for these variables.

## 5. Discussion and Theoretical Contributions

### 5.1. Key Findings and Interpretation

Our study reveals that utilitarian value is the strongest predictor of usage intention, indicating that consumers are motivated to adopt AI-generated review summaries when they perceive them as useful for decision-making and reducing effort during online shopping. This finding aligns with prior technology adoption research (Hollebeek et al. 2024) and confirms that functional benefits remain a central prerequisite for the adoption of AI-based information tools in e-commerce.

Trust in AI emerges as another key determinant of usage intention. Consumers are more likely to use AI-generated summaries when they trust the algorithm's competence and impartiality, underscoring the role of trust in shaping technology acceptance (Kelly et al. 2023; Singh et al. 2024). Beyond its direct effect, trust in AI enhances utilitarian value, indicating that trusted AI tools are more likely to be perceived as useful and reliable sources of information. This finding highlights the central role of algorithm-related trust for the adoption

of AI-generated review summaries in online shopping contexts.

Interestingly, trust in others negatively affects usage intention, pointing to a compensatory mechanism: when consumers question the credibility of individual reviewers, they appear more inclined to rely on AI-generated review summaries that aggregate multiple opinions and potentially reduce reviewer-specific bias. This finding contributes to understanding how AI may become particularly attractive in contexts characterized by low interpersonal trust (Foehr and Germelmann 2020; Yang and Wibowo 2022).

In contrast, trust in the platform provider does not significantly influence usage intentions. This implies that consumers are more strongly driven by functional performance, pleasing value, and easy handling of the AI tool rather than the reputation of the hosting platform provider. This finding indicates a shift in evaluative focus from provider-level trust toward tool-specific assessments in the context of AI-generated review summaries. This is in line with prior research indicating that technologies' trustworthiness may overshadow the platform-related trust traditionally associated with providers (Kuen et al. 2023).

**Tab. 2** Summary of hypothesis testing

| Hypothesis                                   | Standardized coefficient | <i>p</i> -value | Result                           |
|----------------------------------------------|--------------------------|-----------------|----------------------------------|
| H1: Utilitarian Value→Usage Intention        | .562                     | < .001          | Supported                        |
| H2: Perceived Ease of Use→Usage Intention    | .120                     | .001            | Supported                        |
| H3: Pleasure→Usage Intention                 | .116                     | .072            | Rejected                         |
| H4: Trust in AI→Usage Intention              | .336                     | .001            | Supported                        |
| H5: Trust in Provider→Usage Intention        | -.136                    | .073            | Rejected                         |
| H6: Trust in Others→Usage Intention          | -.134                    | .004            | Rejected<br>(opposite direction) |
| H7a: Perceived Ease of Use→Utilitarian Value | .157                     | < .001          | Supported                        |
| H7b: Pleasure→Utilitarian Value              | .431                     | < .001          | Supported                        |
| H7c: Pleasure→Perceived Ease of Use          | .482                     | < .001          | Supported                        |
| H8: Trust in AI→Utilitarian Value            | .403                     | < .001          | Supported                        |

Perceived ease of use positively affects usage intention, indicating that AI-generated review summaries are more likely to be adopted when they are experienced as intuitive and easy to integrate into the shopping process. It also positively affects utilitarian value. Pleasure, by contrast, does not directly influence usage intention but contributes indirectly by enhancing perceptions of ease of use and utilitarian value. While these findings reflect a well-established pattern in technology acceptance research (e.g., Wu et al. 2011), they underscore that usability remains a necessary baseline condition for adoption while enjoyment supports adoption primarily by reinforcing functional evaluations rather than acting as an independent driver. Finally, while several theory-consistent interrelationships among the key drivers of usage intention are observed, these effects primarily serve to contextualize the direct drivers of usage intention rather than constituting central findings of the study. Overall, our findings emphasize that consumers' intentions to use AI-generated review summaries are mainly shaped by functional value and trust-related considerations, with hedonic and usability factors playing secondary, reinforcing roles.

## 5.2. Theoretical Contributions

Our examination of the role of utilitarian and hedonic motivations as well as multidimensional trust in shaping consumers' intentions to use AI-generated review summaries expands the understanding of AI integration within e-commerce.

First, our findings advance prior research by conceptualizing trust as a multidimensional construct in the context of AI adoption in e-commerce. By distinguishing between trust in AI, platform provider, and other reviewers, we reveal how consumers dynamically allocate trust among human and technological actors. This differentiation foregrounds the need to consider technology-related, social, and provider-specific influences as distinct but interrelated drivers of consumer behavior.

Second, the negative relationship between trust in others and usage intention challenges

traditional perspectives on eWOM (Chevalier and Mayzlin 2006; Mudambi and Schuff 2010). While prior work has predominantly emphasized the positive role of interpersonal trust in facilitating reliance on user-generated content, the present findings suggest a compensatory mechanism: when trust in individual reviewers is low, consumers may increasingly rely on AI-generated review summaries that aggregate multiple opinions and reduce perceived bias. By explicitly acknowledging this ambivalence, our results contribute to a more nuanced understanding of how AI-based information aggregation interacts with social trust in online review environments.

Third, the study confirms the continued relevance of established technology acceptance drivers in the context of AI-generated review summaries. Utilitarian value and perceived ease of use remain central determinants of usage intention, underscoring that functional efficiency and usability constitute necessary baseline conditions for adoption. While these effects are well established in prior technology acceptance research (Hollebeek et al. 2024; Longoni and Cian 2020), their persistence in the context of AI-generated review summaries demonstrates their robustness and relevance for emerging AI tools.

Finally, the findings clarify the role of hedonic motivation in this context. Rather than acting as a direct driver of usage intention, pleasure influences adoption indirectly by shaping perceptions of utilitarian value and ease of use. This distinction contributes to a more differentiated understanding of how affective evaluations support, but do not substitute for, functional considerations in the adoption of AI-generated review summaries.

Taken together, these findings contribute to literature by offering a theoretically grounded and empirically differentiated account of how functional evaluations and distinct trust dimensions shape consumers' intentions to use AI-generated review summaries in e-commerce.

## 6. Managerial Implications

Our study provides actionable insights for managers seeking to implement AI-generated review summaries on e-commerce platforms.

First, managers should prioritize utilitarian value when designing AI-generated review summaries, as perceived usefulness emerged as the strongest driver of usage intentions. Generic, one-size-fits-all review summaries may not sufficiently address heterogeneous information needs. Instead, user-configurable designs that allow consumers to control which information is summarized appear particularly promising. Review summaries should therefore focus on delivering concise, decision-relevant information and reducing the effort required to process large volumes of reviews, for example by presenting attribute-specific sections, highlighting consensus trends across reviews, or allowing quick switches between different aspects of interest. Clearly communicating how AI-generated summaries save time or support decision-making can further strengthen perceived utilitarian value.

Second, our results highlight the importance of trust in the AI tool itself. As transparency fosters long-term trust in AI (Vorm and Combs 2022), managers should treat it as a core design principle. Providing clear information about how summaries are generated—for instance, which reviews are included, how information is aggregated, or how filtering works—can help consumers better assess the reliability of AI-generated outputs. Simple transparency cues, such as references to the number of reviews considered or visual indicators of review coverage, may support trust formation without increasing cognitive load.

Third, AI-generated review summaries can be particularly valuable in contexts characterized by low trust in individual reviewers. When consumers question the credibility of single reviews, AI-generated summaries can serve as compensatory information sources. In such contexts, highlighting the aggregated, objective, and consistency-oriented nature of

AI-generated summaries may therefore increase adoption in such settings.

Fourth, usability and user-centered design should be treated as central objectives. Given the positive impact of perceived ease of use, interfaces should be intuitive, easy to navigate, and require minimal effort. Design choices such as clear labeling, simple interaction logic, and structured attribute selection (e.g., predefined options rather than open-text input) can lower perceived effort and support usage, particularly among consumers with limited experience with AI tools.

Finally, hedonic elements should be treated as supportive rather than primary design features. While pleasure does not directly drive usage intention, visually structured summaries or subtle highlighting of key insights may enhance engagement once core functional and usability requirements are met. Importantly, such elements should not compromise clarity or decision relevance.

## 7. Limitations and Future Research

Some limitations of this research provide valuable directions for future research. First, this study examined a written AI-generated review summary for a technical product within a specific e-commerce setting, offering limited flexibility. Different product categories, summary formats, and presentation styles as well as varying levels of AI transparency or personalization may influence consumers' perceptions and usage intention differently. Future research should vary these design characteristics to better understand the broader applicability of such AI tools.

Second, while our findings reveal a negative effect of trust in others, questions remain about how consumers evaluate AI-generated summaries compared to traditional OCR. We therefore recommend future research to explore how these AI-generated summaries affect perceptions of review authenticity, reliability, and fairness. Additionally, although trust

in provider did not significantly affect usage intention, the relevance of different types of providers (e.g., retailers vs. independent third-party platforms) or their characteristics (e.g., perceived neutrality, reputation) could exert a moderating influence and deserve further exploration.

Third, this study did not address the ability of AI tools to identify or mitigate fake reviews, nor did it account for features such as personalization, sentiment sensitivity, or adjustable summary granularity. These factors could influence perceived trustworthiness and usefulness of such AI tools and warrant further investigation.

Finally, while we controlled for age, gender, and algorithm familiarity, future research could incorporate additional control variables such as income, broader AI experience, established review strategies, or prior experience with OCR in general. In addition, alternative decision aids—such as “frequently returned” labels or verified-purchase highlights—interact with or substitute for AI-generated review summaries and warrant further investigation. Beyond these limitations, this research represents an important step in understanding how consumers engage with AI in e-commerce. We encourage future research to build on these insights, ensuring that AI-powered tools enhance, rather than complicate, the overall shopping experience.

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## Appendix

### Appendix A: Participant Instructions and Example from the Questionnaire

To familiarize the participants with the concept of AI-generated review summaries and their application in e-commerce decision-making, we designed a detailed explanation and visual example simulating a real-world example. This was integrated into the survey to ensure that the participants clearly understood the AI tool and its relevance before responding to the questions. The following text was provided to the participants alongside the visual example as part of the questionnaire.

#### Instructions in the Questionnaire

*“On the next page, an example of an AI-generated review summary as it could appear on an e-commerce platform will be displayed. In the example, a customer has requested a summary of reviews on a power bank with a focus on portability and handiness. Please look at the example carefully.”*

#### Explanation of AI-Generated Review Summaries

*“AI-generated review summaries are algorithmically created summaries of customer reviews on e-commerce platforms. These summaries provide insights into products by aggregating reviews and focusing on predefined attributes. For instance, if a customer seeks information about a product’s portability, the AI system generates a summary highlighting relevant reviews for this attribute.”*

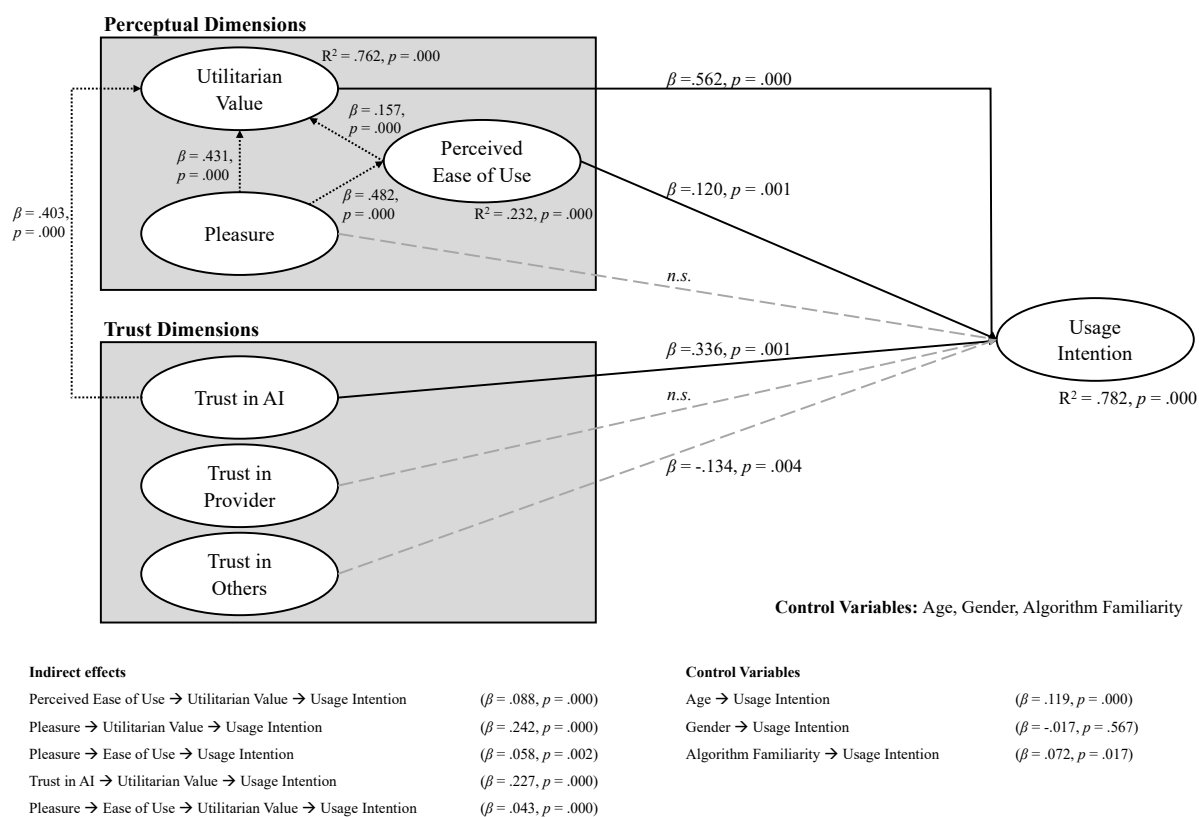
## Appendix B

**Tab. A1** Heterotrait-monotrait ratios and inter-construct correlations of the tested constructs

| Constructs              | 1           | 2           | 3           | 4           | 5           | 6           | 7           | 8           |
|-------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1 Usage Intention       | <b>.926</b> | .866        | .592        | .748        | .788        | .627        | .344        | .261        |
| 2 Utilitarian Value     | .8013       | <b>.873</b> | .601        | .806        | .821        | .711        | .477        | .251        |
| 3 Perceived Ease of Use | .544        | .552        | <b>.877</b> | .495        | .594        | .532        | .389        | .402        |
| 4 Pleasure              | .707        | .779        | .447        | <b>.909</b> | .797        | .748        | .491        | .253        |
| 5 Trust in AI           | .743        | .779        | .550        | .745        | <b>.907</b> | .837        | .615        | .178        |
| 6 Trust in Provider     | .592        | .682        | .499        | .704        | .765        | <b>.891</b> | .638        | .184        |
| 7 Trust in Others       | .318        | .419        | .364        | .426        | .533        | .555        | <b>.876</b> | .165        |
| 8 Familiarity           | .212        | .193        | .313        | .193        | .112        | .153        | .132        | <b>.766</b> |

Notes: Bold values on the diagonal are the square-root of average variance extracted. Below the diagonal are the inter-construct correlations, whereas values above diagonal are heterotrait-monotrait ratios.

## Appendix C



**Note:** All path coefficient values are standardized. Confirmed hypotheses are represented with black arrows and numbers while rejected hypotheses are shown in grey.  $n.s.$   $p > .05$ .

**Fig. A1** Results of the structural equation modeling and hypotheses testing. All path coefficient values are standardized. Solid black arrows represent confirmed hypotheses for direct effects. Grey dashed arrows represent rejected hypotheses for direct effects. Dotted black arrows represent confirmed hypotheses for theory-consistent interrelationships. (Source: Own illustration).