# The Role of Social Proof in Electronic Word of Mouth (eWOM) on Trust and Adoption of AI-Powered Chatbots

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## Abstract

Digital consumer reviews are crucial in building trust and the adoption process of new products. Building on this, this study examined how electronic word-of-mouth (eWOM) in the form of online reviews affects consumer trust and adoption intention for AI-powered chatbots and whether there is a difference to non-AI products. For this purpose, a between-subject experiment was chosen ($n$=326), in which participants were randomly assigned to one of four conditions (positive vs. negative review valence combined with AI chatbot vs. non-AI app). After the participants were exposed to a large number of reviews in one of these scenarios, it was measured how the participants' trust and adoption intention behaved. A moderated mediation analysis was conducted with trust as a mediator and product type as a moderator. The results show that eWOM valence promotes trust, which in turn has a positive effect on the adoption intention. These findings indicate that trust fully mediates the effect of eWOM valence on the adoption intention. Furthermore, the effect of eWOM on trust and adoption did not differ between the AI and non-AI conditions. These results further contribute to the theory of eWOM, technology adoption, and social proof by providing practical and theoretical implications for how to increase trust in AI products and consequently adoption intention.

**Title:** The Role of Social Proof in Electronic Word-of-Mouth (eWOM) on Trust and Adoption of AI-Powered Chatbots

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## Sumário

As opiniões digitais dos consumidores são cruciais para criar confiança e para o processo de adoção de novos produtos. Com base nisto, este estudo examinou a forma como o boca-a-boca eletrónico (eWOM), sob a forma de opiniões online, afecta a confiança do consumidor e a intenção de adoção de chatbots com IA e se existe uma diferença em relação a produtos sem IA. Para este efeito, foi escolhido um experimento entre sujeitos (n=326), no qual os participantes foram aleatoriamente atribuídos a uma de quatro condições (valência de avaliação positiva vs. negativa combinada com chatbot com IA vs. aplicação sem IA). Depois de os participantes terem sido expostos a um grande número de críticas num destes cenários, foi medido o comportamento da confiança e da intenção de adoção dos participantes. Foi efectuada uma análise de mediação moderada com a confiança como mediador e o tipo de produto como moderador. Os resultados mostram que a valência do eWOM promove a confiança, que, por sua vez, tem um efeito positivo na intenção de adoção. Estes resultados indicam que a confiança medeia totalmente o efeito da valência do eWOM na intenção de adoção. Além disso, o efeito do eWOM na confiança e na adoção não diferiu entre as condições de IA e não IA. Estes resultados contribuem ainda mais para a teoria do eWOM, da adoção de tecnologia e da prova social, fornecendo implicações práticas e teóricas sobre como aumentar a confiança nos produtos de IA e, consequentemente, a intenção de adoção.

**Título:** O papel da prova social no boca-a-boca eletrónico (eWOM) na confiança e na adoção de chatbots alimentados por IA

**Autor:** Konrad Andreas Schneider

**Palavras-chave:** Boca-a-boca eletrónica, Prova Social, Inteligência Artificial, Confiança, Intenção de Adoção

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## List of Abbreviations

| | |
|---|---|
| AI | Artifical Intelligence |
| DV | Dependent Variable |
| EWOM | Electronic Word-of-Mouth |
| IV | Independent Variable |
| MEV | Mediator Variable |
| MOV | Moderator Variable |

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# 1 Introduction

## 1.1 Background and Relevance of the Research

In an increasingly digitized world, the role of trust is becoming ever more important (Kelton et al., 2008). Trust is a crucial factor in overcoming customers' concerns about purchasing decisions and the associated risks (Kim et al., 2008). Particularly when dealing with and adapting to new technologies, existing trust is essential (Bahmanziari et al., 2003). According to McKnight et al. (2008) it helps consumers alleviate doubts about new media and influences the purchasing process. During the introduction of e-commerce platforms, a lack of trust was already identified as one of the key reasons why customers were hesitant to interact with websites and make purchasing decisions in this context (McKnight et al., 2002).

This dynamic is also evident in the field of modern technologies, such as artificial intelligence (AI). Trust is a central element here, shaping the further adoption of innovative technologies by businesses and individuals (Glikson & Woolley, 2020; Yang & Wibowo, 2022). Specifically, artificial intelligence, which relies on vast amounts of data and machine learning, is associated with greater uncertainties due to its complexity and lack of transparency (Karim et al., 2023). In this context, the so-called black-box problem is frequently mentioned ((Chakravorti, 2024; Chaudhury, Sadhukhan, & Sengupta, 2024; Karim et al., 2023). Users often cannot understand how and why AI arrives at its results (Chakravorti, 2024). As AI finds increasing application in critical areas such as medicine, transportation, or finance, fostering trust through transparency and traceability becomes even important (Haug & Drazen, 2023; Mitz & Brodie, 2019).

The rapid growth of the AI sector underscores the relevance of this technology. In 2023 alone, 1,812 new companies in the field of AI were founded worldwide, representing a 41% increase compared to the previous year (Stanford University, 2024). The range of AI applications available to businesses and individuals is expanding (Van der Vlist et al., 2024). AI-driven chatbots in particular play a crucial role in the development of AI-based technology (Hou et al., 2020). This relevance is also highlighted by the 400 million weekly active users of ChatGPT, one of the largest chatbot providers worldwide (Singh, 2025). These developments highlight the growing importance of AI, as well as the necessity of building trust in this technology.

Prior to the global spread of the Internet, consumers sought information and opinions from others and used them as a basis for decision-making before purchasing products or services (Lee et al., 2022). However, the development of electronic word-of-mouth (eWOM) has created a new channel of digital communication, allowing consumers to exchange information independently of time and place. Through blogs, tweets, videos, likes, ratings, or reviews, information about products and services is shared online (Babić Rosario et al., 2016). EWOM has become a key mechanism for fostering trust in the context of new technologies. It has established itself as one of the central sources of information for consumers and plays a significant role in influencing consumer behavior and attitudes (Todri et al., 2022).

Word-of-mouth (WOM) is considered by some researchers to be one of the most significant marketing tools of the digital age (Babić Rosario et al., 2016; Daugherty & Hoffman, 2014; Duan et al., 2008). With its enormous reach and ability to directly influence consumers, it is a crucial factor for companies in the digital context (Babić Rosario et al., 2016).

However, despite the rapid rise of AI-based companies, there is still little research that combines these two aspects and examines the specific influence of eWOM on AI products.

### 1.2 Problem Statement

Altough the critical importance of electronic word of mouth as one of the central marketing tools in the digital context and the rapid rise of AI-based companies, there is little research that combines these two aspects and investigates the specific influence of eWOM on AI products (Babić Rosario et al., 2016; Stanford University, 2024). The significant lack of transparency and high complexity are just some of the many relevant risks that companies and consumers face when dealing with AI products (Chakravorti, 2024). AI products involve greater uncertainty than traditional products. At the same time, eWOM is one of the key elements in building customer trust in products and services. The question of how social proof, a consistently high volume of reviews, whether positive or negative, affects the adoption of AI products remains insufficiently researched. This research gap is particularly interesting since trust is critical to the acceptance of new technologies.

### 1.3 Research Questions and Objectives

The objective of this study is to explore the influence of eWOM on trust and purchase intentions for AI-based products. Particular attention is given to the effects of social proof and review valence. This study also examines whether these effects differ from those observed in the context of non-AI products.

Three primary research questions have emerged:

1. How does eWOM valence influence consumer trust and the adoption intention of AI-powered chatbots?
2. Does trust mediate the effect of eWOM valence on the adoption intention of AI-powered chatbots?
3. Are the effects of eWOM valence on trust and adoption intention different for AI-based products compared to non-AI digital products?

### 1.4 Practical and Theoretical Relevance

This study has both practical and theoretical relevance. Electronic word of mouth is an important marketing tool for companies and impacts sales (Babić Rosario et al., 2020). EWOM, especially reviews, plays a dominant role for consumers in purchase decisions. A survey of U.S. online shoppers revealed that over 50% use online reviews as their preferred source of information, even ahead of friends and family. This demonstrates the immense relevance of digital recommendation marketing (Cisco-Internet-Business-Solutions, 2013). Particularly for innovative technologies like AI products, eWOM can help reduce consumer uncertainties and positively influence purchasing decisions. For both businesses and consumers, it serves as a valuable source of information. Given the rapid increase in newly founded AI companies and billion-dollar AI investments, it is critical for businesses to actively address and alleviate consumer concerns and needs in order to compete in a dynamic business environment (Stanford University, 2024).

From a theoretical perspective, this study is also highly relevant. Investigating electronic word of mouth in the context of AI products addresses a key research gap. While eWOM has been highlighted as a critical marketing tool in numerous studies and its impact on consumer trust has been extensively examined, its influence on innovative technologies, especially AI products, remains largely unexplored (Chen et al., 2016; Ismagilova et al., 2020; Tata et al., 2020). This empirical study aims to expand the research field and provide a foundation for further studies on the marketing of AI products and related consumer behavior.

### 1.5 Structure of the Thesis

This thesis is structured into six chapters, which build on each other systematically. The first chapter provides the foundation with the introduction. It highlights trust as a relevant component in the purchasing process and introduces AI and related products. Additionally, eWOM is presented as an important tool for fostering consumer trust. The research objectives and questions are also described. Finally, the theoretical and practical relevance is discussed. The second chapter presents the central theoretical concepts on which this study is based. These include the definitions of eWOM and related concepts, as well as AI and its associated products. Particular attention is given to the unique aspects of AI products, especially regarding consumer trust. The chapter concludes with an overview of existing literature on the connection between eWOM and AI products and identifies research gaps that form the basis for hypothesis development. The third chapter describes the methodological approach. It explains the process of the quantitative survey conducted to answer the research questions. The operationalization of variables, questionnaire design, and data collection methods are outlined. The sample selection is also discussed, and the validity and reliability of the methodology are addressed. The fourth chapter presents the survey results. It begins with a descriptive analysis of the collected data, followed by hypothesis testing using regression and correlation analyses. These results are evaluated in relation to the research questions.The fifth chapter links the results to the theoretical framework and discusses their scientific and practical implications. The extent to which the hypotheses are confirmed or refuted is analyzed. Finally, limitations of the study and potential approaches for future research are outlined. The sixth and final chapter summarizes the key findings and reflects on the scientific and practical contributions.

## 2 Theoretical Framework

To provide a better understanding of eWOM, AI and the associated effect on product adoption, all relevant terms are explained below, and the theoretical foundations are laid.

## 2.1 WOM

### 2.1.1 WOM, the Precursor of eWOM

When purchasing a product or service, consumers go through a multi-stage decision-making process in which, among other things, the search for information and the evaluation of alternatives play a critical role in reducing uncertainty (Armstrong et al., 2014). According to Armstrong et al. (2014), the opinions of others play an important role in influencing decision-making during these stages, both online and in the immediate social environment.

To make decisions, humans repeatedly use heuristics—mental shortcuts or cognitive decision-making processes that allow them to make decisions more efficiently and reduce uncertainty (Gigerenzer & Gaissmaier, 2011).

In the context of reducing uncertainty in social environments, social proof is one of the crucial mechanisms (Rao et al., 2001). According to Cialdini (2009), the principle of social proof describes that people perceive a decision as correct when many others buy a certain product or perform a specific action, interpreting this as an indirect confirmation of their choice. A particularly effective means of implementing social proof in the digital world is eWOM (Amblee & Bui, 2011).

EWOM has established itself as an important tool alongside traditional channels as an effective marketing instrument with a significant influence on financial performance (Babić Rosario et al., 2020). EWOM originates from traditional word of mouth (WOM) (Huete-Alcocer, 2017). WOM is one of the oldest forms of interpersonal communication and plays a central role in disseminating information about products and services (Dellarocas, 2003). Scientists have been discussing WOM in literature since the mid-20th century (Katz & Lazarsfeld, 1955).. In the 1950s, a form of WOM appeared in scientific literature for the first time (Katz & Lazarsfeld, 1955). In their study, Katz and Lazarsfeld (1955) described the role of informal communication by opinion leaders who influence the purchasing decisions of others. This empirical study is considered one of the foundations of WOM research.

In the 1960s, Arndt (1967) expanded WOM literature by investigating how product-related conversations affect the decision-making process for new products. The study showed that positive comments encourage product adoption, while negative comments have a deterrent effect on purchasing decisions (Arndt, 1967). WOM research advanced further under Westbrook (1987), who defined WOM as informal communication between consumers regarding the ownership, use, or characteristics of a particular product. Brown and Reingen (1987) researched the influence of social ties in the WOM context and found that particularly strong social ties (among individuals with similar characteristics) have a greater impact, while weaker social ties act as bridges in larger social networks.

In contemporary research, WOM continues to be recognized as a central mechanism for disseminating information in consumer behavior (Berger, 2014). WOM is defined as an informal exchange between consumers, as well as between consumers and sellers or service providers (Liu, 2006). It has established itself as one of the most influential sources of information for consumers when making purchasing decisions (Daugherty & Hoffman, 2014).

Furthermore, Brown et al. (2007) described WOM as an independent, consumer-driven source of information. This consumer proximity enhances credibility and fosters a stronger connection through reinforced beliefs and trust (Brown et al., 2007). In this context, trust is based on the consumer's personal perception that the message received can be trusted (Ho & Chien, 2010). Trust is a combination of values, attitudes, as well as the moods and emotions of individuals (Jones & George, 1998). According to the study by Ho and Chien (2010), trust has a decisive influence on the consumer's decision making. Trust is an effective way for consumers to reduce uncertainty and help generate the best personal outcome (Liu et al., 2023). According to Haq et al. (2024), the valence of WOM is transferred to the associated brand along with all associated effects in accordance with the trust transfer theory. This means that positive WOM valence can increase trust in the brand, while negative WOM valence can reduce trust in the brand (Haq et al., 2024).

### 2.1.2 Definition and Differentiation of eWOM from WOM

With the rise of Web 2.0, traditional WOM has increasingly shifted to digital channels, leading to the establishment of the term eWOM (Verma & Yadav, 2021). There is no universally accepted definition in the literature, and terms such as online word of mouth, digital word of mouth, user-generated content, and user-created content are often used interchangeably. Nevertheless, eWOM has become the predominant term (Hu et al., 2011; Moore & Lafreniere, 2020; Oum & Han, 2011; Ye et al., 2011).

EWOM is broadly defined as any type of consumer communication, whether positive or negative, that takes place online (Henning-Thurau et al., 2004). In recent years, this definition has expanded to include not only written statements but also videos, likes, and images (Babić Rosario & De Valck, 2020). Social media has created a dynamic and interactive environment, enabling consumers to connect, generate content, and share their opinions more easily than ever before (Daugherty & Hoffman, 2014).

One example of eWOM is microblogging WOM, which refers to short-form posts on platforms such as Twitter, where consumers share firsthand information about a new product or service immediately after its release (Hennig-Thurau et al., 2015). According to Hennig-Thurau (2015), this is particularly relevant in the early stages of a product's life cycle, as it significantly influences consumer purchasing decisions.

Regardless of geographical location, eWOM has enabled flexible and widespread communication between consumers and businesses (Duan et al., 2008). Unlike traditional WOM, which is often limited by physical proximity, eWOM can be disseminated across vast digital networks (Donthu et al., 2021).

According to Kundu and Chakraborti (2022), eWOM is generated through various channels and platforms, with three major categories serving as primary dissemination pathways. Dedicated review sites function as platforms specifically designed for users to write and read reviews of products and services (Kundu & Chakraborti, 2022). In addition, social networking sites provide individuals with the ability to connect with like-minded users and exchange opinions through comments, views, and videos (Kundu & Chakraborti, 2022). Finally, e-commerce platforms serve as an important medium where consumers not only purchase products, but also leave ratings and detailed reviews, thus influencing other potential buyers (Kundu & Chakraborti, 2022). Different platforms utilize eWOM to better understand consumer preferences by employing text analysis tools, sentiment surveys, hashtag analyses, and other machine learning methods (Verma & Yadav, 2021). Compared to traditional WOM, eWOM benefits from lower storage and distribution costs, allowing online discussions to persist over time (Amblee & Bui, 2008).

Huerte-Alcocer (2017) distinguishes Wom and eWOM in the following four key aspects. First, the diffusion speed, eWOM reaches a significantly larger audience than WOM due to its online nature. Second, the credibility perception, Consumers may initially perceive eWOM as less credible due to the anonymity of the internet, leading to greater uncertainty (Huete-Alcocer, 2017). Third, the privacy, while WOM often occurs in private conversations, eWOM is mostly publicly accessible and can be retrieved at any time (Huete-Alcocer, 2017). And lastly the Accessibility, unlike WOM, which is transient, eWOM is stored online and remains accessible long after its initial creation. (Huete-Alcocer, 2017).

Furthermore, eWOM allows consumers not only to evaluate products online but also to access reviews from previous buyers, enhancing transparency and reducing perceived risk (Varadarajan & Yadav, 2002). Additionally, the digital storage and communication capabilities of eWOM grant consumers access to a significantly broader range of opinions from other buyers (He & Bond, 2015).

According to Trustpilot's (2024) Transparency Report, the platform has published 267 million reviews in total, with 54 million added in 2023 alone, making it one of the largest and most influential review platforms globally. Other notable platforms include Yelp (a recommendation site), IMDb (a film and TV rating platform), and CNET (a technology discussion forum), all of which allow consumers to access and contribute to thousands of reviews (He & Bond, 2015). Amazon is also widely recognized for its well-developed customer review system (Duan et al., 2008), having been one of the pioneers in directly integrating consumer reviews with product listings (Mudambi & Schuff, 2010).

### 2.1.3 Digital Consumer Reviews as a central Form of eWOM

Among the many different forms of eWOM, digital consumer reviews play a particularly important role in influencing the costumer journey in the digital environment (Amblee & Bui, 2011, Gerdes et al., 2008). They are largely responsible for consumers' perceptions and purchase decisions (Dhar & Chang, 2009; Sun et al., 2019). This is also confirmed by recent studies. For Instance a, study by Splendid Research (2021) found that online reviews are important to 56% of consumers when making a purchase decision, with the percentage being even stronger among Generation Z with 75 %.

In addition to influencing purchase decisions, online reviews positively help build and brand reputation (Kudeshia & Kumar, 2017). Consumers also tend to trust digital reviews more than company-provided communication (Jeong & Ko, 2015). Digital reviews are perceived as more objective and diverse in evaluating products and services (Cheung et al., 2009). Consumers assume that they receive honest and unbiased opinions that can be useful to others (Allsop et al., 2007). This is particularly relevant for inexperienced consumers, who rely on consumer reviews as a form of social validation when uncertain about a product's quality (Jeong, 2023). Digital consumer reviews can be divided into two main subgroups: textual comments and numerical ratings (Li et al., 2019; Mudambi & Schuff, 2010). They are also categorized in the literature as qualitative and quantitative forms of eWOM (Sridhar & Srinivasan, 2012). Aghakani et al. (2018) distinguish between explicit and implicit eWOM, where explicit eWOM refers to textual reviews, while implicit eWOM includes likes and numerical ratings.

Numerical ratings are usually presented on a Likert scale from one to five (Mudambi & Schuff, 2010). Typically, the rating system is visualized using stars, where one star represents a very negative rating and five stars indicate a very positive rating (Yin et al., 2016). According to Yin et al. (2016), most websites that specializing in product and service ratings provide average ratings and summary statistics alongside individual reviews.

Written reviews or qualitative reviews allow consumers to describe their user experience in detail (Kostyra et al., 2016). Many review platforms now include helpfulness voting functions, enabling users to indicate whether a review was useful, thereby enhancing the evaluation process (Jiménez & Mendoza, 2013).

### 2.1.4 Important eWOM metrics: valence, volume and variance

To evaluate eWOM, especially consumer reviews, three central metrics have been established in the literature: valence, volume and variance (Babić Rosario et al., 2016; Chintagunta et al., 2010; You et al., 2015).

Valence represents the average rating of a product and reflects consumer satisfaction (Chintagunta et al., 2010). According to You et al. (2015), valence describes whether textual reviews are predominantly positive, neutral, or negative. Liu (2006) highlights the persuasive effect of valence, as it conveys crucial information about perceived product quality. Generally, positive reviews should increase purchase likelihood, while negative reviews should decrease it (Tata et al., 2020). However, differences arise based on consumer involvement. High-involvement consumers are more likely to agree with well-written reviews, whereas low-involvement consumers pay less attention to review quality and are more easily influenced by negative reviews (Lee et al., 2008).

Furthermore, Tata et al. (2020) suggest that negative reviews have a stronger impact on consumers than positive ones, a phenomenon known as negativity bias (Kanouse, 1984). In contrast, Floh et al. (2013) found that valence intensity—the degree to which a review is positive or negative—significantly affects purchase decisions for positive and moderate reviews, but has no significant impact when the review is negative.

Volume refers to the total number of reviews available for a product (Kostyra et al., 2016). According to Babić Rosario et al. (2016), valence has a less significant positive effects on purchase decisions compared to volume. This suggests that in the eWOM context, absolute and relative numbers should be analyzed from different perspectives (Babić Rosario et al., 2016). A meta-analysis by You et al. (2015) on eWOM and its effects on sales provides a nuanced picture. Both volume and valence positively impact sales, although valence has a stronger influence than volume (You et al., 2015).

As the literature shows, the effects of valence and volume vary across products and platforms (Babić Rosario et al., 2016; You et al., 2015). The positive effects of valence are not always accompanied by the same positive effects of the volume of reviews, and the same applies to negative valence (Babić Rosario et al., 2016). According to Kordrostami et al. (2021), however, there is a positive synergistic effect between valence and volume.

Variance, a statistical measure, reflects the heterogeneity of consumer ratings (Sun, 2012). According to Sun (2012), variance is a significant research topic as it reveals how differences in reviews impact consumer decision-making. However, for clarity and focus, this study considers variance less extensively.

These meta-analyses are just one example of how diverse the research findings on the effectiveness of eWOM are (Babić Rosario et al., 2016; You et al., 2015). These variations are mostly attributed to differences in product categories, which will be examined in the following section.

### 2.1.5 EWOM and its impact on different types of products

Understanding the role of eWOM in the context of the AI-based chatbots requires differentiating between product categories. EWOM applies to a wide range of products, goods, services, brands and companies (Babić Rosario et al., 2016). Consumers' perceived risk before making a purchase can be of many different natures. These can take many different forms, financial, functional, social, psychological or even security-related risk (Von Wangenheim & Bayón, 2004). EWOM plays a crucial role in reducing these uncertainties (Henning-Thurau et al., 2004). In particular, online reviews and recommendations help reduce information asymmetries and decrease uncertainty about products with social proof (Handoyo, 2024). However, it is important to distinguish how EWOM affects different products and services.

The literature often distinguishes between three different types of goods (Darby & Karni, 1973; Nelson, 1970; Tsao & Hsieh, 2015): search, experience, and credence goods. Search goods can be evaluated based on objective characteristics prior to purchase (Nelson, 1970). Examples include electronics, household appliances, and vehicles (Cui et al., 2012; Tsao & Hsieh, 2015). In contrast, experience goods are products or services whose quality can only be judged after use (Darby & Karni, 1973; Nelson, 1970), such as restaurants, hotels, or movies (Cui et al., 2012; Tsao & Hsieh, 2015). Finally, credence goods are products and services whose quality remains difficult to assess even after use, due to high information asymmetry between providers and consumers (Darby & Karni, 1973; Tsao & Hsieh, 2015).These differences impact how eWOM influences purchase decisions. Consumers of experience goods are highly motivated to leave reviews because their own experiences are easily measurable. Reviews of search goods are also often written based on subjective and personal experiences (Tsao & Hsieh, 2015). However, according to Tsao & Hsieh (2015), electronic word-of-mouth is less frequently generated for credence goods due to a lack of comparison opportunities and increased uncertainty about quality. This aligns with the findings of Lee & Bell (2013), emphasizing that products that are difficult to understand, evaluate, and control are associated with a higher degree of perceived risk.

Further research expands on these distinctions. Tsao and Hsieh (2015) argue that eWOM has a stronger influence on purchase decisions and credibility for credence goods than for search goods. Complementarily, Cui et al. (2012) compare the effect of digital consumer reviews on experience goods and search goods. They conclude that the volume of reviews has a stronger impact on the purchase decision of experience goods compared to search goods, while valence has a stronger impact on the purchase decision of search goods compared to experience goods (Cui et al., 2012).

In turn, the influence of eWOM on novel products appears to be even more pronounced. Babić Rosario et al. (2016) emphasize that novel products, in particular, are associated with a high functional risk for consumers compared to products that have been on the market for a longer period of time. They conclude that electronic word-of-mouth has a stronger effect on novel products than on existing ones (Babić Rosario et al., 2016). Ho-Dac et al. (2013) come to a similar conclusion, namely that new products in particular, where product performance is unclear, have a higher functional risk and consumers are particularly dependent on eWOM in this regard. Parry et al. (2012) extend this perspective by showing that eWOM has a positive influence on perceived usefulness and perceived ease of use, which in turn fosters adoption. Furthermore, the credibility of information can be increased and contributeing to consumers perceiving an innovation as more useful and having greater confidence in its practical use (Parry et al., 2012).

According to Zhu and Zhang (2010), this reliance on eWOM is particularly important for less popular products. Therefore, niche products play a particularly important role in this context. They conclude that even a few negative reviews can have a massive impact. The findings of You et al. (2015) support this: increased competition reduces the influence of volume and valence on sales. This is explained by the fact that the greater the choice, the lower the eWOM (You et al., 2015).

This review has shown that eWOM plays a crucial role in influencing consumer decisions, but this effect differs for certain product characteristics and types of eWOM. eWOM can help reduce uncertainty and increase product adoption. Research has shown that eWOM is especially important for novel products, which might be an implication towards AI-based products. However, a distinction must be made here for AI-based products. These differ fundamentally from traditional goods in their complexity, autonomy and trust-based challenges. Additionally, they cannot be clearly categorized into a single product category. For these specific reasons, AI-based products will be examined in more detail below, particularly with regard to adoption, to determine whether this effect also occurs for AI products.

## 2.2 Artifical Intelligence

### 2.2.1 Definition and Evolution of Artificial Intelligence

Having explained the impact of eWOM on various products, this Study now focus on one specific category: AI-driven products. Dozens of new tools related to artificial intelligence are now being introduced each week (Jutel et al., 2023). AI and related products already have an enormous impact on daily life in business, government, and social issues (Goralski et al., 2020). The term artificial intelligence was first used in the literature in 1955 and has been the basis for further research (McCarthy et al., 2006). McCarthy et al. (2006) started with the first basic principles for testing the mapping of human thought processes. In addition, Newell and Simon (1972) studied the cognitive processes involved in human problem solving. In the mid-1980s, Rumelhart et al. (1986) set another milestone in AI research. They showed that a neural network could learn from mistakes and recognize patterns. This laid the foundation for modern approaches to machine learning. At the time, Gordon Moore predicted that computing power would double every two years, a phenomenon known as Moore's Law (Haug & Drazen, 2023). Another development that sought to mimic human intelligence was the emergence of so-called expert systems at the end of the 20th century - a collection of rules formalized and conceptualized based on a series of if-then statements (Haenlein & Kaplan, 2019). The chess program Deep Blue was a well-known example of such an expert system. It managed to defeat the reigning world chess champion Garry Kasparov (Campbell et al., 2019).

However, it quickly became clear that, especially in areas where such a form of formalization is not possible, only rule-based models would perform significantly worse (Haenlein & Kaplan, 2019; Hutson, 2018). Based on mastering the game of Go, which is much more complex than chess, a new neural network was developed, a mixture of supervised learning, supported by human experts, and reinforcement learning, now also known as deep learning (Silver et al., 2016). This led to the development of the overarching concept of machine learning, which is based on the development of algorithms that enable computers to learn from data, make predictions, make decisions based on existing data, and become more accurate over time - without being explicitly programmed to do so (Jutel et al., 2023). Moore was proven right: due to the constant increase in computing power, big data, and cloud computing, artificial intelligence has been increasingly used in commercial applications, including medicine, engineering, tourism, agriculture, organizational management, and aviation (Haug & Drazen, 2023; Mitz & Brodie, 2019). According to a report by McKinsey & Company (2023), artificial intelligence could contribute $4.4 trillion annually to the global economy if it continues to develop positively.

In the field of human-machine interaction, AI-based chatbots are considered to be one of the most promising applications (Hou et al., 2020). Breakthroughs in machine learning, especially deep learning and natural language processing (NLP), have also generated massive progress in the field of chatbots (Casheekar et al., 2024). AI-based chatbots are defined as intelligent-seeming, conversation-oriented computers that attempt to mimic human interactions (Caldarini et al., 2022; Hou et al., 2020). According to Casheekar et al. (2024), the largest technology companies such as Facebook, Google and, particularly important in the field of artificial intelligence, OpenAI, have contributed a great deal to its further development and dissemination. More and more chatbots are being developed and presented, and one of the most widely used large language models is OpenAI's ChatGPT (Casheekar et al., 2024). An important factor in the adoption of AI, especially the adoption of AI-based chatbots, is of course pricing strategies (Wieberneit, 2024). OpenAI and the other major chatbot providers use a freemium model, where the basic functions are free, while more advanced functions and higher user limits have to be paid for (Goshal, 2024).

### 2.2.2 Importance of AI-adoption models

Despite the enormous technological advances and financial potential, many consumers remain skeptical of AI-driven products such as chatbots, citing concerns about trust, security and transparency (Chakravorti, 2024; McKinsey, 2023). In Harvard Business Review, Chakravorti (2024) describes the so-called AI trust gap that hinders the adoption of AI. He identifies twelve risks that are either real or subjectively perceived by consumers: disinformation, security, the black box problem, ethical concerns, bias, instability, hallucinations in LLM, unknown unknowns, job loss and social inequality, environmental impact, industry concentration, and government overreach. According to Chakravatori et al. (2023), all these risks influence trust in AI. According to Gillath et al. (2021), trust is also one of the main factors hindering the adoption of artificial intelligence. Hasan et al. (2021) come to a similar conclusion: the perceived risk of using an AI-based system has a significant negative effect on brand loyalty to the associated product. And trust in AI companies is declining (Heath & Fried, 2024). The findings of Heath & Fried (2024) show the increasing importance, there has been a decline in global trust in AI from 61% to 53% in over five years.

Due to the existing and rising skepticism, there are models that deal intensively with the AI adoption. The technology acceptance model (TAM) is one of them (Davis, 1989, Sundar et al., 2016). Examining how external factors influence internal beliefs and behaviors is a core component (Davis et al., 1989). Furthermore, this model, developed by Davis (1989), describes how users evaluate the acceptance of new technologies and innovative products. In particular, the decision dimensions of the TAM - perceived ease of use and perceived usefulness - are important for the acceptance of innovative products (Davis, 1989). Ghazizadeh et al. (2012) extend this model to automation and go into more detail on the link to trust. According to Lee & See (2004), trust is critical to the adoption of automation systems. Trust and automation coexist in a vicious circle: if a system is not trusted, it is less likely to be used; if it is not used, there is little information about the services, which means that trust does not increase either (Lee & See, 2004). The current study by Ayanwale & Ndlovu (2024) also shows that users must have trust in a technology before they adopt it. Another extension of the TAM model is the Unified Theory of Acceptance and Use of Technology (UTAUT), which adds the factor of social influence based on the TAM (Brown et al., 2010). Building on this, the Artificially Intelligent Device Use Acceptance Model (AIDUA) was developed, it examines consumer acceptance behavior toward AI-enabled technologies (Gursoy et al., 2019). According to Gursoy et al. (2019), three factors have been identified: social influence, hedonic motivation (the enjoyment and satisfaction of using AI devices), and anthropomorphism, which is the human-like characteristics of the AI device.

### 2.2.3 The effect of social influence on AI-adoption

A particular focus of this work is social influence, as it is significantly reinforced by WOM (Amblee & Bui, 2011). The study by Gursoy et al. (2019) found that social influence has a crucial impact on the adoption of AI devices. A similar result is found by Changalima et al. (2024), who investigate the influence of social influence on the likelihood of using ChatGPT. They find a positive impact of social influence on the use of ChatGPT (Changalima et al., 2024). While in most studies, social influence only refers to the direct social environment, i.e., friends and family, in this work, it is expanded to include the opinions and reviews of other consumers on the Internet (Gursoy et al., 2019). Essentially, social influence is crucial, especially in the early stages of the adoption process, to create a positive image of the product and to strengthen trust (Kim et al. 2024). According to Kim et al. (2024), older, less experienced individuals in particular are more dependent on social confirmation from others if they want to use AI-based products. Research on the previously mentioned social proof, which is closely related to social influence, shows similar results. When potential users see that many others have already used an AI-driven system, it signals to them that the system can be trusted and reduces the perceived risk, which in turn increases adoption (Pálfi et al., 2024). According to Nadella et al. (2023), positive reactions to AI services from the social environment increase trust in the said service, whereas negative reactions to AI-supported systems increase caution and skepticism (Nadella et al., 2023). In summary, social influence shapes consumer perception: If other consumers have positive experiences with AI-driven products, personal use also appears more useful and the products more credible, which in turn seems to have a positive effect on adoption.

## 2.3 Hypothesis Development and Framework

The literature has shown that social influence and social proof are closely related to the adoption of AI-based products. An appropriate means to highlight social confirmation in an online environment is eWOM (Amblee & Bui, 2011).

Previous literature does not address the influence of eWOM on AI-based products. AI products are perceived differently and the decision-making process, the connection to trust, the perception of risk, and the adoption behavior are also different (Kukanja, 2024). Traditional products are usually judged by common characteristics and have a performance that is easy to assess (Aaker & Keller, 1990). Weber et al. (2023) have identified two primary differences between AI and traditional products: inaccessibility and data dependency. In addition, AI-based products are often subject to the above-mentioned black box problem, opaque and adaptive algorithms make it difficult for consumers to assess quality and reliability without external input (Chakravorti, 2024; Kukanja, 2024). This leads to the assumption that consumers would place more trust in external sources, especially for AI-based products, which has not been captured in existing models based on conventional products. As an example, consumers take into account the opinions and knowledge of others when they adopt new, uncertain technologies (Sun, 2009). According to Sun (2009), this is where so-called herd behavior occurs, which is particularly relevant for novel products and less relevant for familiar products. Furthermore, AI-based products are associated with a particular level of perceived risk, which reduces the likelihood of adoption (Hollenbeck, 2024). Here, too, eWOM has been shown to be an effective way to reduce perceived uncertainty and increase trust (Varadarajan & Yadav, 2002). The adoption models have shown that trust, along with social influence, plays a crucial role in the adoption process of AI-based products. The analysis of the effects of eWOM has shown that eWOM can serve as a suitable means to increase trust in products.

The existing adoption models show that trust and social influence are crucial factors in AI adaptation. Due to the special perception of AI products and the influence of social proof, this tries to close this existing gap in the literature.

The following hypotheses have been developed:

***H$_1$:*** *Positive eWOM valence (in a high-volume review environment) increases the likelihood of adopting an AI-powered chatbot.*

Previous studies show that positive online reviews increase the perception of product quality and usefulness (Babić Rosario et al., 2016; Haq et al., 2024). According to Babić Rosario et al. (2016), reviews are particularly effective for new products. Therefore, this study expects that a high volume of positive reviews increase users' willingness to use AI-powered chatbots.

***H$_2$:*** *Trust in the AI-powered chatbot acts as a mediator for the effect of high volume online review valence on adoption. Many Positive reviews first increase trust in the chatbot, which in turn increases the likelihood of adoption.*

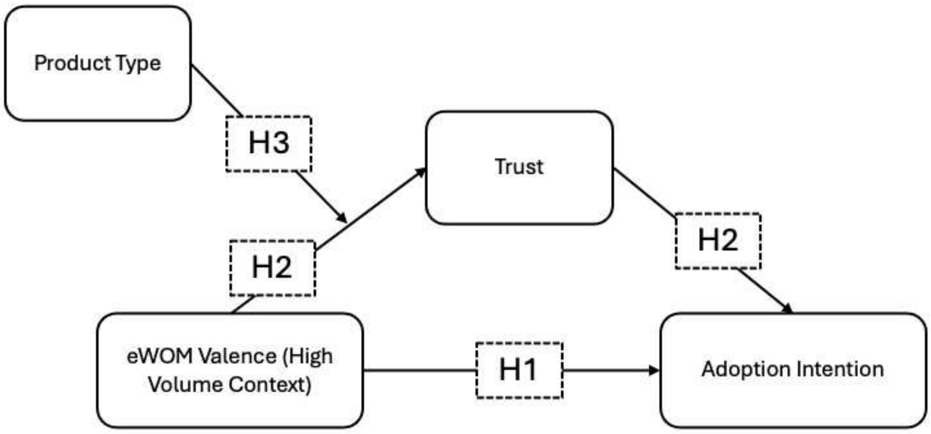
As discussed in Chapter 2.2.2, Trust has been found to play a crucial role in the adoption of AI (Ayanwale & Ndlovu, 2024). According to the mentioned trust transfer theory, this study assumes that positive reviews initially increase trust in the chatbot, which in turn increases the likelihood of use. Trust acts as a mediator in this process. A synergistic effect exists in the literature between review valence and review volume (Kordrostami et al., 2021).

***H$_3$:*** *Product type (AI vs. Non-AI) moderates the effect of high-volume eWOM valence on trust and adoption intention.*

Based on the findings, this study assumes that consumers perceive eWOM differently depending on whether the product is AI-based or not. Research has shown that AI products are perceived differently, particularly in terms of perceived risk and complexity (Chakravorti, 2024). In an eWOM environment, it could be that eWOM valence has a stronger effect on AI products than on non-AI products. Due to the existing synergistic effect between eWOM volume and eWOM valence in the literature, a consistently high eWOM volume is maintained throughout the study under all conditions (Kordrostami et al., 2021). This approach examines eWOM valence in a high-volume environment, whereby it is assumed that the effect of review valence is further strengthened. However, for reasons of complexity and feasibility, eWOM volume is not considered as a stand-alone variable in this study.

The following framework (Figure 1) is intended to illustrate the relationships between the variables discussed above and to show the relationship between review valence, review volume, trust and adoption. The precise research design is presented in the Methodology in Chapter 3.

**Figure 1:** Theoretical Framework




# 3 Methodology

## 3.1 Literature Review Approach

The literature used in this study was selected through a structured process consisting of several steps. This forms the foundation of this study. These steps include an initial investigation of the key concepts of Electronic Word of Mouth and AI adoption, which helped develop an overarching understanding. Based on this, the most relevant search terms were identified, including: Electronic Word of Mouth, Review Valence, Review Volume, Trust in AI and AI adoption. To build a solid literature base, ScienceDirect and JSTOR were used as sources in addition to Google Scholar. Care was taken to ensure that the literature was comprised peer-reviewed articles. With the help of forward and backward citation tracking and the snowball system, both current and longer-standing basic literature was identified (Jalali & Wohlin, 2012). Finally, the literature was systematically categorized and documented to enable a structured analysis of the topic.Through this process, approximately 250 papers were identified, which were screened based on relevance, research area, publication date (1955-2024), and journal quality. The SJR Journal Ranking was used as a quality check, with over 90 percent of the papers used published in a Q1-ranked journal. After further analysis, 146 sources were ultimately included in this study. The focus of the selected literature was on eWOM dynamics, consumer trust in AI and technology adaptation models.

### 3.2 Empirical Study

Based on the literature review, a quantitative study design is used in this research. The goal of this study is to find a causal relationship between the effect of social proof in the form of eWOM on the adoption of AI-driven chatbots as the dependent variable (DV). Specifically, the study focuses on eWOM valence (positive vs. negative) combined with high eWOM volume (high volume of reviews) as an independent variable (IV). This means that participants are either exposed to positive eWOM with high volume or negative eWOM with high volume via the chatbot. This design should make it possible to isolate social proof as a key mechanism and thus determine the effect of the intention to adopt to the chatbot. The joint consideration of valence and volume is based on the previously established synergistic effects of the two and should enable a holistic view (Kordrostami et al., 2021).

Trust acts as a mediator variable (MEV) between eWOM and AI-based chatbots. The MEV is used to observe if there is an indirect effect of the IV on the DV, thus monitoring the causality between the two (MacKinnon et al., 2007). Trust was chosen as a key variable between system properties and reliance on automation as a mediator due to its widespread recognition (Chancey et al., 2015).

Additionally, product type (AI-powered chatbot vs. non-AI note-taking app) was selected as a moderator (MOV). This MOV is helpful to analyze whether the influence of trust on the adoption intention differs for AI and non-AI products. By including the MOV, it is possible to determine whether AI-based products respond more strongly to eWOM than non-AI products.
Combining all these variables, a causal moderated mediation model, where eWOM valence acts as IV, trust as MEV, product type as MOV, and finally adoption intention as DV was obtained (Qin & Wang, 2024).

### 3.2.1 Experimental Design

The study design follows a 2×2 between-subjects factorial design with one independent variable (IV) and one moderator variable (MOV) (Healing & Prion, 2020). First, eWOM valence (positive vs. negative online reviews) serves as the IV, and second, product type (an AI-based chatbot and a note-taking app) serves as the MOV and the respective control group.
Both product groups were presented with either a positive (4.5-star rating) or negative (1.5-star rating) review valence; for realism, neither was exclusively positive or negative. The review volume was kept consistently high across all groups at 3,249 reviews each to avoid possible distortions due to different numbers of reviews.

To ensure a neutral evaluation and to avoid biased sources of error, both treatment levels for the product type were fictitious (Park & Lee, 2009). The interfaces were manipulated using Microsoft PowerPoint. This should help isolate the effect of eWOM valence and trust-building without prior brand knowledge influencing the results. Previous studies have shown that brand familiarity can have a significant impact on the intention to adopt and the associated trust (Gulati, 1995; Zhou et al., 2024).

Furthermore, both product types were labeled as free, including in-app purchases, to avoid price as a possible reason for distortion. In addition, chatbots are usually associated with freemium pricing models (Goshal, 2024). WorkSmart, an AI-based chatbot, was created as an AI treatment condition. A chatbot was chosen because it is already one of the most important applications in the field of AI (Hou et al., 2020). The focus was on increasing productivity, especially for students and employees, as this is one of the main areas of application for commercial chatbots (Noy & Zhang, 2023). Deliberately, no AI in a highly specialized field such as medicine or finance was chosen to ensure accessibility and comprehensibility for a broad mass.
As a control group, a note-taking app was created under the fictitious name EasyNote. This was chosen primarily to create a neutral, non-AI-based, functionally different product that can also be assigned to the productivity category.

Both WorkSmart and EasyNote are designed to appeal to a similar target audience, which consists primarily of students, professionals and researchers. This is to ensure that the observed effects are not due to product categories, but to AI vs. non-AI.

To create a realistic scenario, the Apple App Store was chosen as the presentation medium. With over eight hundred thousand rated apps, the Apple App Store, along with the Google Play Store, is one of the most highly frequented and most used app stores worldwide (42matters, 2025). This choice created an identical environment for both product types in which it was possible to manipulate the effect of eWOM.

### 3.2.2 Study Procedure & Measurements

The structure and the associated measurements are presented (Appendix 1, Appendix 2).
The study starts with the explanation of the purpose of the study, how long the expected processing time is and the clarification of the voluntary nature of the study. After the consent had been explained, the participants were asked about their usage behavior with AI-based products in order to check for familiarity. This was tested using the adapted Frequency Scale for Technology Use by Rosen et al. (2013). Then the study participants were randomly assigned to one of the four experimental conditions. They were asked to imagine that they were thinking about using an AI-based chatbot. Each condition was shown the manipulated app store page and either the AI-based chatbot, WorkSmart, or the note-taking app EasyNote. Each product group contained either positive eWOM valence at a rating of 4.5 stars or negative eWOM valence at a rating of 1.5 stars, while eWOM volume was held constant. The purpose of these manipulation checks was to see how participants perceived eWOM valence combined with high volume, so the synergistic effect of eWOM valence and volume. These manipulation checks were adapted from Kane & Barabas (2019) and serve to see if the manipulation of the variable of the participants' perception and how it is perceived. All of the following measurements, except demographics, were evaluated using a 7-point Likert scale. This ranges from 1 “Strongly Disagree” or “very negative” to 7 “Strongly Agree” or “very positive”. According to Finstad (2010), the 7-point Likert scale provides the most accurate results for electronic studies that cannot be monitored further. After the participants had evaluated their perception of eWOM valence and volume, they were asked about their trust in the previously presented AI-based chatbot WorkSmart. The measurement of MEV, trust in AI products, was initially adapted from Koufaris & Hampton-Sosa (2004) and adapted accordingly. Based on the trust evaluation, the measurement of the adoption intention of the respective product treatment presented followed. For this, the Adoption Intention Scale by Hong & Tam (2006) was adapted. This is originally based on the already discussed TAM by Davis & Bagozzi (1989) and the associated intent of use. Participants were asked about the likelihood of using the presented product in the future. Before

the demographics, the participants were also asked about their general trust in online reviews. For this purpose, the Factor Analysis of trust in eWOM source by Zainal et al. (2017) was adapted. This was to measure the participants' pre-existing trust in eWOM to determine if there were potential variations in how participants perceive eWOM. This measure was used as a control variable. In addition, an attention check was built in to detect and filter out inactive or inattentive participants (Abbey & Meloy, 2017). Finally, the participants were asked about their demographics. These included age, gender, nationality, education level and occupation.
The survey structure and response format were identical for all participants, except for an adapted product description, depending on the AI-based chatbot and note-taking app and the corresponding adoption in the questions (Appendix 1). Keeping all variables constant ensured that differences in responses were related to the different treatment levels, such as product type and eWOM valence, and not to external influences of the survey format.

### 3.2.3 Data Collection and Participant Recruitment

The three primary sources for the survey responses were personal networks such as friends and family, academic research platforms, and student participants. Prolific was chosen as the research platform because it is a platform that specializes in providing researchers with quick and reliable answers (Palan & Schitter, 2018). The study by Douglas et al. (2023) showed that participants on Prolific provide significantly more precise, well-thought-out answers compared to other research platforms such as MTurk. To ensure high data quality, various screening filters were applied. First, participants had to have a minimum approval rate of 95%, meaning that they had to have successfully completed at least 95% of the last studies without rejection. This ensured that only reliable participants were recruited. Furthermore, participants had to have completed at least five studies on Prolific, which ensured that they were familiar with the website interface. It was also stated that they had to be fluent in English, since the study design was in English. This was to ensure that misunderstandings were avoided. In order to avoid geographical bias, no country-specific filters were applied. As part of this study, Prolific participants received a payment of 55 cents for their participation. This compensation rate was chosen based on Prolific's recommendation to maintain a fair payment ratio. A total of 343 participants were recruited through this combination of sources.

# 4 Results

## 4.1 Data Cleaning and final sample

The unadjusted sample (*n*) included 343 participants. In order to obtain reliable results of high quality, the data had to be cleaned before the comprehensive analysis. In the first step of the data cleansing, 4 participants were excluded who did not pass the attention check (1.16% of the total sample). In addition, three participants were removed from the study due to missing values (.875% of the total sample). While this part was still being carried out in Qualtrics, the rest of the data cleansing and analysis was carried out using IBM SPSS Statistics 30, which is a widely used software for statistical analysis and data management. This identified 10 (2.9% of the total sample) outliers based on the z-score. The standardized threshold value here is $|z| > 3.29$. This threshold is subject to a significance level of $p < .001$. This means that approximately 99.9% of z-scores are between -3.29 and + 3.29. All values above this value are considered outliers. After careful consideration, the identified outliers were removed from the data set to ensure that the statistical analysis and the integrity of the analyzed relationships were maintained.

Including the corrections, the final sample consisted of 326 participants, of whom 48.5% were men, 49.4% were women, and 2.1% other. The participants were on average 31 years old, of whom 34% were from South Africa, 11% from Poland, 9% from Portugal and 5.8% from Germany. A total of 48 different nationalities were represented among the participants. The highest level of education was on average a bachelor's degree with 47.5% and employed full-time was the most frequently given answer for occupation with 48.8% (Appendix 3). The questions about the use of AI showed that the participants used AI-based products on average once a week. The same applied to the group of digital productivity apps.

## 4.2 Descriptive Statistics

The following is a brief description of the most important descriptive statistics and bivariate statistics. The frequency of use for AI and digital productivity apps was analyzed to see if prior exposure influenced trust and adoption intention. The participants reported an average level of trust ($M = 4.41$, $SD = 1.80$) and an adoption intention of ($M = 3.87$, $SD = 1.96$). To gain more detailed insights, trust and adoption intent were examined, Table 1 shows a graphical representation. It was shown that trust and adoption intention were significantly higher in the positive eWOM condition than in the negative one. Trust and adoption intention were slightly lower for AI products compared to non-AI products, but these differences were not statistically significant. These results support the assumption that positive eWOM increases the adoption intention. This will be examined in more detail below.

**Table 1:** Descriptive Statistics

*Trust Adoption * eWOM_Val*

| eWOM_Val | | Trust | Adoption |
|---|---|---|---|
| Negative | Mean | 3.1524 | 2.6706 |
| | N | 168 | 168 |
| | Std. Deviation | 1.57955 | 1.81734 |
| Positive | Mean | 5.7392 | 5.1456 |
| | N | 158 | 158 |
| | Std. Deviation | .78674 | 1.13706 |
| Total | Mean | 4.4061 | 3.8701 |
| | N | 326 | 326 |
| | Std. Deviation | 1.80487 | 1.96373 |

*Trust Adoption * ProdType*

| ProdType | | Trust | Adoption |
|---|---|---|---|
| Non-AI | Mean | 4.5481 | 3.9815 |
| | N | 162 | 162 |
| | Std. Deviation | 1.80277 | 1.94977 |
| AI | Mean | 4.2659 | 3.7602 |
| | N | 164 | 164 |
| | Std. Deviation | 1.80145 | 1.97722 |
| Total | Mean | 4.4061 | 3.8701 |
| | N | 326 | 326 |
| | Std. Deviation | 1.80487 | 1.96373 |

Table 2 shows the frequency of use of AI-related products. The most frequently reported categories were “Every Day” (31.1%) and “Several Times per Week” (32.9%), which shows that a majority of participants deal with AI-based technology on a regular basis.

**Table 2:** Usage Frequency AI-based products

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Every Day | 56 | 17.2 | 34.1 | 34.1 |
| | Several Times per week | 54 | 16.6 | 32.9 | 67.1 |
| | Once per Week | 11 | 3.4 | 6.7 | 73.8 |
| | Several times per month | 22 | 6.7 | 13.4 | 87.2 |
| | Once per month | 9 | 2.8 | 5.5 | 92.7 |
| | Several times per year | 6 | 1.8 | 3.7 | 96.3 |
| | Once per year | 3 | .9 | 1.8 | 98.2 |
| | Never | 3 | .9 | 1.8 | 100.0 |
| | Total | 164 | 50.3 | 100.0 | |
| Missing | System | 162 | 49.7 | | |
| Total | | 326 | 100.0 | | |

Table 3 shows a very similar picture for the use of digital productivity apps. Most responses were for “Every Day” (34.6%) and “Several Times per Week” (34.6%).

**Table 3:** Usage Frequency digital productivity apps

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Every Day | 56 | 17.2 | 34.6 | 34.6 |
| | Several Times per week | 56 | 17.2 | 34.6 | 69.1 |
| | Once per Week | 8 | 2.5 | 4.9 | 74.1 |
| | Several times per month | 14 | 4.3 | 8.6 | 82.7 |
| | Once per month | 6 | 1.8 | 3.7 | 86.4 |
| | Several times per year | 9 | 2.8 | 5.6 | 92.0 |
| | Once per year | 1 | .3 | .6 | 92.6 |
| | Never | 12 | 3.7 | 7.4 | 100.0 |
| | Total | 162 | 49.7 | 100.0 | |
| Missing | System | 164 | 50.3 | | |
| Total | | 326 | 100.0 | | |

To see if the usage frequencies differ significantly from each other, a Mann-Whitney U test was performed. The results indicated that the two groups do not differ significantly ($U = 13190.5$, $Z = -0.115$, $p = .909$). This suggests that prior exposure to AI-based products does not significantly differ from their experience with digital productivity apps.

Table 4 shows the relationships between key variables of this study, Pearson correlations were conducted as all variables were treated as continuous and approximately normally distributed.

**Table 4:** Pearson Correlation Matrix for Key Variables

| | | Trust | eWOM_Val | ProdType | Adoption |
|---|---|---|---|---|---|
| Trust | Pearson Correlation | -- | | | |
| | N | 326 | | | |
| eWOM_Val | Pearson Correlation | .717** | -- | | |
| | Sig. (2-tailed) | <.001 | | | |
| | N | 326 | 326 | | |
| ProdType | Pearson Correlation | -.078 | .006 | -- | |
| | Sig. (2-tailed) | .158 | .909 | | |
| | N | 326 | 326 | 326 | |
| Adoption | Pearson Correlation | .917** | .631** | -.056 | -- |
| | Sig. (2-tailed) | <.001 | <.001 | .310 | |
| | N | 326 | 326 | 326 | 326 |

**. Correlation is significant at the 0.01 level (2-tailed).

### 4.3 Scale Reliability and Manipulation Checks

After cleaning the data and including the final sample, internal consistency was measured. Although the measures are based on validated scales, they have been adapted and therefore require re-evaluation (Koufaris & Hampton-Sosa, 2004; Hong & Tam, 2006; Davis & Bagozzi, 1989). In order to evaluate internal consistency, Cronbach's alpha ($\alpha$) was applied in this study. This is a widely established procedure that provides a reliability coefficient that measures how well a series of items measure a single construct (Gliem & Gliem, 2003). Cronbach's alpha ranges between 0 and 1, with higher values indicating better internal consistency. A value above .9 indicates excellent reliability, values between .8 and.9 indicate very good reliability, and values above.7 are acceptable.

The reliability analysis in this study shows excellent internal consistency for the trust scale, with Cronbach's alpha ranging from .913 to.960 across all conditions. Cronbach's alpha for the adaptation intention scale also ranging from .882 to .970 across all conditions, which confirms robust reliability.

To test the effectiveness of the eWOM valence manipulation, two separate one-way analyses of variance (ANOVAs) were conducted with perceived valence and impression as variables. The independence of observations was ensured by randomly assigning participants to the experimental conditions. The homogeneity of the variances was violated according to the significant Levene test (all $p < .05$), for this reason the welch test was additionally carried out. The ANOVA remains robust for all violations of normality and homogeneity, due to the large central size that significantly exceeds $n > 30$.

For the AI products, it was shown that participants in the positive eWOM condition rated them significantly higher ($M = 5.76$, $SD = 1.02$) than those randomly assigned to the negative condition ($M = 2.17$, $SD = 1.65$), $F(1,162) = 278.53$, $p <. 001$, Welch test $p < . 001$. The same applies to the impressions; significantly higher impressions were measured in the positive eWOM group ($M = 5.98$, $SD = 0.86$) compared to the negative eWOM group ($M = 2.60$, $SD = 1.58$), $F(1,162) = 284.86$, $p <. 001$, Welch test $p < .001$.

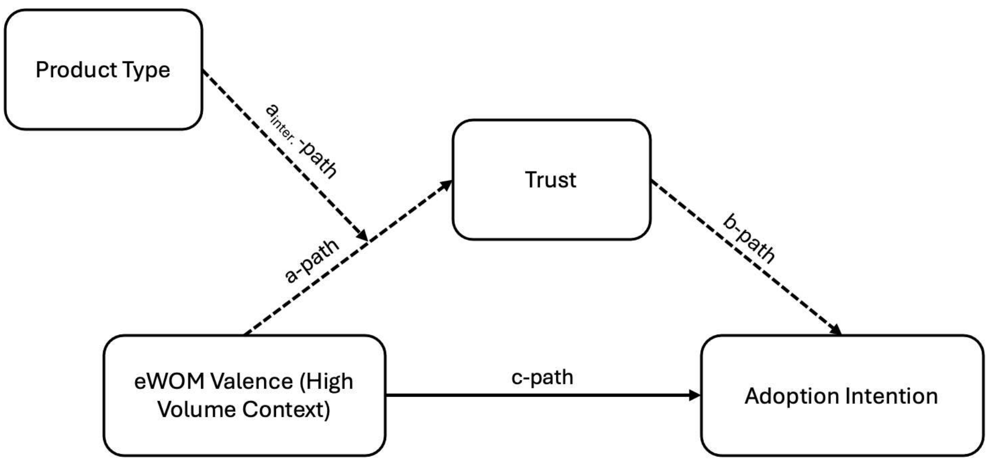
For the non-AI products, a very similar picture emerges: the positive eWOM condition also led to significantly higher valence ratings ($M = 5.99$, $SD = 0.92$) compared to the negative condition

($M = 3.05$, $SD = 2.01$), $F(1,160) = 140.21$, $p <. 001$, Welch test $p < .001$. The impression ratings were also significantly higher for the positive condition (M = 6.08, SD = 0.82) compared to the negative condition ($M = 2.85$, SD = 2.11), $F(1,160) = 160.71$, $p < .001$, Welch test $p < . 001$. These aggregate results confirm that the manipulation of the IV eWOM valence was successful.

### 4.4 Hypothesis Testing

A causal moderated mediation analysis was conducted in this study to test whether trust mediates the effect of eWOM valence (positive vs. negative) on adoption intention, while it is moderated by product type (AI vs. non-AI). For this purpose, PROCESS Version 4.2 was used. PROCESS is a statistical tool developed by Hayes (2018) that facilitates mediation, moderation, and conditional processes (mediated mediation) in SPSS, R, and SAS. For this study, PROCESS MODEL 7 was chosen because it measures exactly our desired moderated meditation model (Chapter 3.2). PROCESS MODEL 7 (Figure 2) is based on three central paths, which were adapted according to the variables in this study (Hayes, 2018). First, the a-path: The influence of eWOM Valence (X) on Trust (M), whereby this effect is moderated by the product type (W). Second, the b-path: This measures the direct influence of the mediator Trust (M) on the adoption intention (Y). And third, the c-path: The direct effect of eWOM Valence on the adoption intention.

**Figure 2:** PROCESS Model 7 adapted by Hayes (2018)




Before the moderated mediation analysis could be conducted, the relevant assumptions for this model had to be checked. These include linearity, homoscedasticity, and normality of residuals. Based on the scatterplot, a positive linear relationship between trust (mediator) and adoption intention (dependent variable) could be found in the b-path, confirming the assumption of linearity (Appendix 4). Due to the categorical nature of the predictors in the other two paths, the assumption of linearity was made and did not need to be further examined.

Based on the Breusch-Pagan test, homoscedasticity could be examined separately for the individual paths. The Breusch-Pagan test for the a-path, eWOM valence, product type, and their interaction on trust, showed no significant heteroscedasticity ($F(3,322) = 0.374$, $p = .772$). Thus, the assumption of homoscedasticity was met. The Breusch-Pagan test for the b-path, Trust to adoption intention showed significant heteroscedasticity ($F(1,324) = 10.415$, $p = .001$). This is a violation of trust and means that the variance of residuals varies systematically with the level of trust. The results of this path should be considered with caution. For the c-path, no significant heteroscedasticity was found either ($F(2,323) = 2.067$, $p = .128$). Thus, the assumption of homoscedasticity was also met here.In general, it can be said that homoscedasticity was largely adhered to, except for the b-path. In the following moderated mediation analysis, this should be remedied after model 7 with the help of robust estimation techniques, such as the bootstrap confidence intervals (Hayes, 2018). Inspection of the residuals indicated that the assumption of normality was sufficiently met. The histogram of the residuals appeared symmetrical, and the normal P–P plot showed close adherence to the diagonal line, supporting the assumption of normality (Appendix 5). Minimal deviations were negligible, given the large sample size ($n$ = 326), in line with the central limit theorem.

After all assumptions of the moderated mediation model were tested, robust standard errors (HC3 estimator) and bootstrap sampling (5,000 samples) were used to ensure that there were no violations of the assumptions. The analysis was performed with and without covariates and showed that there were no substantial differences.

For the c-path in the Process Model 7 analysis, i.e. the direct effect of the eWOM valence (IV) on the adoption intention (DV), no significant effect could be determined ($b$ = -.22, $SE$ = .13, $p = .081$). However, the two-way ANOVA showed that valence has a significant effect on adoption intention (F(1,322) = 214.680, p < .001). Thus $H_1$ was supported, the ANOVA analysis confirmed that eWOM valence significantly influences adoption intention. However eWOM valence is fully mediated by trust in the moderated mediation model, highlighting its central role in the adoption process.

The a-path showed that eWOM valence is significantly influenced by trust ($b = 2.59$, $SE = .14$, $p < .001$). This confirms the assumption that positive reviews lead to higher trust. Furthermore, trust significantly predicted the intention to adopt ($b = 1.04$, $SE = .03$, $p < .001$), meaning that more trust leads to a higher probability of adopting the product (b-path). The indirect effect of eWOM valence on adoption mediated by trust was significant at both levels of product type (low: $b = 2.64$, 95% *CI* [2.24, 3.05]; high: $b = 2.75$, 95% *CI* [2.36, 3.11]). The effect of the AI-based chatbot group was slightly higher, but not high enough to be significant. Because the direct effect, i.e., the c-path, was not significant when accounting for trust, this study confirms full mediation by trust, which strongly supports $H_2$.

The product type, i.e., AI vs. non-AI, was not a significant moderator between eWOM valence and trust ($b = .101$, $SE = .274$, $p = .713$). Indicating that the effect of eWOM valence on trust does not differ significantly between AI and non-AI products. The moderated mediation index was also not significant ($b = .1052$, 95% *CI* [-.4607, .6569]). This implies that the product type does not significantly influence the mediation effect. As a result, $H_3$ is not supported and eWOM does not affect trust differently for an AI-based chatbot than for a non-AI productivity app.

The inclusion of demographic covariates did not alter the main effect of this study and the results remained stable, which demonstrates that the observed effects are robust and not influenced by additional variables. None of the covariates included in the model were statistically significant. The model explained 52.17% of the variance in Trust ($R^2 = .5217$) and 84.34% of the variance in Adoption ($R^2 = .8434$), indicating strong explanatory power.

In summary, $H_1$ was supported by the ANOVA analysis, which suggests that when trust was not included in the model, eWOM valence significantly influenced adoption intention. In the moderated mediation model, however, this direct effect was no longer significant. This implies that trust is a full mediator. This brings us to the next hypothesis, $H_2$ was strongly supported, confirming that trust fully mediates the effect of eWOM valence on adoption intention. $H_3$ is not supported because product type does not significantly affect the effect of eWOM valence on either trust or adoption intention.

# 5 Discussion

## 5.1 Interpretation of Results

The results of this study support and reinforce the findings of existing theories on eWOM, consumer trust and technology adoption. Based on the research questions and consistent with the existing literature, it was confirmed that positive eWOM acts as a strong form of social proof that reduces consumer uncertainty and increases product adoption intention. This effect seems to be particularly strong for new products that are also associated with a higher risk. Previous studies have shown that online reviews have a particularly strong effect on products where performance is unclear in advance. In these cases, consumers are more dependent on eWOM in their decision-making. Babić Rosario et al. (2016) showed in their study that the influence of eWOM is stronger for new products than for longer established ones, while Ho-Dac et al. (2013) demostrated that consumers rely more heavily on the opinions of others when product performance is uncertain. This study focused on AI-powered chatbots, as AI services tend to be highly complex and relatively new. Thus, consumers use feedback from others as an effective source to learn about quality and usefulness. These findings suggest that social influence in the form of eWOM is a robust phenomenon that can be extended from traditional products to AI-based products.

It has been shown that trust is particularly important for consumers when it comes to adopting new technologies, and eWOM serves as a key mechanism for generating trust in the online environment. The results in this study support the positive effect of eWOM on trust.

This study tested whether a high volume of positive eWOM valence would directly increase consumers' adoption intentions. The ANOVA, which did not include trust as a mediator, showed that eWOM valence significantly influences the adoption intention. These study results align with previous studies that positive review valence alone promotes the consumer purchase decision (You et al., 2015). Thus, $H_1$ was supported by the results showing that eWOM valence significantly influences adoption. However, the moderated mediation model shows that this effect primarily operates through trust in the decision-making process, leading to the next Hypothesis.

Trust was examined as a mediator, and the strongest results were found here. The study confirmed that trust in the AI-powered chatbot mediates the overall effect of eWOM valence on adoption intention. Exposure to a large number of positive reviews significantly increased the consumer's trust in the chatbot, and this increased trust then also led to a higher adoption probability, which is consistent with $H_2$. This result is consistent with previous findings that positive eWOM signals reliability and quality (Chapter 2), thereby strengthening trust in the product. According to the previously discussed Trust Transfer Theory, the positive sentiment of the user reviews is transferred to the brand or product, further reinforcing trust (Haq et al., 2024). The data from this study supports these findings; participants who were exposed to the positive reviews showed significantly greater trust in the AI-based chatbot and a greater desire to use the chatbot in the future. These results underscore the critical relevance of trust in consumer decision-making.

Trust is a well-established mechanism to reduce uncertainty, and here positive eWOM works to reduce uncertainty by demonstrating social proof. If many others rate the chatbot positively, it signals that the system is trustworthy. The results confirm eWOM builds trust, and thus trust is the key factor through which online reviews influence adoption intentions.

In this study, product type was proposed as a moderator to examine whether the effect of eWOM valence differs between an AI-driven product and a non-AI product. The assumption based on $H_3$ is that the product type moderates the influence of product reviews. AI products are associated with greater uncertainty or the described black-box problem (Chakravorti, 2024). The assumption was that positive eWOM would be particularly critical to building trust in AI products at this point, or conversely that consumers would be particularly critical. However, this study showed that there was no significant moderation by product type. Participants thus reacted similarly to eWOM, regardless of whether it was an AI product or not. These results were unexpected due to the identified uncertainties and the relevance for trust. One possible explanation is that social proof with a high volume of positive reviews already had a high level of credibility that was strong enough to overcome initial biases for both product types. The consistently high volume of reviews may have ensured that both the AI-based chatbot and the productivity app were accepted and seemed reliable. Another explanation could be that the non-AI product, i.e., the productivity app, is also an unknown digital service, which, like other novel software, requires trust and user feedback to promote adoption. By designing both as novel tech products, eWOM acted as a crucial trust builder in both cases. While previous literature has identified differences in the perception of eWOM in relation to product characteristics, this study found no significant differences between AI and non-AI products. In general, slightly less trust was observed in AI products, which is consistent with previous literature, but the product type did not act as a significant moderator of eWOM effects. This means that *$H_3$* was not supported. The results show that the mechanism of eWOM via trust on adoption for various product types was robust, and that AI products do not significantly increase the influence of social proof.

## 5.2 Theoretical Implications

The discussed results provide insights into eWOM, trust, and AI product adoption. Trust is a crucial factor that links social influence and consumer behavior. This is consistent with decades of research showing that trust significantly influences consumers' risk perception and can promote the adoption of new products. In the specific context of the AI literature, which has gained significant relevance in the 2020s, uncertainties can slow down the adoption of AI products. This study shows that trust, once established via eWOM, can effectively contribute to adoption intentions. This provides important empirical evidence that confirms the findings in the literature that trust is a crucial element in AI adoption.

Furthermore, this study contributes to the existing theories and literature on social proof and eWOM. It is shown that a high volume of positive reviews increases trust and then adoption intention, aligning with the principle of social proof (Cialdini, 2009). Previous literature, suggested that if many others have previously adopted an AI-based system, it signals trustworthiness, reduces perceived risk and translates into individual trust. This study confirms that this mechanism works equally well for AI products and non-AI products, which suggests that the influence of eWOM is generalizable across different product types. Consumers may use the same cognitive shortcuts to make decisions about AI as they do about other digital products. This is an important theoretical contribution, as it demostrates that existing eWOM theories, such as trust transfer and social proof, also apply to AI products. Thus, this study adresses an important research gap in understanding the context of how eWOM affects AI adoption. This study is one of the first to show that positive eWOM can influence consumer uncertainty and positively impact the adoption intention of AI products.

## 5.3 Practical Implications

In addition to the theoretical implications, this study also offers some important insights for AI companies and marketers on how to increase both consumer trust and the intention to adopt.

Based on the results, companies should be proactive in creating satisfied consumers, but they should also pay particular attention to ensuring that satisfied consumers share their positive opinions in the form of online reviews. This study has shown that positive eWOM significantly increases trust in AI products, which in turn increases the intention to adopt them. By highlighting positive feedback on their website, for example by displaying positive reviews more prominently in advertising or by presenting a success story that a customer has had with the product, companies can strengthen trust and reduce the concerns of potential consumers. Since trust mediates the overall effect of eWOM in this study, it is all the more important for companies that consumers trust the application.

Due the synergistic effect of eWOM valence and volume, the quantity of reviews also plays a crucial role in activating social proof mechanisms. Showing that many others have already tried the product and are satisfied with it demonstrates, through social proof, that the product is widely accepted. Companies should encourage as many consumers as possible to leave reviews, as higher review volume enhances credibility and consumer trust.

For the reason that trust is crucial for AI products and was measured slightly lower than for non-AI products, AI companies should be all the more careful to break down trust barriers that arise from intransparency or complexity. This was not tested in this work, but taking more account of privacy concerns, for example by underpinning increased data privacy safeguards and performance and decision-making of AI products, could help to reduce uncertainty and strengthen trust in addition to eWOM.

## 5.4 Limitations and Future Research

Despite the important informal findings of this study, some limitations have also emerged that need to be considered.

This study did not explicitly include the possibility that some of the reviews shown could be fake reviews or reviews that were not written on the author's own initiative. This is an important point, as the presence of fake reviews can have a significant effect on the perception and trust of eWOM (Genc-Nayebi & Nayebi, 2017). And conversely, this also applies to the adoption of AI-based chatbots. The literature shows that, regardless of the platform, a significant proportion of reviews are classified as fake (Martens & Maalej, 2019; Luca & Zervas, 2019). According to Martens & Maalej (2019), almost one-third of all app store reviews are fake. And according to Luca & Zervas (2016), one in five reviews on Yelp is also identified as fake. If the study participants unknowingly came into contact with fake reviews in advance of the study, it could change their perception of the reviews. In the real world, consumers might become suspicious if they were exposed to fake reviews, which could potentially have a moderating effect on the influence of eWOM. Future research could aim to control for participant's awareness of fake reviews. The results of the study were interpreted in the light of the fact that the effect of eWOM is based on honesty.

Another important limitation of this study is the high market concentration in the AI sector. This was not examined in detail in this work for reasons of focus, but it could distort the participants' perception. According to van der Vlist et al. (2024), the AI market is dominated by a few large companies such as OpenAI, Google or Microsoft, and many smaller, independent AI apps are mostly dependent on the cloud infrastructures or APIs of these companies. The industrialization of AI could influence user trust and affect adoption in ways that are not explicitly considered in this study in isolation. For example, if users know or assume that a new AI-based chatbot is based on a well-known AI system, they may be more willing to trust and adopt it. Vice versa, if a small company were to launch an AI-based chatbot, consumers might be more cautious or skeptical and wait for a solution from the leading AI companies. This study did not test for the difference between a chatbot from a Bigtech company and a startup. Thus, one limitation could be that the eWOM effect is distorted in this vacuum. Outside of the study design, it could be that the high degree of trust in a company may oberride the overall effect of eWOM. Previous studies have shown that pre-existing trust in a company also influences purchasing decisions (Nosi et al., 2022). Future studies could examine whether there are significant differences between established AI companies and their products and novel AI startups and their associated products. This would show whether a strong brand would also strengthen the effect of eWOM in the AI context or perhaps even reduce it. Addressing this would help to educate about external trust factors.

Finally, while the relevance of the freemium pricing model in the context of AI-based chatbots was mentioned in this study; price was not explicitly included as a variable in the model. The pricing model could have a significant influence that is not fully understood. Firstly, because the app is free, the adoption rate in this study could be generally high, so a kind of ceiling effect could occur (Wang et al., 2008). This means that the results could be conservative. In a scenario where you have to pay for the app immediately, positive eWOM could be all the more important when it comes to spending money. Likewise, negative eWOM might be an even bigger obstacle when money is involved. In addition to the above, trust might be related to pricing, so offering a freemium version might contribute to distrust, especially with regard to data privacy (Schreiner & Hess, 2015). This study does not include price information for reasons of complexity, so it is not possible to see how adoption would change if a price component were included. I recommend that future research include price, specifically to compare how consumer reviews differ for free and paid AI-services. In particular, by comparing consumer trust and adoption between free and paid AI services.

# 6 Concluison

In summary, this study confirms that eWOM acts as a powerful social proof mechanism that builds trust among consumers and thus strengthens their intention to adopt AI-driven products. This is consistent with established theories about traditional product categories. Positive eWOM valence significantly builds trust and strengthens the adoption intention for AI-driven products. The mediating effect of trust was highly significant and thus crucial. However, trust mediates the full effect of eWOM on the adoption intention. Furthermore, it was found that product type has no moderating effect on eWOM; the participants rated the influence of reviews similarly for the AI and non-AI condition. These results support the notion that trust is crucial to linking social influence and technology adoption. This study contributes to the existing literature by showing that even new AI-based products, online reviews effectively build trust and thus promote adoption, addressing an important research gap. In practice, this work is particularly relevant for AI companies and marketers, who should actively encourage consumers to write positive reviews and showcase them more prominently to increase consumer trust and reduce uncertainty. Finally, future research should focus more on how the established nature of the AI product affects trust and the intention to adopt. In addition, further research into the pricing model for AI products would be interesting to see how it behaves in the eWOM-trust-adoption relationship.

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# Appendix

## Appendix 1: Survey Flow

Standard: Introduction (1 Question)

BlockRandomizer: 1 - Evenly Present Elements

Group: Group 1

Standard: AI-Usage (1 Question)
Standard: Introduction Situation (1 Question)
Standard: Introduction Chatbot Group 1 Low AI (2 Questions)
Block: Review Valence and Volume Group 1 Low AI (5 Questions)
Standard: Trust in AI-Powered Products (5 Questions)
Standard: AI Adoption Intention (4 Questions)

Group: Group 2

Standard: AI-Usage (1 Question)
Standard: Introduction Situation (1 Question)
Standard: Introduction Chatbot Group 2 High AI (2 Questions)
Block: Review Valence and Volume Group 2 (5 Questions)
Standard: Cognitive Trust in AI-Powered Products 2 (5 Questions)
Standard: AI Adoption Intention 2 (4 Questions)

Group: Group 3

Standard: Digital Product Usage (1 Question)
Standard: Introduction Situation Notes (1 Question)
Standard: Introduction Group 3 Notes Low (2 Questions)
Standard: Review Valence and Volume Group 3 (5 Questions)
Standard: Cognitive Trust in Digital Products (5 Questions)
Standard: Digital Product Adoption intention (4 Questions)

Group: Group 4

Standard: Digital Product Usage 2 (1 Question)
Standard: Introduction Situation Notes 2 (1 Question)
Standard: Introduction Group 4 High (2 Questions)
Standard: Review Valence and Volume Group 4 (5 Questions)
Standard: Trust in Digital Products 2 (5 Questions)
Standard: Digital Product Adoption intention 2 (4 Questions)

Standard: Trust in eWOM (3 Questions)
Block: Demographics (5 Questions)

Branch: New Branch
If
If PROLIFIC_PID Is Not Empty

EndSurvey: Advanced

Branch: New Branch
If
If PROLIFIC_PID Is Empty

EndSurvey: Advanced

## Appendix 2: Survey design Exemplary for a group

Start of Block: Introduction

Welcome and thank you for considering participating in this experiment on Social Proof. I, Konrad Schneider am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Professor Filipa de Almeida. The study consists of answering multiple choice questions. And it will take about 3 minutes to complete. The purpose is to gain insight into the effect of digital social proof on the Adoption of Digital-Products. Your participation will contribute to research on Adoption of digital products and Social Proof. Please answer as honestly as possible. All answers will be kept strictly confidentially and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in an aggregated form, never about any individual response. We ask you to take the study in one go, without interruptions. There are no expected side effects of participating in this study beyond those associated with looking at a computer screen for circa 3 minutes. You may change your mind and drop out at any point of the study during its completion. If you have any questions about this study, please email Konrad Schneider (s-koschneider@ucp.pt). By continuing you agree to participate. Thank you!

End of Block: Introduction

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Start of Block: AI-Usage

How often do you use AI-related Products?

- ◯ Every Day
- ◯ Several Times per week
- ◯ Once per Week
- ◯ Several times per month
- ◯ Once per month
- ◯ Several times per year
- ◯ Once per year
- ◯ Never

End of Block: AI-Usage

---

Start of Block: Introduction Situation

Imagine you are browsing the App Store for an AI-powered chatbot, but you are not ready to download one yet. You are scrolling through different options, looking at their ratings, number of reviews, and overall impressions. Even if you have no experience with AI products, imagine you were looking for a chatbot.

End of Block: Introduction Situation

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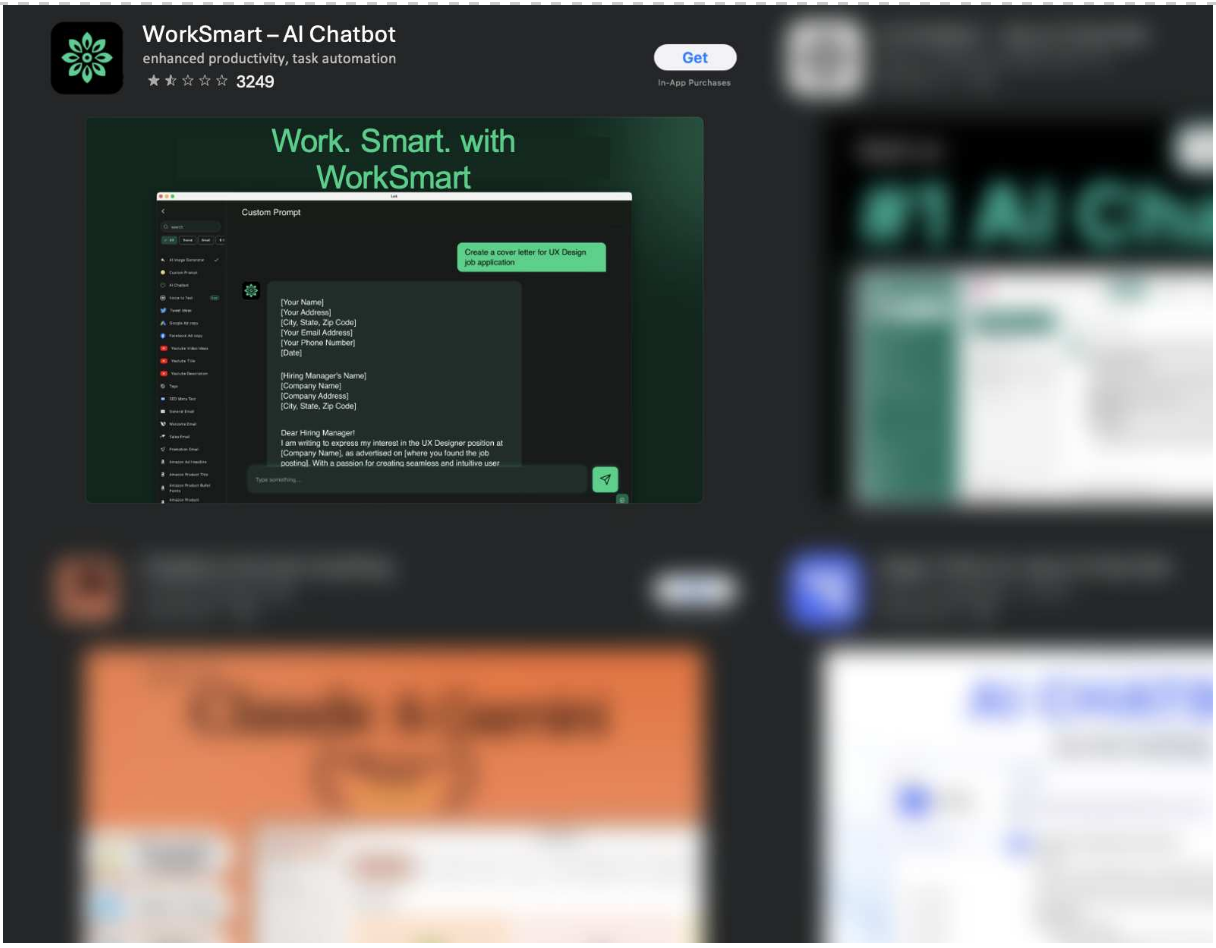
Start of Block: Introduction Chatbot Group 1 Low AI

One of the options you come across is **WorkSmart**, an AI chatbot designed to assist with both work and study tasks.

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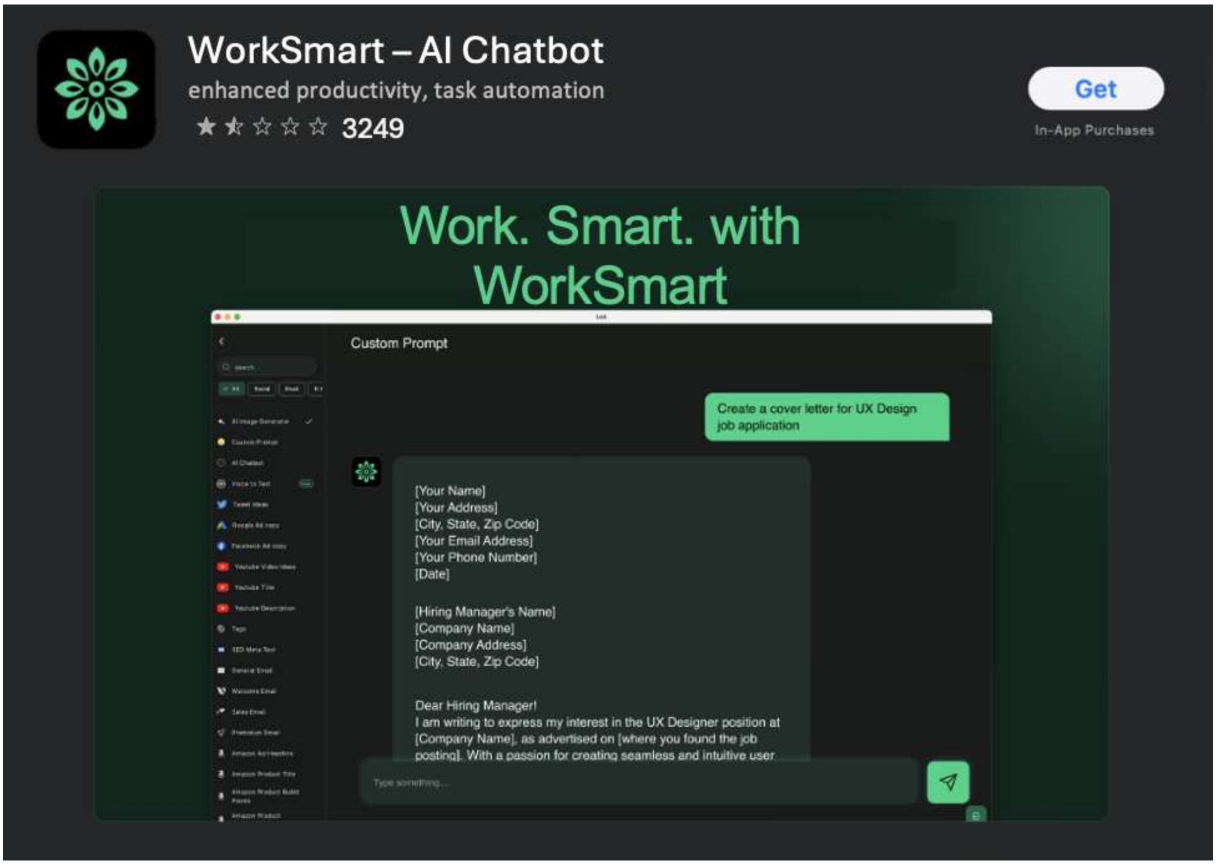
End of Block: Introduction Chatbot Group 1 Low AI

Start of Block: Review Valence and Volume Group 1 Low AI




How do you perceive the star rating of WorkSmart?

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 = Very Negative, 7 = Very Positive | | | | | | | |

The reviews of WorkSmart create a positive impression of the chatbot.

- ○ Strongly disagree
- ○ Disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Agree
- ○ Strongly agree

The number of reviews for WorkSmart appear to be high.

- ○ Strongly disagree
- ○ Disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Agree
- ○ Strongly agree

I trust the overall rating of a product more when it has a high number of reviews compared to when it has only a few.

- ○ Strongly disagree
- ○ Disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Agree
- ○ Strongly agree

**End of Block: Review Valence and Volume Group 1 Low AI**

Start of Block: Trust in AI-Powered Products

Based on the reviews, I believe WorkSmart is trustworthy.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

WorkSmart seems to provide serious and reliable responses.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

I believe that WorkSmart will keep its promises in terms of performance.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

I trust that WorkSmart provides a secure and reliable service.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

Overall, WorkSmart seems to be credible.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

**End of Block: Trust in AI-Powered Products**

**Start of Block: AI Adoption Intention**

I am likely to use WorkSmart in the future.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Agree
- ◯ Strongly agree

If I needed an AI assistant, I would consider WorkSmart first.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Agree
- ◯ Strongly agree

I expect to use WorkSmart frequently in the future.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Agree
- ◯ Strongly agree

To check your attention, please select 'Other' as your answer.

- Label
- Price
- Other

**End of Block: AI Adoption Intention**

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**Start of Block: Trust in eWOM**

I believe reviews where a lot of people say the same thing verify the reliability of the product.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

I believe that most reviewers provide honest reviews of their experience.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

The opinions of others in online reviews are important for my decision to use a product.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Agree
- Strongly agree

**End of Block: Trust in eWOM**

---

**Start of Block: Demographics**

Please indicate your gender

- Male
- Female
- Other
- Prefer not to say

Please indicate your age

________________________________________________________________

What is your nationality?

▼ Afghanistan ... Zimbabwe

What is your highest level of education?

- No formal education
- Primary education
- High school diploma
- Bachelor´s degree
- Master´s degree
- Doctorate
- Prefer not to say

---

What is your occupation?

- Student
- Employed (full-time)
- Employed (part-time)
- Self-employed
- Unemployed
- Retired

End of Block: Demographics

## Appendix 3: Demographics

*Occupation*

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Student | 76 | 23.3 | 23.3 | 23.3 |
| | Employed (full-time) | 159 | 48.8 | 48.8 | 72.1 |
| | Employed (part-time) | 35 | 10.7 | 10.7 | 82.8 |
| | Self-employed | 28 | 8.6 | 8.6 | 91.4 |
| | Unemployed | 19 | 5.8 | 5.8 | 97.2 |
| | Retired | 9 | 2.8 | 2.8 | 100.0 |
| | Total | 326 | 100.0 | 100.0 | |

*Education*

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | No formal education | 1 | .3 | .3 | .3 |
| | Primary education | 3 | .9 | .9 | 1.2 |
| | High school diploma | 83 | 25.5 | 25.5 | 26.7 |
| | Bachelor´s degree | 155 | 47.5 | 47.5 | 74.2 |
| | Master´s degree | 74 | 22.7 | 22.7 | 96.9 |
| | Doctorate | 9 | 2.8 | 2.8 | 99.7 |
| | Prefer not to say | 1 | .3 | .3 | 100.0 |
| | Total | 326 | 100.0 | 100.0 | |

*Nationality*

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Algeria | 1 | .3 | .3 | .3 |
| | Andorra | 1 | .3 | .3 | .6 |
| | Antigua and Barbuda | 1 | .3 | .3 | .9 |
| | Argentina | 1 | .3 | .3 | 1.2 |
| | Austria | 1 | .3 | .3 | 1.5 |
| | Bangladesh | 1 | .3 | .3 | 1.8 |
| | Brazil | 2 | .6 | .6 | 2.5 |
| | Bulgaria | 2 | .6 | .6 | 3.1 |
| | Canada | 8 | 2.5 | 2.5 | 5.5 |
| | Chile | 4 | 1.2 | 1.2 | 6.7 |
| | China | 1 | .3 | .3 | 7.1 |
| | Colombia | 1 | .3 | .3 | 7.4 |
| | Czech Republic | 2 | .6 | .6 | 8.0 |
| | Denmark | 1 | .3 | .3 | 8.3 |
| | Finland | 1 | .3 | .3 | 8.6 |
| | France | 7 | 2.1 | 2.1 | 10.7 |
| | Germany | 19 | 5.8 | 5.8 | 16.6 |
| | Greece | 1 | .3 | .3 | 16.9 |
| | Hungary | 6 | 1.8 | 1.8 | 18.7 |
| | India | 1 | .3 | .3 | 19.0 |
| | Ireland | 1 | .3 | .3 | 19.3 |
| | Israel | 3 | .9 | .9 | 20.2 |
| | Italy | 8 | 2.5 | 2.5 | 22.7 |
| | Japan | 1 | .3 | .3 | 23.0 |
| | Kenya | 5 | 1.5 | 1.5 | 24.5 |
| | Latvia | 2 | .6 | .6 | 25.2 |
| | Malawi | 1 | .3 | .3 | 25.5 |
| | Malaysia | 1 | .3 | .3 | 25.8 |
| | Mexico | 9 | 2.8 | 2.8 | 28.5 |
| | Mongolia | 1 | .3 | .3 | 28.8 |
| | Namibia | 1 | .3 | .3 | 29.1 |
| | New Zealand | 1 | .3 | .3 | 29.4 |
| | Nigeria | 6 | 1.8 | 1.8 | 31.3 |
| | Norway | 1 | .3 | .3 | 31.6 |
| | Oman | 1 | .3 | .3 | 31.9 |
| | Peru | 2 | .6 | .6 | 32.5 |
| | Poland | 36 | 11.0 | 11.0 | 43.6 |
| | Portugal | 29 | 8.9 | 8.9 | 52.5 |
| | Romania | 1 | .3 | .3 | 52.8 |
| | Slovenia | 3 | .9 | .9 | 53.7 |
| | South Africa | 111 | 34.0 | 34.0 | 87.7 |
| | Spain | 6 | 1.8 | 1.8 | 89.6 |
| | Sweden | 1 | .3 | .3 | 89.9 |
| | United Kingdom | 27 | 8.3 | 8.3 | 98.2 |
| | United States | 2 | .6 | .6 | 98.8 |
| | Vietnam | 1 | .3 | .3 | 99.1 |
| | Zimbabwe | 3 | .9 | .9 | 100.0 |
| | Total | 326 | 100.0 | 100.0 | |

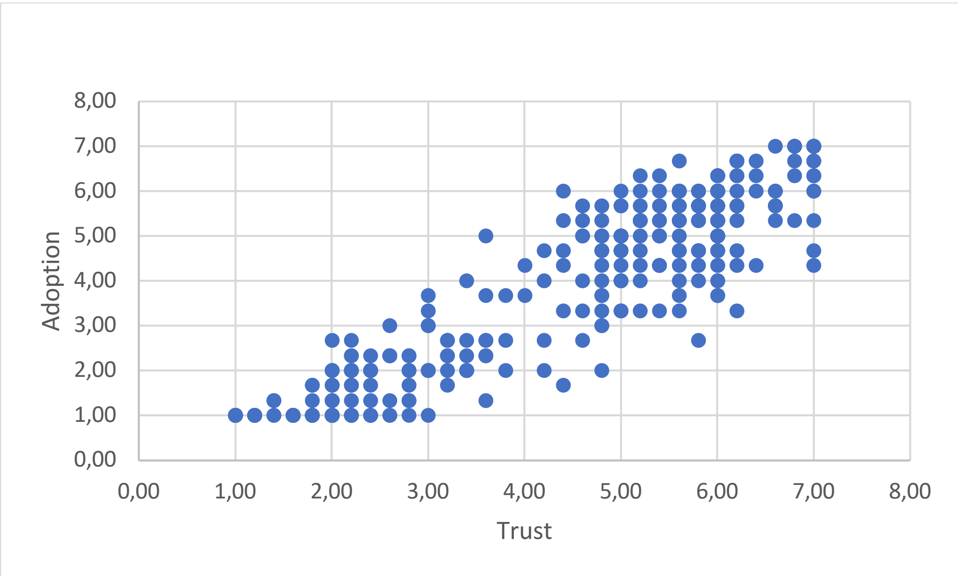
*Age*

| Please indicate your age | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | 39 | 5 | 1.5 | 1.5 | 84.4 |
| | 40 | 6 | 1.8 | 1.8 | 86.2 |
| | 41 | 1 | .3 | .3 | 86.5 |
| | 42 | 4 | 1.2 | 1.2 | 87.7 |
| | 12 | 1 | .3 | .3 | .3 |
| | 19 | 5 | 1.5 | 1.5 | 1.8 |
| | 20 | 4 | 1.2 | 1.2 | 3.1 |
| | 21 | 24 | 7.4 | 7.4 | 10.4 |
| | 22 | 23 | 7.1 | 7.1 | 17.5 |
| | 23 | 21 | 6.4 | 6.4 | 23.9 |
| | 24 | 27 | 8.3 | 8.3 | 32.2 |
| | 25 | 23 | 7.1 | 7.1 | 39.3 |
| | 26 | 17 | 5.2 | 5.2 | 44.5 |
| | 27 | 20 | 6.1 | 6.1 | 50.6 |
| | 28 | 20 | 6.1 | 6.1 | 56.7 |
| | 29 | 11 | 3.4 | 3.4 | 60.1 |
| | 30 | 18 | 5.5 | 5.5 | 65.6 |
| | 31 | 9 | 2.8 | 2.8 | 68.4 |
| | 32 | 4 | 1.2 | 1.2 | 69.6 |
| | 33 | 6 | 1.8 | 1.8 | 71.5 |
| | 34 | 10 | 3.1 | 3.1 | 74.5 |
| | 35 | 6 | 1.8 | 1.8 | 76.4 |
| | 36 | 8 | 2.5 | 2.5 | 78.8 |
| | 37 | 8 | 2.5 | 2.5 | 81.3 |
| | 38 | 5 | 1.5 | 1.5 | 82.8 |
| | 43 | 1 | .3 | .3 | 88.0 |
| | 44 | 2 | .6 | .6 | 88.7 |
| | 47 | 1 | .3 | .3 | 89.0 |
| | 48 | 2 | .6 | .6 | 89.6 |
| | 49 | 2 | .6 | .6 | 90.2 |
| | 50 | 3 | .9 | .9 | 91.1 |
| | 51 | 2 | .6 | .6 | 91.7 |
| | 52 | 3 | .9 | .9 | 92.6 |
| | 53 | 1 | .3 | .3 | 92.9 |
| | 54 | 2 | .6 | .6 | 93.6 |
| | 55 | 3 | .9 | .9 | 94.5 |
| | 56 | 1 | .3 | .3 | 94.8 |
| | 58 | 1 | .3 | .3 | 95.1 |
| | 59 | 2 | .6 | .6 | 95.7 |
| | 60 | 4 | 1.2 | 1.2 | 96.9 |
| | 61 | 2 | .6 | .6 | 97.5 |
| | 63 | 3 | .9 | .9 | 98.5 |
| | 64 | 1 | .3 | .3 | 98.8 |
| | 65 | 3 | .9 | .9 | 99.7 |
| | 68 | 1 | .3 | .3 | 100.0 |
| | Total | 326 | 100.0 | 100.0 | |

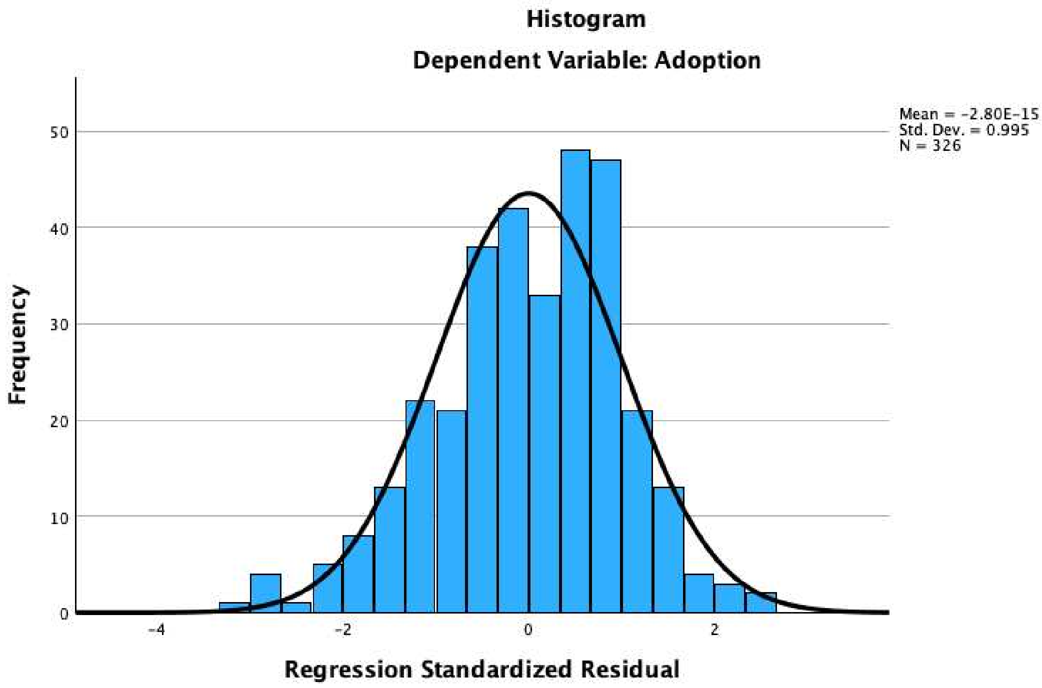
*Gender*

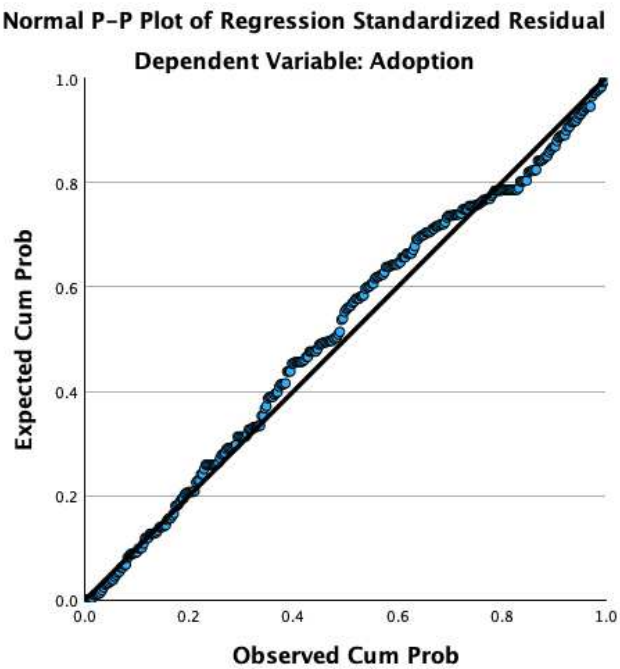
| | Frequency | Percent |
|---|---|---|
| Male | 158 | 48.5 |
| Female | 161 | 49.4 |
| Other | 6 | 1.8 |
| Prefer not to say | 1 | .3 |
| Total | 326 | 100.0 |

## Appendix 4: Linearity Scatterplot




## Appendix 5: Normality of Errorterms Histogram & P-P Plot






## Appendix 6: Correlation table

*Correlations*

| | | Trust | eWOM_Val | ProdType | Adoption |
|---|---|---|---|---|---|
| Trust | Pearson Correlation | -- | | | |
| | N | 326 | | | |
| eWOM_Val | Pearson Correlation | .717** | -- | | |
| | Sig. (2-tailed) | <.001 | | | |
| | N | 326 | 326 | | |
| ProdType | Pearson Correlation | -.078 | .006 | -- | |
| | Sig. (2-tailed) | .158 | .909 | | |
| | N | 326 | 326 | 326 | |
| Adoption | Pearson Correlation | .917** | .631** | -.056 | -- |
| | Sig. (2-tailed) | <.001 | <.001 | .310 | |
| | N | 326 | 326 | 326 | 326 |

**. Correlation is significant at the 0.01 level (2-tailed).