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Bachelor's Thesis

The Impact of AI Transparency on Advertising Credibility

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Abstract

As artificial intelligence (AI) fundamentally reshapes the landscape of digital advertising, the question of how consumers perceive AI-generated content (AIGC) has become a critical concern for marketers. Specifically, the strategic dilemma of whether to transparently disclose the use of AI remains unresolved. This thesis investigates the impact of AI transparency on the perceived credibility of advertising, examining whether a disclosure label ("AI-generated") influences consumer perceptions of *Competence*, *Trustworthiness*, *Clarity*, and *Engagement*. Furthermore, it explores the moderating role of consumers' general attitude towards AI.

A quantitative online experiment was conducted with 140 participants from the DACH region. Using a between-subjects design, participants were randomly assigned to view either a hedonic (premium chocolate) or utilitarian (running shoe) advertisement, generated entirely by AI (DALL·E 3), with or without a transparency label. The results revealed no significant negative main effect of the AI label across the total sample, suggesting a general indifference to AI disclosure when visual quality is high. However, exploratory analyses uncovered a significant generational divide: while participants under 30 were insensitive to the label, participants over 30 rated labeled advertisements significantly lower in competence, trustworthiness, and engagement. Additionally, the study found that a consumer's general attitude towards AI did not moderate their specific evaluation of the ad.

These findings challenge the universal applicability of "algorithm aversion" in creative contexts, proposing instead that acceptance is generation-dependent. For practitioners, this suggests that transparency is a low-risk strategy for younger target audiences but requires caution when targeting older demographics. The study concludes that high-quality visual execution can override potential biases, positioning AI as a viable tool for efficient content creation.

Keywords: Artificial Intelligence, AI Transparency, Advertising Credibility, Algorithm Aversion, Generative AI, Consumer Perception

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1 Introduction

This introductory chapter establishes the context and framework for the entire study.

It begins with Section 1.1, which provides the background and motivation for the research, situating the topic within the current landscape of digital advertising. Section 1.2 then narrows this focus, identifying the specific problem statement and the corresponding research gap in the existing literature. Following this, Section 1.3 formulates the formal research question and outlines the primary objectives of the thesis. Finally, Section 1.4 presents a comprehensive outline, detailing the structure of the subsequent chapters.

1.1 Background and Motivation

AI has become a central topic of discussion in recent years. In marketing, especially, AI is being applied in an increasing number of processes. Sufficient computing power, affordable technologies, and extensive data allow AI to unfold its potential. Through correct implementation, human capabilities can be surpassed, and data can be analyzed faster and more efficiently, leading to a decisive competitive advantage [1].

In particular, AIGC has moved into the focus of the general public. More and more people are using products from large technology companies to generate AI content. The most well-known are pioneering AI models like ChatGPT and DALL·E, developed by OpenAI [2]. In 2022, OpenAI released ChatGPT, an AI language model that understands human language and responds meaningfully [3]. DALL·E is another generative AI model that creates unique, high-quality images from text descriptions in a very short time [2]. In the time since, a large number of providers have emerged offering similar technologies, and the options for applying AI continue to grow [4].

Companies, individuals, and marketers are using AIGC to automate and optimize business processes [5]. AIGC is applied as a new approach to content creation, supplementing traditional methods like professional generated content and user generated content. Unlike human-created content, AIGC is developed using generative AI techniques, allowing large volumes of content to be created and automated quickly. Key technologies such as machine learning and neural networks have drastically improved the precision and effectiveness of AI in content creation [6]. This rise of AI offers new opportunities and challenges for marketing. Research in this area is evolving rapidly, meaning current studies can quickly become outdated as attitudes toward AI continue to develop [7].

1.2 Problem Statement and Research Gap

The rise of AI has led to an increasing volume of AIGC, as its generation has become simpler and more accessible. This presents a challenge, as content generated by humans can no longer be reliably distinguished from that generated by AI [5].

This ambiguity is being countered by policy. In the near future, transparency in the use of AI must be ensured, especially as regulations like the EU AI Act are implemented, making AI transparency a legal obligation in many countries [8, 9]. Consequently, negative consumer perceptions of AI can become a critical issue for companies that have heavily integrated AI into their activities, such as content creation for websites and social media. It is therefore essential for these companies to understand how to avoid negative perceptions and how to use AI transparently while receiving positive feedback from consumers [6].

As transparency becomes more relevant and AI becomes an integral part of digital strategies, there is a growing interest in understanding how consumers judge the use of AI in advertising. The influence of AIGC on perceived credibility is particularly interesting [1]. However, based on the author's synthesis of current research in Section 2.4, there is a significant gap in the literature regarding the influence of knowing (versus not knowing) that an advertisement was generated by AI on brand credibility. Furthermore, the impact of a consumer's general attitude toward AI on this credibility perception has not been sufficiently investigated.

1.3 Research Question and Objectives

Based on the identified research gap, this thesis aims to answer the following research question:

To what extent does the transparent disclosure of AI-generated content in advertising impact its perceived credibility?

The primary objective of this thesis is to investigate how the knowledge of AI use in advertising influences the perceived credibility of the advertisement. It will be examined whether the credibility assessment of an advertisement differs when its AI origin is known versus when it is not. A secondary objective is to analyze the role of the consumer's general attitude toward AI as a potential moderator of this effect.

This study seeks to close the identified knowledge gap in the current research on AI and the credibility of advertising content. By doing so, it aims to provide a basis for further research and contribute to the marketing literature. The findings are intended to provide implications for marketing managers, deepening their understanding of how AI in advertising influences credibility and, consequently, brand perception and image. This should help companies optimize their marketing strategies with AI while still addressing consumer needs.

This thesis will not investigate the difference between transparent and non-transparent strategies, as regulations like the EU AI Act will soon mandate transparency. Instead, the focus is on whether an AI disclosure label itself has an impact on the credibility of an advertisement. This study differentiates itself from other research by not focusing on text-based content but specifically on the visual component of a complete advertisement.

1.4 Thesis Outline

The structure of this thesis comprises a theoretical and an empirical section.

Chapter 1, the present chapter, has introduced the research topic, established the background and motivation (Section 1.1), defined the core problem and research gap (Section 1.2), and formulated the guiding research question and objectives (Section 1.3). This section concludes the chapter by outlining the structure of the remaining thesis.

Chapter 2 builds the theoretical foundation for the study. It begins by defining AI within the context of digital advertising (Section 2.1). It then provides a detailed conceptualization of the study's dependent variable, perceived advertising credibility (Section 2.2), including the distinction between source and message credibility (2.2.1) and the multidimensional framework used for its measurement (2.2.2). Following this, the chapter reviews the literature on the independent variable, AI transparency, disclosure, and labeling (Section 2.3), and consumer responses to such content (2.3.2). A synthesis of the current research (Section 2.4) consolidates these findings, leading to the development of the conceptual framework and the formal hypotheses (Section 2.5).

Chapter 3 details the research methodology. It describes the experimental design (Section 3.1), the process for developing the stimulus material (Section 3.2), and the sampling and data collection procedures (Section 3.3). It then specifies the measurement instruments used to operationalize the independent, dependent, and moderating variables (Section 3.4), and concludes with the data analysis strategy (Section 3.5).

Chapter 4 presents the empirical results of the experiment. This chapter includes a profile of the sample characteristics (Section 4.1), the results of the manipulation checks (Section 4.2), and the formal hypothesis testing (Section 4.3), along with exploratory analyses (Section 4.4).

Chapter 5 provides a comprehensive discussion of the findings. This includes a summary and interpretation of the results (Section 5.1) and an exploration of their broader theoretical (Section 5.2) and managerial implications (Section 5.3).

Finally, Chapter 6 concludes the thesis with a concluding summary (Section 6.1) and a reflection on the study's limitations, which provides a basis for suggesting future research directions (Section 6.2).

2 Theoretical Foundations and Hypothesis Development

The following chapter establishes the theoretical foundation for the present thesis and summarizes the current state of research. The objective is to develop a comprehensive understanding of the central constructs, critically review existing knowledge, and identify the research gaps that necessitate this study.

First, the core concepts of AI are defined within the context of digital advertising (Section 2.1). Following this, a detailed conceptualization of perceived advertising credibility, the central dependent variable of this study, is provided (Section 2.2). Subsequently, the independent variable—AI transparency, disclosure, and labeling—is examined, along with current findings on consumer responses to such disclosures (Section 2.3).

A synthesis of current research (Section 2.4) will then consolidate relevant findings and highlight existing gaps in the literature. Finally, based on these gaps, the conceptual framework for the study is developed, from which the hypotheses, including the moderating role of general AI attitude, are derived (Section 2.5).

2.1 AI in Digital Advertising

The field of digital marketing is increasingly permeated by terms such as AI, Machine Learning, and Big Data Analytics. Despite their frequent use, the definitions of these terms are not yet standardized, and there is a lack of clear, universally accepted delineations.

AI is the central concept of this thesis. A universally valid definition remains elusive, in part because the concept of "intelligence" itself is not precisely settled [1, 10]. For example, the German dictionary Duden [11] defines intelligence as "the ability [of humans] to think abstractly and rationally and to derive purposeful actions from it" [author's translation]. According to Amazon [12], AI is a field of computer science focused on solving cognitive problems normally associated with human intelligence, such as learning, problem-solving, and pattern recognition. A more functional definition considers

AI to be a machine employing algorithms or statistical models to carry out tasks associated with the human mind, including perception, cognition, and conversation [13]. This technology enables the development of self-learning systems that can interpret data to acquire knowledge, which can then be applied to solve new tasks. AI can, for example, respond meaningfully to human conversation, create images and texts, and make decisions based on real-time data inputs. When integrated into a firm, AI can improve business processes, optimize customer experiences, and drive innovation [12].

The concept of AI is not new; it has been in development since the 1950s [1]. Its "birth" is widely attributed to the "Summer Research Project on Artificial Intelligence" at Dartmouth College in 1956. While this conference established the field, it was followed by a period of stagnation in the 1980s, often referred to as the "AI winter," as the technology of the time failed to produce tangible business success [1, 10].

Today's AI boom is driven by a fundamental shift: the availability of abundant, low-cost computing power and the exponential growth of customer data available for marketing. While the world's largest companies were once primarily in the oil industry, today they are organizations that possess and analyze massive data sets [1]. These companies collect customer data, image data, and purchase data, often leveraging sources like user-generated content [12]. In this environment, data quality is a primary driver of competitive advantage. AI provides the means to analyze this data faster and more effectively than humanly possible, making the combination of high-quality data and AI a significant competitive tool [1]. This growing volume of data, in turn, fuels the development of larger and more capable models, making their outputs increasingly realistic and sophisticated [2].

From an economic perspective, AI can be seen as a contributor to the productivity of the classical production factors of labor and capital, or even as an independent production factor in its own right, leading to new growth effects [14]. However, the full extent of AI's impact on economic growth remains unclear, with different research findings pointing to varied outcomes [10].

According to Bünte, marketing and sales are considered primary beneficiaries of AI, as these departments focus on the often costly interaction with customers. As early as 2018, 80% of marketing managers recognized the enormous importance of AI for business success [1]. In marketing, AI can be used to reduce time expenditure and increase efficiency, particularly in creative endeavors like advertising, which traditionally requires significant human effort [15]. By enabling targeted customer engagement, AI can also foster long-term customer loyalty and in rapidly changing markets, AI allows for the cost-effective and rapid modification of products and campaigns [10].

A particularly transformative subset of AI is AIGC. AIGC utilizes generative AI techniques to create digital content such as images, videos, music, and natural language. In marketing, this is applied to create blog posts, articles, product descriptions, and other materials efficiently and at high quality. [3]

This capability is primarily powered by Large Language Models (LLMs), such as the one underpinning ChatGPT, which can understand and respond meaningfully to human language [3, 16]. Users provide a prompt, and the system completes the request with a desired output. This process is continually refined through human feedback, which improves the quality of the output and its alignment with user intent. However, these models must be used with caution, as they are trained predominantly on internet data, which can lead to errors and biased information [17]. Simultaneously, generative image models like DALL·E allow users without specialized skills to generate unique images, or modify existing ones, in seconds [3]. For advertisers, this means that creating a new logo, poster, or campaign visual is no longer a bottleneck.

This shift moves AI from a background tool for data analysis to a visible, active participant in the creation of the advertising message itself. However, for this technology to be effective, its use must be aligned with the brand's values and personality. This alignment is essential for building a foundation of credibility, which in turn has a positive effect on brand perception [18, 19].

2.2 Conceptualizing Perceived Advertising Credibility

The credibility of advertising campaigns is of great importance for the success of a company. Consumers assess the credibility of advertisements by critically examining both the source and the message of the content. This perceived credibility ultimately affects the attitude toward the brand [7].

According to Lange, it is important to create a consistent and stable brand identity and perception. A clear and differentiated idea should be established in the minds of customers. A brand can be viewed from an internal perspective (the brand's self-concept) and an external perspective (perception by external reference groups). The brand identity reflects emotional and symbolic characteristics and consists of the brand's values and personality. Values are fundamental beliefs that the brand represents, while personality includes human characteristics attributed to the brand. In contrast, the brand image is the result of the subjective perception and interpretation of the brand identity by external target groups. The stronger the alignment between the self-image and the external image, the stronger the brand identity. A consistent brand image is crucial for the credibility of and trust in the brand [19]. Through this, the brand communicates continuity and individuality against competitors [7].

In the context of AI, companies must understand the needs and expectations of their stakeholders to create an unforgettable and credible brand experience. A consistent brand identity and communication must be maintained when integrating AI into advertising to strengthen perceived credibility [7].

Credibility has been regarded as an essential factor in the persuasive power of a person and their message since antiquity. In the early 20th century, the concept of credibility was recognized as a scientific discipline in communication research [20, 21]. Research shows that no linear relationship exists between the perceived credibility of a communication source and its persuasive effect. "Credibility is a perceptual state, i.e. [sic] the outcome of an attribution process in which recipients of messages form judgments about their sources and therefore assess them as credible or not." [22] How the credibility of a message is perceived depends on several interlocking factors. The person speaking is just as important as the message itself. Perceived credibility can vary from one recipient to another; one person may perceive it as very credible, while another finds it not credible at all. Therefore, all parts of the communication process must be considered [22, 23].

According to Eisend, a source is perceived as credible if the following aspects are met from the customer's perspective: the company makes valid claims (competence), conveys information conscientiously (trustworthiness), and actively addresses the desires of consumers (dynamism). Eisend describes credibility as the customer's assessment of received information and existing knowledge. [24]

The credibility of a media message is also influenced by factors unrelated to the source, such as the medium, the transmission channel, and the message itself [23]. In general, credibility exists on three different levels: the source level (source credibility), the media level (media credibility), and the message level (message credibility) [21]. At the source level, credibility refers to the sender of the information and interpersonal influence. Media credibility concerns the trustworthiness of the communication form and the channel through which the message is sent. Research on message-level credibility focuses on the characteristics and formulations of messages that make them more or less credible [23, 25].

2.2.1 Source vs. Message Credibility

This study focuses on message-level and source-level credibility. The media level is not considered, as the focus is not on the channels through which the AIGC is communicated.

Message credibility illustrates how the content of a message impacts the perception of credibility, both in relation to the source and the message itself. The two concepts, therefore, overlap. Message factors can often have a greater impact on credibility assessment than source factors. According to the Elaboration Likelihood Model, message factors, in particular, exert greater influence than source characteristics when consumers have high personal relevance and knowledge regarding the message content. This is because such factors increase the motivation to analyze the content of the message. How credible information is perceived thus depends on the recipient's attitudes toward the relevant topics. While disinterested recipients primarily engage with the information superficially, highly involved individuals scrutinize the message more intensively. The former pay more attention to the credibility of the source, while the latter rely on the information in the message and often disregard source characteristics [22]. In situations where little information about the source is available, recipients must rely even more heavily on message factors to assess credibility [23]. Viewers then concentrate on the message level, while the source recedes into the background [22]. This is particularly relevant to the present study, as participants will not be aware of the advertising's origin.

The significance of source credibility, the second concept considered in this work, was demonstrated as early as 1951 by Hovland & Weiss. In their study, they had the same message disseminated by a well-known, credible expert and by a non-trustworthy source. The study showed that the credibility of a message depends on the trustworthiness of the source disseminating it [26]. Source credibility is understood as a multidimensional construct comprising at least two dimensions: competence and trustworthiness. Competence describes the perceived ability of a source to make valid and reliable statements. Perceived trustworthiness, on the other hand, assesses whether the source intends to communicate correct information. These source-level dimensions can also be expanded by other factors such as security, qualification, and expertise [20].

Institutions can also disseminate persuasive messages, and their perceived credibility can influence consumer attitudes. In marketing literature, the term "corporate credibility" is used to describe the trustworthiness of institutions. Corporate credibility defines how trustworthy and competent an organization is perceived to be. Organizational credibility shows that the source of a message is not an individual person but a complex institution with an established history. Studies show that the credibility of an organization has a direct influence on consumer attitudes [23]. In this thesis, however, the factor of corporate credibility is intentionally excluded to isolate the influence of AI transparency on credibility perception, independent of a specific company's reputation.

2.2.2 A Multi-Dimensional Framework for Credibility

While the distinction between source and message credibility is foundational, these concepts are themselves multi-dimensional. To create a robust measurement model for the specific context of AIGC, this thesis will adopt a framework based on recent research in this domain. Which, according to Huschens et al. [20], "was inspired by well-established questionnaires and measurement approaches in previous studies" [21, 23, 26, 27, 28, 29].

This model synthesizes the source and message levels into a single, four-dimensional framework for assessing content credibility. These four dimensions are:

1. **Competence**: This dimension reflects the perceived expertise and knowledgeability of the source, operationalized through items like "accurate," "complete," and "knowledgeable."

2. **Trustworthiness**: This dimension captures the perceived honesty and reliability of the source, measured with items such as "honest," "trustworthy," and "reliable."

3. **Clarity**: This dimension assesses the quality of the message itself, focusing on its comprehensibility. It is measured with items like "clear," "confusing[1]," and "understandable."

4. **Engagement**: This dimension measures the content's ability to capture and hold the reader's attention, using items like "interesting" and "maintaining attention."

This model is particularly advantageous as it cleanly maps onto the foundational concepts discussed in 2.2.1. The **Competence** and **Trustworthiness** factors directly measure the classic components of source credibility. The **Clarity** and **Engagement** factors, conversely, provide a clear measurement of message credibility [20].

2.3 AI Transparency, Disclosure, and Labeling

As AI transitions from a background tool for data analysis to an active creator of advertising content, its use becomes a salient and potentially critical piece of information for the consumer. This creates a new strategic imperative for marketers regarding transparency. The decision whether and how to disclose the use of AI in creating an advertisement is a novel challenge. This dilemma is intensified by the fact that AIGC is now often perceived as having similar credibility to human-created content [20], placing the burden of disclosure entirely on the company. The following sections 2.3.1 and 2.3.2 will explore the theoretical mechanisms of how such transparency is defined and how consumers are likely to react to it.

2.3.1 Defining AI Transparency in Advertising

In the context of this thesis, AI transparency is defined as the deliberate and overt communication by a firm to inform consumers that a piece of advertising content was

[1] Reverse-coded item.

generated or significantly assisted by AI. This act of disclosure is a specific form of informational "signal" sent by the company (the "signaler") to the consumer (the "receiver"), who has less information [30].

This signal can be interpreted through multiple theoretical lenses. On one hand, transparency can be a core component of a brand's identity, used to build trust and demonstrate a commitment to honesty [19, 7]. From this perspective, an AI disclosure label is a signal of forthrightness. This signal could positively influence perceptions of the source's (i.e., the brand's) credibility, specifically its trustworthiness dimension.

On the other hand, the signal also conveys information about the process of the ad's creation. It explicitly states that the creative output is not the product of human endeavor but of an algorithm. This process-related information is what triggers a secondary, more complex set of consumer evaluations, which are explored in the following section 2.3.2. For the purpose of this study, this transparency is operationalized through a clear disclosure label, which serves as the primary independent variable.

2.3.2 Consumer Response to AIGC

The consumer's response to the knowledge that content is AI-generated is theoretically complex and represents the central tension of this study. The literature suggests two conflicting potential outcomes: a negative reaction to the process and a positive or neutral reaction to the content's quality.

The predominant view in behavioral science is that consumers often exhibit an "algorithm aversion" [31]. This is a documented cognitive bias where individuals tend to distrust, dislike, or penalize decisions and content made by an algorithm, even when its performance is equal to or superior to that of a human [32]. This aversion is often rooted in a perception that algorithms lack human intuition, empathy, "heart," or genuine creativity. When applied to advertising, this bias would predict a negative outcome. Upon seeing an AI disclosure label, consumers may devalue the advertisement, perceiving it as less authentic, less creative, or less reliable. This would lead to a direct decrease in perceived credibility, particularly on the trustworthiness and engagement dimensions.

However, this negative bias is not the only possible outcome. Recent research comparing human- and AIGC has introduced a significant nuance. A study by Huschens et al. [20] found that while participants did not rate AI-generated texts differently on competence or trustworthiness, they surprisingly rated them as clearer and more engaging than the human-written equivalents. This finding suggests that consumers may, in some contexts, perceive the output of AI as being of higher quality on certain message-level attributes (like clarity), even if they are averse to the process.

This study is therefore positioned to investigate this critical trade-off: What is the net effect on overall perceived credibility when a consumer is explicitly told that an advertisement was created by AI?

2.4 Synthesis of Current Research

The research on the perception and credibility of AIGC provides varying and sometimes contradictory results.

For instance, Chaisatitkul et al. [15] examined attitudes and perceptions towards work created by generative AI compared to human-generated content. They analyzed ad scripts from ChatGPT and storyboards from DALL·E, surveying three groups: end-users, marketing professionals, and agency employees. The findings showed that end-users (Group 1) held a positive attitude towards the AIGC; interest in the script even increased slightly after its AI origin was revealed. The professional groups (2 and 3) also showed positive attitudes, particularly regarding the visual content, practicality, and brand trust. Notably, all groups preferred the first script and storyboard, which they knew was AI-generated, over the second, human-created one.

In contrast, other studies underscore the negative effects of AI. Haupt et al. [6] investigated the potential of human-AI collaboration in creating advertising copy, examining the impact of authorship on message credibility and brand attitude. Their study analyzed texts authored by: (1) a human, (2) a human with AI support, (3) an AI under human control, or (4) an AI alone. The results showed that AI-based texts are evaluated similarly to human-created texts as long as their authorship is concealed. However, with transparent AI use, consumer reactions varied. Ad copy created by an AI or by a human with AI support was perceived as less credible and had negative effects on brand attitude. Conversely, content written by an AI under human control had no significant negative impact. This suggests that negative perceptions—a phenomenon known as algorithm aversion—can be mitigated if human control is emphasized.

The study by Hofmann [7] examined how the use of AI algorithms in brand management affects brand credibility, focusing on the streaming industry, particularly Netflix. Netflix is transparent about its use of AI in data analysis and product management, a deliberate strategy to position itself as an innovator. The findings showed that the discussion of AI in brand management is relevant to the perception of brand credibility. The study concluded that AI integration must not only be technologically sensible but also align with the established values and personality of the brand to be effective.

Adding nuance, Huschens et al. [20] investigated the perceived credibility of content created by humans versus content generated by LLMs like ChatGPT. The results showed that participants judged the credibility of both human and AI-created content to be roughly the same. Furthermore, no differences were reported in the perceptions of competence or trustworthiness. Notably, the AIGC was even rated as clearer and more engaging than the human-generated content.

Finally, research by Marsden [18] argues for the importance of transparent communication, suggesting that companies should clearly explain how AI is used to reduce skepticism and maintain trust. Marsden emphasizes that a company's persuasive power is a decisive factor in mitigating mistrust towards AI and fostering a positive attitude. Because credibility plays a crucial role in brand assessment, companies must understand their stakeholders' expectations regarding AI to create an authentic brand experience.

The existing literature, therefore, presents a mixed and incomplete picture. Although research on AI and marketing is increasing, there are still significant gaps concerning advertising, credibility, and AIGC. Conflicting evidence exists, and given the novelty of the topic for the general public, consumer perceptions are still in flux.

Several specific gaps emerge from this body of research, which the present thesis aims to address. First, while studies like Huschens et al. [20] compare AI vs. human content, the critical gap is the effect of disclosure itself. This study will, therefore, test the difference in credibility perceptions when the same advertisement is presented with and without an AI disclosure label. Second, much of the research has focused on text-based content (e.g., ad copy, news articles). This thesis will address a gap by focusing on the impact of disclosure on visual advertisements. Finally, this study will focus specifically on the end-consumer, providing clear managerial implications for how AI disclosure strategies directly impact brand perception.

2.5 Conceptual Framework and Hypothesis Development

Based on the theoretical foundations and the research gaps identified in the synthesis of current literature, this thesis proposes a moderated-mediation model. The central research question is:

To what extent does the transparent disclosure of AI-generated content in advertising impact its perceived credibility?

The conceptual framework posits that an AI disclosure label (independent variable) will have a direct effect on the perceived credibility of an advertisement (dependent variable).

This study will adopt the multi-dimensional credibility model from section 2.2.2, which breaks perceived credibility into four distinct dimensions: competence, trustworthiness, clarity, and engagement [20]. The hypotheses will therefore test the effect of the AI label on each of these four dimensions individually.

Furthermore, this relationship is not assumed to be uniform across all consumers. As credibility is a subjective "perceptual state" that varies by recipient [22, 23], this framework introduces a key moderator: the consumer's general attitude toward AI. This pre-existing attitude is expected to influence the strength or direction of the consumer's reaction to the AI disclosure label.

The following sections 2.5.1 and 2.5.2 will now formally derive the testable hypotheses from this framework [33, 34].

2.5.1 The Effect of AI Transparency on Perceived Credibility

As established in section 2.3.2, the literature presents a central conflict. On one hand, consumers exhibit a well-documented "algorithm aversion" [31], which suggests a negative reaction to content known to be non-human [32, 6]. This bias would predict that labeling an ad as AI-generated will harm its credibility. On the other hand, research has also shown that AIGC can be perceived as equal to or even better than human content on specific message-level attributes like "clarity" and "engagement" [20].

The experimental design of this thesis is built to test this exact question. It will compare consumer reactions to advertisements that include explicit AI disclosure labels against a control-group version of the same advertisement that has no label at all. This design isolates the specific, real-world impact of adding a transparency label to an otherwise standard advertisement.

The following hypotheses are posited, predicting that the negative effects of algorithm aversion will outweigh any potential perceived benefits of the content's quality, leading to an overall negative impact on credibility. Based on the four-dimensional credibility model [20], this leads to the following four hypotheses:

- **H1**: The presence of an AI disclosure label will cause consumers to evaluate an advertisement's competence (accurate, complete, knowledgeable) more negatively than the same advertisement presented without a label.
- **H2**: The presence of an AI disclosure label will cause consumers to evaluate an advertisement's trustworthiness (honest, trustworthy, reliable) more negatively than the same advertisement presented without a label.

- **H3**: The presence of an AI disclosure label will cause consumers to evaluate an advertisement's clarity (clear, confusing, understandable) more negatively than the same advertisement presented without a label.

- **H4**: The presence of an AI disclosure label will cause consumers to evaluate an advertisement's engagement (interesting, maintaining attention) more negatively than the same advertisement presented without a label.

2.5.2 The Moderating Effect of General AI Attitude

As noted, perceived credibility is subjective and can vary significantly depending on the individual recipient [22, 23]. In the context of AI, one of the most salient individual differences is a person's pre-existing disposition or "general attitude."

It is logical to assume that the negative impact predicted in H1-H4 will not be universal. Consumers who already have a positive attitude toward AI (e.g., they find it useful, innovative, or exciting) may not experience algorithm aversion. For them, an "AI-created" label might be a neutral or even positive signal. Conversely, consumers who hold a negative attitude (e.g., they find AI threatening, inauthentic, or untrustworthy) will likely have their biases confirmed by the label, leading to a much stronger negative evaluation.

Therefore, the general attitude toward AI is hypothesized to act as a moderator, influencing the strength of the relationship between the AI label and the perceived credibility dimensions.

- **H5**: The consumer's general attitude toward AI has an influence on the perceived competence of the advertisement.

- **H6**: The consumer's general attitude toward AI has an influence on the perceived trustworthiness of the advertisement.

- **H7**: The consumer's general attitude toward AI has an influence on the perceived clarity of the advertisement.

- **H8**: The consumer's general attitude toward AI has an influence on the perceived engagement of the advertisement.

3 Research Methodology

This chapter details the empirical methodology used to test the hypotheses developed in Chapter 2. It provides a comprehensive overview of the research design, data collection, and analysis procedures.

The chapter begins by outlining the quantitative Experimental Design (Section 3.1), which forms the basis for this study. Following this, the process of Stimulus Material Development (Section 3.2) is described, detailing how the advertisements for the experimental conditions were created and validated.

Next, the Sampling Strategy and Data Collection Procedure (Section 3.3) are explained. The subsequent section details the Measurement Instruments (Section 3.4) used to operationalize the study's core constructs, including the manipulation of the Independent Variable: AI Transparency (Subsection 3.4.1), the measurement of the Dependent Variable: Perceived Credibility (Subsection 3.4.2), and the measurement of the Moderating Variable: General AI Attitude (Subsection 3.4.3).

Finally, the chapter concludes by specifying the Data Analysis Strategy (Section 3.5), which outlines the statistical methods that will be employed to analyze the collected data and test the hypotheses.

3.1 Experimental Design

To test the hypotheses developed in Chapter 2 and answer the research question, a quantitative research method is conducted. Quantitative research methods allow for the investigation of complex structures and social phenomena. In this approach, theoretical hypotheses are translated into measurable dimensions using numerical values, and the relationships between variables are tested using suitable mathematical-statistical procedures. A formulated hypothesis is referred to as the alternative hypothesis (H1), which represents a new thesis intended to expand the current state of knowledge. The existing theory is represented as the null hypothesis (H0), which the alternative hypothesis rejects. The statistical analysis will test whether the null hypotheses can be rejected and the alternative hypotheses accepted. [33, 34]

The study employs a quantitative between-subjects experimental design. Data for this experiment is collected using a structured online survey. The advantages of this method include the elimination of potential interviewer influence, uncomplicated data collection, and the possibility for sophisticated questionnaire design [35].

3.2 Stimulus Material Development

The stimulus material consisted of two distinct advertising campaigns, each comprising a high-quality promotional image, a brand name, and a slogan. To ensure high internal validity and control over the visual aesthetics, the content for these advertisements was generated exclusively using generative AI tools.

Two distinct product categories were selected to test the hypotheses across different contexts: a premium chocolate brand (hedonic) and a performance running shoe (utilitarian). All visual imagery was created using ChatGPT's integrated DALL·E 3 capabilities. To ensure that the advertisements differed significantly in their product type while maintaining a consistent level of professional quality, specific prompts were engineered and refined. While the AI generated the core visuals and text, minor typographic corrections and the final layout (including the placement of the AI transparency label for the treatment groups) were adjusted using the design software Figma to ensure perfect readability and consistency.

For the hedonic product, a premium dark chocolate brand was conceptualized. The AI was instructed with the following prompt: "A high-quality, photorealistic advertisement for a premium dark chocolate brand called 'Noir Délice'. The image features a square of rich chocolate snapping open, revealing a smooth, silky truffle filling inside. The chocolate rests on a dark, luxurious satin fabric or dark slate stone. Dramatic, warm spotlighting highlights the texture and the shine of the chocolate. Cocoa powder is lightly dusted around. The atmosphere is indulgent and sensual. Include the brand name 'Noir Délice' in an elegant serif font on the packaging foil nearby and a small tagline 'Taste the Forbidden'. Square aspect ratio (1:1)." The resulting image features a close-up of a rich chocolate square on a dark, luxurious background, accompanied by the brand name "Noir Délice" and the slogan "Taste the Forbidden." This visual was chosen to evoke a strong affective response typical of hedonic consumption.

Figure 3.1: Stimulus Material 1: Premium Chocolate (Control Condition: No Label)

For the utilitarian product, a high-performance running shoe was selected to represent functional benefits and performance. The AI was prompted with the instruction: "A high-quality, photorealistic advertisement for a high-performance running shoe called 'AeroStride'. The shoe is modern, featuring breathable mesh and a thick, advanced foam sole, colored in dynamic electric blue and neon lime. It is positioned dynamically on an asphalt running track or a clean city street surface, bathed in bright, crisp morning sunlight. The lighting emphasizes the technical materials and cushioning. The background is a slightly blurred urban cityscape, suggesting motion. Include the brand name 'AeroStride' clearly on the image and a clean, sans-serif tagline 'Engineered for Speed'. Square aspect ratio (1:1)." The resulting image displays a modern, dynamic running shoe in a bright, urban setting, accompanied by the brand name "AeroStride" and the slogan "Engineered for Speed." This visual aims to trigger cognitive evaluations regarding functionality and quality.

Figure 3.2: Stimulus Material 2: Running Shoe (Control Condition: No Label)

To test the effect of AI transparency, a manipulation was applied to these base images. For the treatment groups (Groups A and C), a disclosure label was added to the advertisements. Using Figma, a standardized badge containing the text "AI-generated" (German: "KI-generiert") was placed in the bottom right corner of both the premium chocolate and the running shoe advertisements. This phrasing was chosen based on recent findings by Gamage et al. [36], which indicate that "AI-generated" is the term most consistently associated by users with content created using AI. Great care was taken to ensure that the label was legible and resembled realistic disclosure markers found on social media platforms. The text was set in the Roboto typeface (weight: Semibold, size: 32px) in white, overlaid on a semi-transparent background to ensure contrast without obscuring the main product. The control groups (Groups B and D) saw the identical images without this label.

(a) Noir Délice with Label

(b) AeroStride with Label

Figure 3.3: Treatment Conditions: Advertisements with AI Disclosure Label

3.3 Sampling Strategy and Data Collection Procedure

The participants of this study were primarily recruited via social media channels, locally at the Faculty of Computer Science and Information Systems of the Technical

University of Applied Sciences Würzburg-Schweinfurt, and through personal networks (family, friends, and acquaintances). Participation was restricted to individuals residing in the DACH region (Germany, Austria, Switzerland). Ultimately, the sample consisted exclusively of participants from these three countries.

To ensure a broad representation of the population, the minimum age was set at 1 year and the maximum age at 100 years. The actual age range of the participants at the time of submission was between 12 and 89 years. The age limit was deliberately kept broad to identify potential perception differences attributable to age. A total of 140 participants successfully completed the survey. The online survey was conducted from November 19th to November 25th, 2025.

A questionnaire was developed as the measurement instrument. This represents a standardized tool that maps systematic assignments of numbers to objects and is formed from various indicators [34]. The online survey was created using Google Forms based on the derived hypotheses.

The structure of the questionnaire was divided into four parts: socio-demographics, attitude towards AI, randomized assignment to one of the four advertisements, and finally, the assessment of ad perception according to the framework established in Section 2.2.2. However, the adjectives were rearranged into a random order to prevent response patterns and ensure that participants evaluated each item independently.

At the beginning, questions regarding the participant's profile (gender, age, country, formal education, and occupation) were asked. In the second section, participants' general attitude towards AI was queried on a 5-point Likert scale, where 1 = "very negative" and 5 = "very positive." Subsequently, based on the input of their birth month, participants were randomly assigned to one of the four advertisement conditions. They then evaluated the assigned advertisement using the credibility perception adjectives according to Huschens et al. [20] on a 5-point Likert scale from 1 = "Strongly disagree" to 5 = "Strongly agree."

As detailed in Section 3.2, two different advertising scenarios were tested to determine if differences exist across different product types. If this is the case, it would suggest that factors such as the type of advertisement (hedonic vs. utilitarian) could also influence credibility perception.

Table 3.1 below presents the components of the questionnaire along with the respective response options, the associated hypothesis, and the source.

No.	Variable	Response Options	Hypothesis	Source
1	Gender	Female Male Non-Binary Prefer Not To Say	-	-
2	Age	Number (1–100 Input)	-	-
3	Country	Germany Austria Switzerland Other	-	-
4	Formal Education	Compulsory School Apprenticeship Secondary School Uni-Entrance Qualification Bachelor's Degree Master's Degree Doctorate (PhD) No / Other Degree	-	-
5	Occupation	Pupil / Apprentice Student Employee Civil Servant Self-Employed Retired Unemployed	-	-
6	AI Attitude	Very Negative Rather Negative Neutral Rather Positive Very Positive	H5-H8	[22, 23]
7	Randomization	Jan–Mar (Group A) Apr–Jun (Group B) Jul–Sep (Group C) Oct–Dec (Group D)	-	-
8	Ad-Perception (Section 2.2.2)	Strongly disagree Disagree Neutral Agree Strongly agree	H1-H4	[20]

Table 3.1: Components of the Questionnaire

3.4 Measurement Instruments

The data collection instrument was a structured online questionnaire divided into four main sections: socio-demographics, general attitude towards AI (moderator), the experimental manipulation, and the assessment of the advertisement's credibility (dependent variable).

3.4.1 Independent Variable: AI Transparency Manipulation

The independent variable in this study is AI Transparency, operationalized through the presence or absence of a disclosure label on the advertisement. This resulted in two experimental conditions:

1. **Treatment Condition (Labeled)**: Participants were shown an advertisement containing a conspicuous text badge in the bottom-right corner reading "AI-generated" (German: "KI-generiert"). This label was designed according to the recommendations by Gamage et al. [36], who identified "AI-generated" as the most effective phrase for user recognition. The label's design followed a standardized format (semi-transparent background, white Roboto font, size 32px) to simulate realistic social media disclosure practices.

2. **Control Condition (Unlabeled)**: Participants were shown the identical advertisement without any disclosure label or text indicating the use of AI.

This binary manipulation allows for the isolation of the label's effect on consumer perception, independent of the visual content itself.

3.4.2 Dependent Variable: Perceived Credibility

The dependent variable, Perceived Credibility, was measured using the multi-dimensional framework proposed and validated by Huschens et al. [20]. This model is particularly suitable for this study as it was developed specifically to compare human- and AIGC. It decomposes credibility into four distinct dimensions: Competence, Trustworthiness, Clarity, and Engagement.

Participants were asked to rate the extent to which specific adjectives described the advertisement they had just viewed. The items were measured on a 5-point Likert scale ranging from 1 = "Strongly disagree" to 5 = "Strongly agree" (German: 1 = "Stimme überhaupt nicht zu" / 5 = "Stimme voll und ganz zu").

The scale consists of the following 11 items:

- **Competence**: Measured by the items *accurate*, *complete*, and *knowledgeable*. These items assess the perceived expertise of the source [26].
- **Trustworthiness**: Measured by the items *honest*, *trustworthy*, and *reliable*. These items assess the perceived integrity of the source.
- **Clarity**: Measured by the items *clear*, *not confusing*[1], and *understandable*. These items evaluate the comprehensibility of the message itself.
- **Engagement**: Measured by the items *interesting* and *maintaining attention*. These items assess the ability of the message to capture the viewer's interest.

To mitigate potential order effects and response sets, the items were administered in a fixed, pseudo-randomized order, ensuring that adjectives belonging to the same credibility dimension were not clustered together. The presented order of the items was: *interesting*, *accurate*, *trustworthy*, *clear*, *maintaining attention*, *reliable*, *knowledgeable*, *understandable*, *honest*, *complete*, and *not confusing* (German: "*interessant*, *akkurat*, *vertrauenswürdig*, *klar*, *zieht Aufmerksamkeit auf sich*, *zuverlässig*, *sachkundig*, *verständlich*, *ehrlich*, *vollständig*, *nicht verwirrend*").

3.4.3 Moderating Variable: General AI Attitude

To investigate the potential moderating effect of pre-existing beliefs (Hypotheses H5-H8), the study measured the participants' General Attitude towards AI.

This variable was assessed prior to the experimental stimulus to avoid priming effects. A single-item global measure was used, asking participants: "How is your general attitude towards AI?" (German: "Wie ist Ihre generelle Einstellung zu KI?").

The response was recorded on a 5-point Likert scale:

- Very negative (German: "Sehr negativ")
- Rather negative (German: "Eher negativ")
- Neutral (German: "Neutral")

[1] The original item "confusing" from Huschens et al. [20] was reverse-coded in the questionnaire design and presented as "not confusing" (German: "nicht verwirrend") to ensure consistent polarity across all scale items.

- Rather positive (German: “Eher positiv”)
- Very positive (German: “Sehr positiv”)

This measure allows for the segmentation of the sample into groups with positive, neutral, and negative predispositions towards AI, facilitating the analysis of interaction effects with the transparency label.

3.5 Data Analysis Strategy

Upon completion of the data collection phase, the raw dataset was exported from Google Forms in CSV format. The data was subsequently subjected to a rigorous cleaning and preparation process to ensure structural integrity for analysis. This involved recoding raw categorical data into numerical values, screening for and eliminating inconsistent or incomplete responses, and removing variables that were irrelevant to the specific hypotheses of this study [34, 37].

Descriptive statistics regarding socio-demographics and the moderator variable (General AI Attitude) were visualized using the Python library matplotlib. Pie charts were generated to illustrate the distribution of gender and country of residence, providing a clear overview of the sample composition. For the analysis of age distribution, formal education levels, occupational status, and the general attitude towards AI, histograms were employed. These histograms map the frequency of occurrences for specific variable values, providing insights into the distribution patterns of the sample data [37].

The primary hypothesis testing was conducted using Google Colab, a hosted Jupyter Notebook service that provides free access to computing resources [38]. The cleaned dataset was imported into the environment using the Python libraries pandas and scipy. To prepare the data for inferential analysis, aggregated mean scores were calculated for the four superordinate credibility dimensions (Competence, Trustworthiness, Clarity, and Engagement) based on the individual items associated with each dimension.

To determine the appropriate statistical procedures for hypothesis testing, the assumption of normality was assessed using both the Shapiro-Wilk and Kolmogorov-Smirnov tests [37], which were conducted using Python’s scipy library. While these tests can occasionally yield diverging results depending on the sample size and distribution characteristics [39], in the context of this study, they produced consistent findings. The null hypothesis for these tests posits that the data follows a normal distribution; a significance value (p-value) below 0.05 necessitates the rejection of the null hypothesis in favor of the alternative hypothesis [40]. The results of these tests are presented in Table 3.2, where bold values indicate a statistically significant deviation from a normal distribution.

Dimension	**Total Dataset**		**No Label (Control)**		**Label (Treatment)**	
	S-W (p)	**K-S** (p)	**S-W** (p)	**K-S** (p)	**S-W** (p)	**K-S** (p)
Competence	**.001**	**.021**	.070	.249	**.008**	.071
Trustworthiness	**.023**	.065	.079	.233	.398	.474
Clarity	**.000**	**.008**	**.000**	.097	**.001**	.087
Engagement	**.000**	**.003**	**.011**	.240	**.008**	**.027**

Table 3.2: Tests of Normality

As the data demonstrates, non-normal distributions are prevalent not only in the aggregate dataset but also across both the labeled and unlabeled experimental conditions. Consequently, the null hypothesis of normality was rejected for the majority of variables.

Due to this violation of the normality assumption, parametric tests such as the independent samples t-test or Analysis of Variance (ANOVA) could not be utilized. Instead, robust non-parametric tests were employed to analyze the hypotheses. Specifically, the analysis utilized rank-based procedures such as the Mann-Whitney U Test (often referred to as the Wilcoxon rank-sum test for independent samples) and the Kruskal-Wallis Test. These methods compare rank sums rather than means and are valid even in the absence of normal distribution, effectively bypassing distribution issues by converting scores to ranks and minimizing the influence of outliers [39, 40, 41].

4 Results

This chapter presents the empirical findings of the study.

First, Section 4.1 provides a comprehensive overview of the sample, detailing the sociodemographic profile of the participants (Subsection 4.1.1) and presenting descriptive statistics for the key variables, including the dependent measures of credibility and the moderating variable of AI attitude (Subsection 4.1.2).

Section 4.2 then addresses the validity of the experimental procedure by reporting on manipulation and confound checks.

Following this, Section 4.3 constitutes the core of the analysis, where the specific hypotheses derived in Chapter 2 are rigorously tested using non-parametric statistical methods.

Finally, Section 4.4 explores additional patterns and potential interaction effects within the data that extend beyond the primary hypotheses, offering further insights into the nuances of consumer perception.

4.1 Sample Characteristics and Descriptive Statistics

The empirical data for this study was collected via an online survey conducted between November 19th and November 25th, 2025. A total of 140 participants completed the questionnaire. Following the data collection phase, the raw dataset was subjected to a data cleaning procedure to ensure data quality. No datasets required exclusion due to incompleteness or unrealistic completion times. Consequently, the final sample consists of $N = 140$ valid responses.

This section provides a detailed overview of the sample composition, including sociodemographic factors, and presents the descriptive statistics for the central variables of interest: the perceived credibility dimensions and the moderating variable of general AI attitude.

4.1.1 Sociodemographic Profile

This section presents the sociodemographic characteristics of the study sample. To ensure sufficient data density for the four experimental groups, a target sample size of 120 participants was defined. This target was successfully exceeded, resulting in a final total of 140 valid responses ($N = 140$). The visualizations presented in the following subsections were generated using the Python library matplotlib.

The geographical distribution of the sample was restricted to the DACH region (Germany, Austria, Switzerland). As illustrated in Figure 4.1, the vast majority of participants reside in Germany ($n = 138$, 98.6%). Austria and Switzerland are represented by only one participant each (0.7% respectively). This heavy skew towards Germany suggests that the findings are primarily reflective of German consumer perceptions [37].

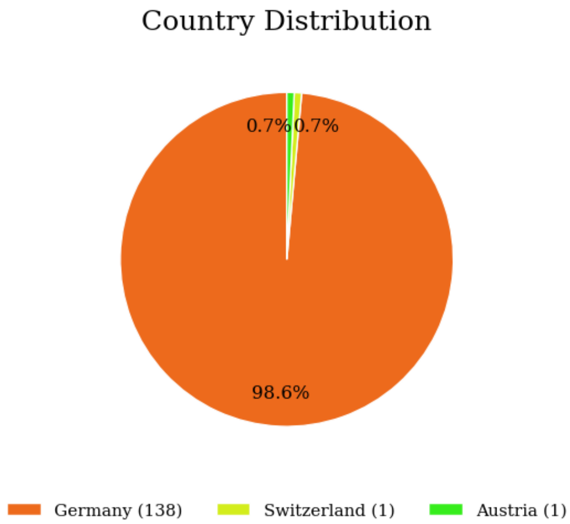

Figure 4.1: Distribution of Participants by Country of Residence

The gender distribution of the sample was fairly balanced, though slightly skewed towards male participants. As depicted in Figure 4.2, 73 participants identified as male (52.1%), while 66 participants identified as female (47.1%). Additionally, one participant identified as non-binary (0.7%). This relatively even split between male and female respondents strengthens the generalizability of the findings across gender lines, reducing the risk of gender-specific bias in the overall results [37].

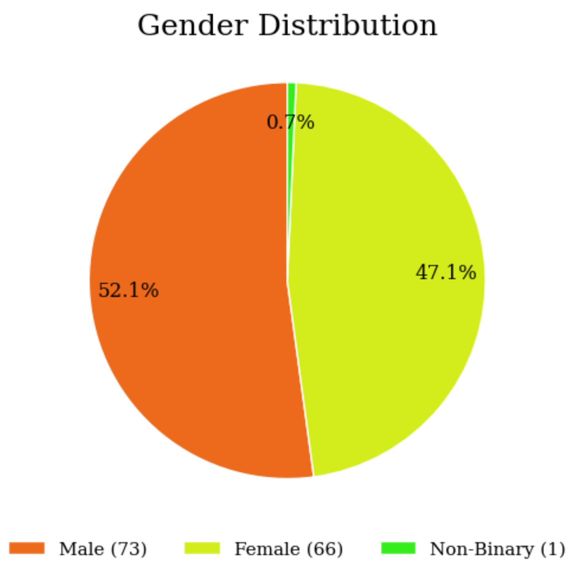

Figure 4.2: Distribution of Participants by Gender

The age of the participants ranged from 12 to 89 years, covering a broad spectrum of the population. As illustrated in Figure 4.3, the sample is predominantly young, with nearly half of the participants falling into the 20–29 age group ($n = 67$, 47.86%). The next largest groups were those aged 50–59 ($n = 23$, 16.43%) and 40–49 ($n = 14$, 10.00%). While the study successfully recruited participants across various life stages, including the oldest represented bracket of 80–89 years (2.14%), the concentration in the 20–29 range reflects the primary recruitment channels within the university environment and social media [37].

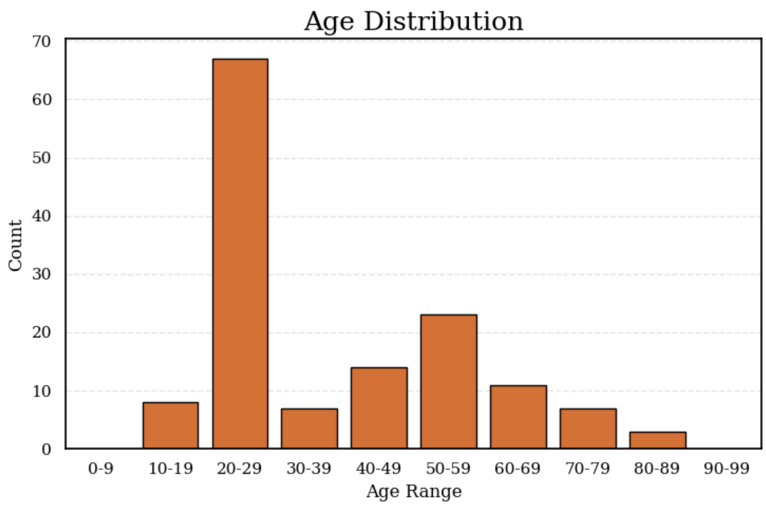

Figure 4.3: Distribution of Participants by Age Group

Regarding the highest level of formal education, the sample exhibits a relatively high level of educational attainment. As shown in Figure 4.4, the largest share of participants ($n = 61$, 43.57%) reported holding a University Entrance Qualification (High School Diploma / A-Levels / Abitur / Matura).

A significant portion of the sample has completed higher education, with 21.42% holding a university degree (Bachelor's: 10.00%, Master's: 10.71%, PhD: 0.71%). Vocational training also plays a substantial role, with 16.43% of participants having completed an apprenticeship and 14.29% a secondary school certificate. Only a small minority (1.43%) indicated compulsory school as their highest level of education. This educational structure suggests a sample that is well-educated, which aligns with the recruitment strategy focusing on academic and professional networks [37].

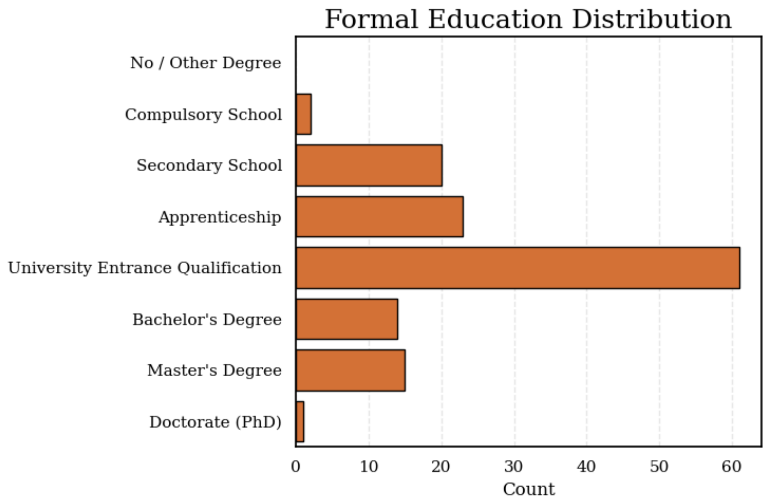

Figure 4.4: Distribution of Participants by Formal Education Level

The analysis of the participants' current occupational status reveals a diverse sample, though with a clear predominance of individuals in education and employment. As illustrated in Figure 4.5, the largest single group consists of Students ($n = 56$, 40.00%), reflecting the academic context of the recruitment process.

The second largest group is comprised of Employees ($n = 40$, 28.57%), followed by Retired individuals ($n = 18$, 12.86%). Smaller segments of the sample identified as Pupils / Apprentices ($n = 11$, 7.86%), Civil Servants ($n = 7$, 5.00%), and Self-Employed ($n = 6$, 4.29%). No participants reported being unemployed at the time of the survey. This distribution confirms that the study captures a wide range of life stages, from those in early training to those in retirement, although the student population is overrepresented [37].

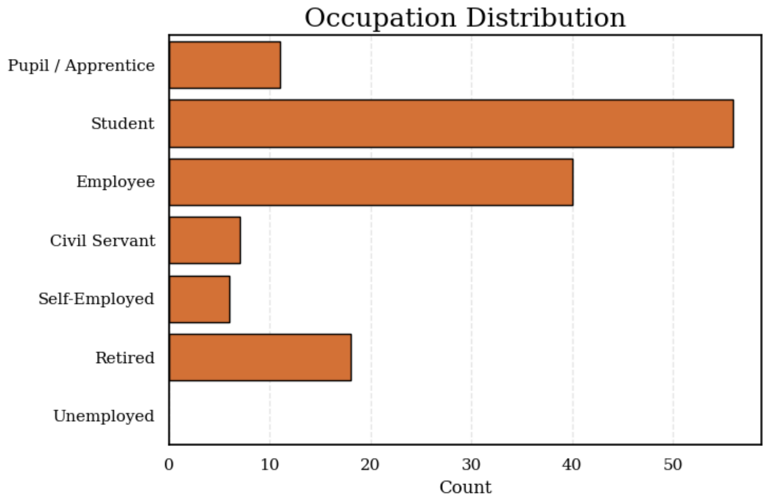

Figure 4.5: Distribution of Participants by Occupation

4.1.2 Descriptive Statistics for Key Variables

This section presents the descriptive analysis of the study's key variables, starting with the participants' general predisposition towards AI.

Participants' general attitude towards AI was measured on a 5-point Likert scale ranging from 1 (Very Negative) to 5 (Very Positive). The overall sample exhibited a tendency towards a positive perception of AI, with a mean score of 3.60 ($SD = 0.92$).

As illustrated in Figure 4.6, the largest group of participants reported a Rather Positive attitude ($n = 71$), followed by those with a Neutral stance ($n = 35$). Only a small minority ($n = 4$) expressed a Very Negative attitude towards AI. This generally positive baseline suggests that the sample population is relatively open to technological innovation, which aligns with the high proportion of students and young professionals in the sample.

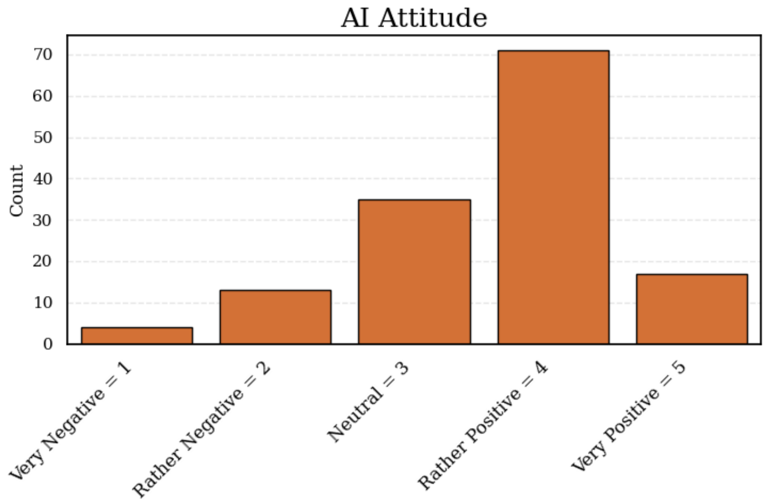

Figure 4.6: General Attitude towards AI (Total Sample)

To investigate potential generational differences, the attitude scores were further analyzed by age cohorts (see Figure 4.7). The age ranges for these cohorts were determined based on the definitions provided by the Library of Congress [42]. Note that other generations (such as the Silent Generation and Generation Alpha) were omitted from this specific analysis due to insufficient data points in the sample.

- **Generation Z** ($n = 76$): This youngest cohort showed the most pronounced positive skew, with the majority of participants rating their attitude as Rather Positive.
- **Millennials** ($n = 15$) & **Generation X** ($n = 28$): These groups displayed a more balanced distribution but maintained a generally positive trend.
- **Baby Boomers** ($n = 17$): Interestingly, this oldest cohort showed a distinct peak in the Neutral category, suggesting a more cautious or undecided stance compared to the younger generations.

This generational breakdown highlights that while the overall sentiment is positive, age plays a role in shaping the intensity of this approval, with younger digital natives appearing more enthusiastic than older cohorts.

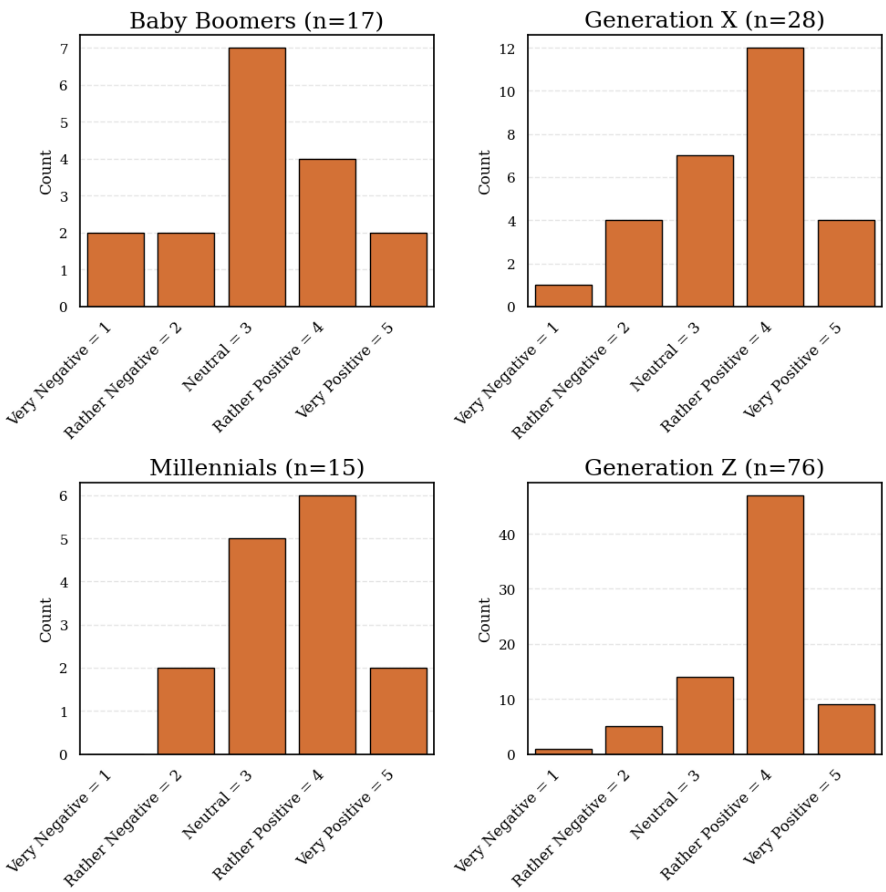

Figure 4.7: AI Attitude Distribution by Generation

The dependent variable, perceived credibility, was measured across four dimensions: Competence, Trustworthiness, Clarity, and Engagement. Table 4.1 displays the means and standard deviations for these dimensions across the total dataset, as well as split by the experimental manipulation (AI Label vs. No Label).

Overall, the mean scores for all credibility dimensions hover around the midpoint of the scale (3.0), with Clarity receiving the highest average rating ($M = 3.78$, $SD = 1.00$) and Competence the lowest ($M = 2.85$, $SD = 0.88$). This suggests that participants generally found the advertisements clear but were moderately skeptical regarding their competence and trustworthiness.

When comparing the experimental groups, the differences appear marginal. For instance, the mean score for Trustworthiness in the "No Label" group (Label = 0) was 2.88 ($SD = 0.92$), whereas the "Label" group (Label = 1) reported a slightly higher mean of 2.94 ($SD = 0.87$). Similarly, Engagement scores were higher in the labeled condition ($M = 3.33$) compared to the unlabeled condition ($M = 3.00$).

These descriptive statistics provide a first indication that the presence of an AI disclosure label may not have the strong negative impact hypothesized, a finding that will be rigorously tested in Section 4.3.

Table 4.1: Descriptive Statistics for Credibility Dimensions

Dimension	**Total Dataset**		**No Label (0)**		**AI Label (1)**	
	M	**SD**	**M**	**SD**	**M**	**SD**
Competence	2.85	0.88	2.83	0.91	2.87	0.85
Trustworthiness	2.91	0.89	2.88	0.92	2.94	0.87
Clarity	3.78	1.00	3.79	1.08	3.76	0.92
Engagement	3.17	0.99	3.00	1.06	3.33	0.90

4.2 Manipulation and Confound Checks

To ensure the internal validity of the experiment, it is critical to verify that the observed effects are attributable to the manipulation of the independent variable (the AI transparency label) and not to inherent differences between the two product types used as stimuli (premium chocolate vs. running shoe). While the use of multiple product types increases the generalizability of the findings, it also introduces a potential confounding variable if one product is systematically perceived differently from the other.

To address this, a confound check was conducted by comparing the credibility ratings of the "Premium Chocolate" advertisement (representing a hedonic product) against the "Running Shoe" advertisement (representing a utilitarian product) across all four credibility dimensions. Given the non-normal distribution of the data, a series of Mann-Whitney U tests were performed.

The statistical analysis revealed no significant differences between the two product types for three of the four credibility dimensions. Specifically, participants rated both advertisements similarly in terms of Competence ($U = 2450.00$, $p = .975$), Trustworthiness ($U = 2577.00$, $p = .572$), and Clarity ($U = 2217.50$, $p = .346$). This indicates that the base stimuli were well-matched on these key attributes, minimizing the risk of product-specific bias for these variables.

However, a statistically significant difference was observed for the Engagement dimension ($U = 2910.50$, $p = .048$). As illustrated in Figure 4.8, the premium chocolate advertisement was perceived as significantly more engaging ($M = 3.34$, $SD = 1.00$) than the running shoe advertisement ($M = 2.98$, $SD = 0.96$).

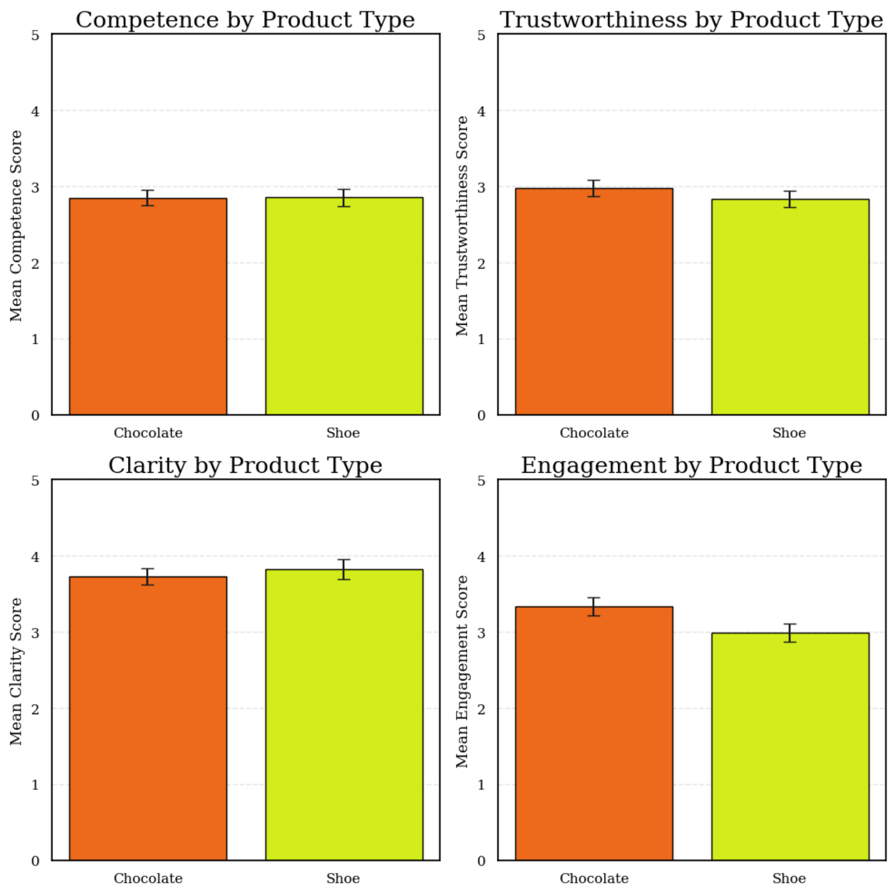

Figure 4.8: Comparison of Credibility Dimensions by Product Type

This finding identifies product type as a potential confounder specifically for the Engagement dimension. Since the premium chocolate ad is inherently more engaging, an unequal distribution of product types across the experimental groups (Label vs. No Label) could skew the results for Hypothesis 4. Therefore, when testing H4 (Effect of Label on Engagement), it is necessary to control for product type or to analyze the effects separately for each product to ensure that any observed differences are genuinely attributable to the AI label and not merely a reflection of the product category. For the remaining hypotheses (H1-H3), the lack of significant differences suggests that the product type does not pose a confounding threat.

4.3 Hypothesis Testing

This section presents the results of the inferential statistical analysis used to test Hypotheses H1 through H8, beginning with H1-H4. These hypotheses postulated that the presence of an AI disclosure label ("AI-generated") would negatively impact the perceived credibility of the advertisement across four dimensions: Competence, Trustworthiness, Clarity, and Engagement.

Given the non-normal distribution of the data identified in Section 3.5, the Mann-Whitney U Test was employed to compare the central tendencies of the two independent groups: the No Label control group ($N_{Control}$) and the AI Label treatment group ($N_{Treatment}$). The significance level was set at $\alpha = 0.05$. Effect sizes were calculated using the Rank-Biserial Correlation (r), where values closer to 0 indicate no effect, and values closer to 1 (or -1) indicate a strong effect [41].

H1: The Effect on Competence predicted that the presence of an AI label would lead to a more negative evaluation of the advertisement's Competence (accuracy, completeness, knowledge). Descriptive statistics indicated a negligible difference in means between the unlabeled ($M = 2.87$, $Mdn = 2.67$) and labeled advertisements ($M = 2.83$, $Mdn = 2.67$). The Mann-Whitney U test confirmed that this difference was not statistically significant ($U = 2378.00$, $p = 0.770$). The effect size was extremely small ($r = 0.03$). Consequently, H1 is rejected. The disclosure of AI generation did not significantly diminish the perceived competence of the advertisement.

H2: The Effect on Trustworthiness posited that the AI label would negatively impact the advertisement's Trustworthiness (honesty, reliability). While the mean score for the unlabeled group ($M = 2.94$) was slightly higher than that of the labeled group ($M = 2.88$), the Mann-Whitney U test revealed no statistically significant difference ($U = 2307.00$, $p = 0.555$). The effect size remained negligible (r=0.06). Therefore, H2 is rejected. Participants did not rate the advertisement as significantly less trustworthy when explicitly informed it was generated by AI.

H3: The Effect on Clarity suggested that the AI label would reduce perceived Clarity (understandability, lack of confusion). Contrary to the hypothesis, the labeled group actually reported a marginally higher mean score ($M = 3.79$) compared to the control group ($M = 3.76$), although the medians were identical ($Mdn = 4.00$). The statistical test confirmed that there is no significant difference between the groups ($U = 2600.00$, $p = 0.525$), with a near-zero effect size ($r = -0.06$). Thus, H3 is rejected. The transparency label had no impact on how clear or understandable the content was perceived to be.

H4: The Effect on Engagement predicted that the AI label would negatively affect Engagement (interest, attention). The data showed a trend consistent with the hypothesis: the unlabeled advertisements received higher engagement scores ($M = 3.33$, $Mdn = 3.50$) than the labeled ones ($M = 3.00$, $Mdn = 3.00$). The Mann-Whitney U test yielded a p-value of 0.067 ($U = 2014.00$), which approaches but does not meet the standard significance threshold of 0.05. The effect size was small ($r = 0.18$). Although a trend toward a negative effect was observed, the result is technically not statistically significant. Therefore, H4 is rejected, though it is worth noting that Engagement was the only dimension to show a notable (albeit non-significant) sensitivity to the label.

Table 4.2 summarizes the test statistics for all four hypotheses. Overall, the analysis suggests that the mere presence of an AI transparency label does not trigger the strong "algorithm aversion" effects predicted in the literature for this specific context.

Table 4.2: Impact of AI Transparency on Advertisement Credibility (Mann-Whitney U)

Hypothesis	**No Label**	**Label**	**U-Statistic**	**p-value**	**Result**
H1: Competence	2.87	2.83	2378	.770	Not Supported
H2: Trustworthiness	2.94	2.88	2307	.555	Not Supported
H3: Clarity	3.76	3.79	2600	.525	Not Supported
H4: Engagement	3.33	3.00	2014	.067	Not Supported

Hypotheses H5 through H8 postulated that a consumer's general attitude towards AI would moderate their perception of the advertisement's credibility. Specifically, it was expected that participants with a more positive pre-existing attitude towards AI would evaluate the advertisements more favorably than those with a negative attitude.

To test these hypotheses, the sample was categorized into three distinct groups based on their responses to the 5-point General AI Attitude scale:

- **Negative Attitude Group**: Participants who selected "Very Negative" (1) or "Rather Negative" (2).
- **Neutral Attitude Group**: Participants who selected "Neutral" (3).
- **Positive Attitude Group**: Participants who selected "Rather Positive" (4) or "Very Positive" (5).

Given the non-normal distribution of the data and the ordinal nature of the grouping variable, a Kruskal-Wallis H Test was conducted to determine if there were statistically significant differences in the four credibility dimensions across these three attitude groups [41].

The analysis revealed no statistically significant differences for any of the four dimensions.

H5: The Kruskal-Wallis test indicated no significant variation in perceived competence across the attitude groups ($H(2) = 2.60$, $p = 0.273$). Participants with a negative attitude ($M = 2.69$) rated competence similarly to those with a positive attitude ($M = 2.80$) or neutral attitude ($M = 3.07$). Thus, H5 is rejected.

H6: Similarly, no significant difference was found for trustworthiness ($H(2) = 1.41$, $p = 0.493$). Mean scores were comparable across negative ($M = 2.61$), neutral ($M = 3.04$), and positive ($M = 2.92$) groups. H6 is rejected.

H7: The test for clarity also yielded non-significant results ($H(2) = 2.07$, $p = 0.355$), indicating that pre-existing AI attitudes did not influence how clear or understandable the advertisement was perceived to be. H7 is rejected.

H8: Finally, engagement scores showed the least variation across groups ($H(2) = 0.26$, $p = 0.879$), with mean scores nearly identical between the negative ($M = 3.24$) and positive ($M = 3.17$) groups. H8 is rejected.

These findings indicate that the general attitude towards AI did not serve as a significant moderator in this study. Whether a participant viewed AI skeptically or enthusiastically did not significantly alter their specific credibility assessment of the presented advertisements. Table 4.3 summarizes these results.

Table 4.3: Moderating Effect of General AI Attitude (Kruskal-Wallis H)

Hypothesis	**Neg.**	**Neut.**	**Pos.**	**H-Statistic**	**p-value**	**Result**
H5: Competence	2.69	3.07	2.80	2.60	.273	Not Supported
H6: Trustworthiness	2.61	3.04	2.92	1.41	.493	Not Supported
H7: Clarity	3.47	3.95	3.77	2.07	.355	Not Supported
H8: Engagement	3.24	3.14	3.17	0.26	.879	Not Supported

4.4 Exploratory Analyses

While the primary hypothesis testing did not reveal a significant main effect of the AI label across the total dataset, further exploratory analyses were conducted to investigate potential nuances that might be masked by the aggregation of data. Specifically, the analysis focused on the influence of product type (hedonic vs. utilitarian) and key demographic factors (age and gender).

As identified in the confound check (Section 4.2), the two stimuli used in the experiment represented distinct product categories: "Premium Chocolate" (hedonic) and "Running Shoe" (utilitarian). To determine if the AI label had a differential impact depending on the nature of the product, the dataset was split by product type, and the effect of the label was tested within each subgroup using the Mann-Whitney U test.

For the premium chocolate advertisement, comparisons between the labeled (Group A) and unlabeled (Group B) conditions yielded no statistically significant differences across any of the four credibility dimensions.

- **Competence**: $p = 0.842$
- **Trustworthiness**: $p = 0.899$
- **Clarity**: $p = 0.129$
- **Engagement**: $p = 0.105$

These results suggest that for a product driven by sensory pleasure and emotion, the explicit disclosure of AI generation did not alter consumer perception. The visual appeal of the chocolate appeared to be robust against any potential "algorithm aversion."

Similarly, for the running shoe advertisement, comparisons between the labeled (Group C) and unlabeled (Group D) conditions also showed no statistically significant differences.

- **Competence**: $p = 0.730$
- **Trustworthiness**: $p = 0.361$
- **Clarity**: $p = 0.324$
- **Engagement**: $p = 0.582$

Consequently, the null result observed in the main hypothesis testing appears consistent across both product categories. The presence of an AI label did not significantly diminish the credibility of either the emotional (hedonic) or the functional (utilitarian) product advertisement in the general sample.

While gender did not yield any significant interaction effects with the AI label (all $p > 0.05$ for female participants), a striking pattern emerged when analyzing the data by age cohorts. The sample was divided into two groups: Younger Adults (Under 30, $n = 101$) and Older Adults (Over 30, $n = 39$).

For participants under 30, the presence of the AI label had no significant impact on any credibility dimension. This cohort, largely consisting of "digital natives," appears to be indifferent to the disclosure of AI generation in advertising.

In stark contrast, participants over the age of 30 showed a significant negative reaction to the AI label. As summarized in Table 4.4, the labeled advertisements were rated significantly lower than the unlabeled ones across three key dimensions:

- **Competence**: The labeled ads were perceived as significantly less competent ($M_{\text{Label}} = 2.56$ vs. $M_{\text{NoLabel}} = 2.99$; $U = 368.5$, $p = 0.037$).
- **Trustworthiness**: Trustworthiness ratings dropped significantly when the label was present ($M_{\text{Label}} = 2.53$ vs. $M_{\text{NoLabel}} = 3.02$; $U = 367.5$, $p = 0.035$).
- **Engagement**: The labeled ads were also found to be significantly less engaging ($M_{\text{Label}} = 2.94$ vs. $M_{\text{NoLabel}} = 3.56$; $U = 365.5$, $p = 0.032$).

This finding uncovers a hidden "algorithm aversion" that is specific to older demographics. While the aggregate data masked this effect due to the large proportion of students in the sample, this exploratory analysis suggests that age is a critical boundary condition for the acceptance of disclosed AI content.

Table 4.4: Effect of AI Label on Credibility for Participants Over 30 Years ($n = 39$)

Dimension	**No Label**	**Label**	**U-Statistic**	**p-value**	**Result**
Competence	2.99	2.56	368.5	**.037**	Significant
Trustworthiness	3.02	2.53	367.5	**.035**	Significant
Clarity	3.61	3.34	423.5	.513	Not Sig.
Engagement	3.56	2.94	365.5	**.032**	Significant

5 Discussion

The primary objective of this thesis was to investigate the impact of AI transparency on consumer perception. Specifically, it sought to answer the research question:

To what extent does the transparent disclosure of AI-generated content in advertising impact its perceived credibility?

While the theoretical framework suggested that disclosing non-human authorship would trigger "algorithm aversion" and thus lower credibility, the empirical results of this study paint a more nuanced picture. This chapter summarizes and interprets these findings (Section 5.1), discusses their implications for academic theory (Section 5.2), and derives concrete recommendations for marketing practitioners (Section 5.3).

5.1 Summary and Interpretation of Findings

The empirical investigation yielded results that largely contradicted the initial negative expectations derived from traditional algorithm aversion theory, while uncovering a critical demographic divide.

Hypotheses H1 through H4 postulated that the presence of an AI disclosure label ("AI-generated") would negatively impact the advertisement's perceived Competence, Trustworthiness, Clarity, and Engagement.

Contrary to these expectations, the analysis of the total dataset ($N = 140$) revealed no statistically significant negative effects across any of the four dimensions. The advertisements were rated similarly in competence and trustworthiness, regardless of whether the AI label was present or absent. Interestingly, for the dimension of Clarity, the labeled advertisements even received marginally higher scores, though not to a significant degree. Only for Engagement was a slight negative trend observable ($p = 0.067$), yet it failed to reach statistical significance.

Consequently, Hypotheses H1, H2, H3, and H4 were rejected.

These findings suggest that for the average consumer in this sample, the mere knowledge that an advertisement was created by AI does not inherently act as a warning signal or a mark of inferiority. This “algorithm indifference” could be attributed to the high visual quality of the stimuli used (generated by DALL·E 3), which may have overridden potential biases. If the content looks professional and convincing, the “process” of its creation appears to become secondary to the “outcome.”

Hypotheses H5 through H8 proposed that a consumer’s general attitude toward AI would moderate the effect of the label—i.e., that AI-skeptics would penalize the label more than AI-enthusiasts.

The results indicated no significant interaction effects. Whether participants viewed AI generally positively, neutrally, or negatively did not significantly alter their specific credibility assessment of the labeled advertisement.

This suggests that the evaluation of a specific creative asset (an ad) is distinct from abstract technological beliefs. A consumer might fear AI’s impact on the job market (negative general attitude) but still find an AI-generated image of premium chocolate appealing and credible (positive specific evaluation).

Consequently, Hypotheses H5, H6, H7, and H8 were rejected.

While the aggregate data showed no effect, the exploratory analysis in Section 4.4 uncovered a significant hidden pattern. When the sample was stratified by age, a clear dichotomy emerged:

- **Participants under 30** showed absolutely no sensitivity to the AI label. Their ratings were identical across conditions.
- **Participants over 30**, however, rated the labeled advertisements significantly lower in Competence ($p = .037$), Trustworthiness ($p = .035$), and Engagement ($p = .032$).

This is the central insight of the study. The “null result” of the main hypotheses was likely driven by the large proportion of younger participants in the sample. For older cohorts, the “algorithm aversion” predicted by theory is indeed present. They perceive AIGC as less reliable and less engaging when they are made aware of its origin. This suggests that AI transparency is not a universal negative signal, but rather a generation-dependent one.

5.2 Theoretical Implications

These findings offer several important contributions to the existing literature on AI in marketing and consumer behavior.

1. **Nuancing Algorithm Aversion**: Classic research on algorithm aversion (e.g., Dietvorst et al. [31]) suggests that people generally mistrust algorithmic performers, especially after seeing them error. However, this study suggests that this aversion is not a static trait of the entire population. Instead, it appears to be a generational phenomenon. Younger generations, who have grown up with digital intermediaries, appear to have normalized the presence of algorithmic content to the point of indifference. This thesis contributes to the theory by proposing age as a critical boundary condition for algorithm aversion in creative contexts.

2. **The Dominance of Content Quality**: The results align with recent findings by Huschens et al. [20], who found that AIGC is often perceived as equal or superior to human content in terms of clarity. This study extends this by showing that even transparency—the explicit admission of AI authorship—does not diminish this perception for the majority of users, provided the output quality is high. This challenges the Signaling Theory assumption that an "AI" signal is inherently interpreted as a cost-saving or low-quality cue [43].

3. **Product Type Independence**: Interestingly, the study found that the effect of the AI label did not differ between a hedonic product (premium chocolate) and a utilitarian product (running shoe). This contradicts some prior assumptions that AI might be accepted for functional tasks but rejected for emotional ones. The data suggests that if the visual execution is high-quality, the "soul" or "emotion" of the ad is perceived regardless of its computational origin, at least for younger consumers.

5.3 Managerial and Practical Implications

For marketing practitioners, the results of this study provide clear, actionable guidance on how to navigate the increasing pressure for AI transparency.

1. **Target Audience Matters Most**: Marketers must segment their transparency strategies based on demographics.

   - **For Gen Z and Young Millennials**: Transparency is a "safe" strategy. Disclosing the use of AI does not harm the brand or the ad's credibility.

Companies targeting this demographic (e.g., fast fashion, tech, gaming) can comply with ethical guidelines or legal mandates for labeling without fear of backlash.

- **For Gen X and Boomers**: Caution is advised. For older target groups (e.g., luxury goods, insurance, healthcare), an "AI-generated" label can significantly damage trust and engagement. If labeling is not legally required, these brands might benefit from retaining a human-centric narrative or emphasizing the "human-in-the-loop" aspect to mitigate skepticism.

2. **Focus on Visual Excellence**: The high credibility scores across the board (even with labels) validate the use of advanced generative tools like DALL·E 3 for content creation. The results imply that consumers primarily judge "with their eyes." If the image is aesthetically pleasing and professional, the method of creation is secondary. Marketers should therefore invest in quality control rather than worrying excessively about the stigma of the tool.

3. **Transparency as a Hygiene Factor**: Since the label did not increase credibility, transparency should be viewed as a hygiene factor (to avoid scandals or legal issues) rather than a performance enhancer. It doesn't make the ad perform better, but for younger audiences, it doesn't make it perform worse.

6 Conclusion

This final chapter concludes the thesis by summarizing the key findings in relation to the research question and the established theoretical framework (Section 6.1). Building on these results, the study's limitations are critically examined, and avenues for future research are proposed (Section 6.2).

6.1 Concluding Summary

AI is becoming increasingly integral to marketing strategies. Generative AI tools like ChatGPT and DALL·E allow for the rapid creation of high-quality, unique text and visual content, optimizing processes and reducing time expenditure, particularly in creative advertising tasks [1, 2, 15]. As AI becomes a staple of advertising strategy, there is a growing imperative to understand how consumers perceive and evaluate its use [1].

The primary objective of this thesis was to investigate the extent to which the transparent disclosure of AIGC in advertising impacts its perceived credibility. The study tested whether consumers who are aware that an advertisement was created by AI perceive it as less credible than consumers who are unaware of its origin. Furthermore, given that credibility is a subjective perceptual state [22, 23], the study also examined whether the consumer's general attitude towards AI moderates this effect.

To answer the research question derived in Section 1.3, a quantitative research method was employed. A structured online survey was conducted with a sample of 140 participants from the DACH region (Germany, Austria, Switzerland), ranging in age from 12 to 89 years. The measurement instrument was a questionnaire developed using Google Forms, based on the hypotheses derived in Chapter 2. Perceived credibility was assessed using the multi-dimensional framework by Huschens et al. [20], which decomposes credibility into four dimensions: Competence, Trustworthiness, Clarity, and Engagement. Participants were randomly assigned to one of four experimental groups (2 product types $\times$ 2 label conditions) and evaluated an advertisement using 11 adjectives on a 5-point Likert scale. Both the visual and textual content of the advertisements were generated entirely by AI (DALL·E 3 and ChatGPT), a fact that was disclosed to the treatment group via a transparency label.

Data analysis was conducted using Python (Google Colab). Due to the non-normal distribution of the data, non-parametric tests such as the Mann-Whitney U Test and the Kruskal-Wallis H Test were utilized [41].

Key Findings:

1. **No Negative Impact of Transparency in the Aggregate**: Contrary to the initial hypotheses (H1–H4), the study found no statistically significant difference in the perceived credibility of AI-labeled versus unlabeled advertisements across the total sample. The dimensions of Competence, Trustworthiness, and Clarity were rated similarly in both conditions. Engagement showed a slight negative trend for the labeled group, but this did not reach statistical significance. This suggests that for the general population in this sample, the "AI-generated" label does not inherently act as a stigma or a signal of low quality.

2. **Indifference of General AI Attitude**: The study also found no evidence that a consumer's general attitude towards AI (positive, neutral, or negative) moderates their specific evaluation of the advertisement (H5–H8). This implies that consumers can separate their abstract views on technology from their concrete appreciation of a high-quality visual stimulus.

3. **The Critical Role of Age**: A crucial exploratory finding was the significant influence of age. While participants under 30 years of age showed no sensitivity to the AI label, participants over 30 rated the labeled advertisements significantly lower in Competence, Trustworthiness, and Engagement. This reveals that "algorithm aversion" in advertising is not a universal phenomenon but appears to be generation-dependent.

In conclusion, this thesis contributes to the marketing literature by providing empirical evidence that AI transparency does not necessarily harm advertising credibility, particularly among younger audiences. It challenges the assumption that AI content is viewed as inferior, suggesting instead that high visual quality can override potential biases—at least for digital natives. However, for older demographics, transparency remains a risk factor that can diminish trust and engagement.

6.2 Limitations and Future Research Directions

While this study was conducted with the utmost rigorousness, several limitations must be acknowledged, which in turn open meaningful avenues for future research.

- **Sample Composition and Representativeness:** The study utilized a convenience sample ($N = 140$) recruited primarily through social media and university networks. Consequently, the sample is heavily skewed towards younger participants (47.86% aged 20–29) and students (40.00%), as well as residents of Germany (98.6%). While this demographic is highly relevant for digital marketing, the results may not be fully generalizable to the broader DACH population or other cultural contexts. The strong "null result" in the main analysis is likely influenced by this overrepresentation of younger, tech-savvy participants. Future research should strive for a more balanced probability sample, particularly to further investigate the significant negative effects found in the older age cohorts.

- **Stimulus Material:** The study focused on two specific product categories: a hedonic product (premium chocolate) and a utilitarian product (running shoe). While this design aimed to cover different consumption motives, the results are specific to these product types and the specific static image format used. It remains unclear whether these findings would hold for high-involvement services (e.g., financial advice, medical services) or different media formats (e.g., video, audio). Future studies could expand the scope to include service marketing or political advertising, where the "human touch" and truthfulness might be scrutinized more heavily than in product advertising.

- **Operationalization of Transparency:** The "AI Transparency" variable was operationalized as a static visual label ("AI-generated") placed on the image. In real-world scenarios, disclosure might be more subtle (e.g., in the caption) or more prominent (e.g., a platform-imposed tag). The study did not test different variations of the label design or wording. Future research could investigate whether the phrasing (e.g., "Assisted by AI" vs. "Fully Generated by AI") or the prominence of the disclosure moderates consumer reaction.

- **Short-term Focus:** Finally, this study measured immediate reactions to a single exposure. It does not account for long-term effects or repeated exposure. It is possible that a "sleeper effect" exists, where the negative stigma of the AI source fades over time, or conversely, that "disclosure fatigue" sets in after repeated exposure. Longitudinal studies would be valuable to understand the temporal dynamics of AI transparency acceptance.

Despite these limitations, this thesis provides a robust foundation for understanding the evolving relationship between consumer trust and AI. It highlights that as generative AI becomes ubiquitous, the "human vs. machine" distinction may become less relevant for younger consumers, provided the creative output meets their quality expectations.

Appendix

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