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Exploring the Impact of Artificial Intelligence on Content Creation for Social Media: The example of Personal Brands on LinkedIn

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Department of Marketing, Operations & General
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For professor João Guerreiro for his guidance.

*For my family, Sonja and Stefan,
for the motivation and love.*

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Resumo

O crescimento das redes sociais tornou o *personal branding* uma estratégia essencial para profissionais, sendo o LinkedIn a principal plataforma para a construção de credibilidade e confiança. Paralelamente, ferramentas de inteligência artificial generativa (GenAI), como o ChatGPT, estão transformando a criação de conteúdos ao possibilitar maior eficiência e escalabilidade. Apesar do seu potencial, essas tecnologias suscitam preocupações quanto à autenticidade, à confiança e à aceitação por parte dos consumidores.

Este estudo investiga o impacto da autenticidade percebida da voz da marca pessoal sobre a autenticidade da marca pessoal e analisa como a autenticidade, por sua vez, molda a atitude em relação à marca pessoal, bem como o word of mouth (WOM) positivo e negativo, a carga emocional e a lealdade. Além disso, o tipo de autoria é considerado como fator moderador.

Foi desenvolvido um modelo conceitual, testado por meio de um inquérito com respondentes ($n = 141$). Os dados foram analisados utilizando Partial Least Squares Structural Equation Modeling (PLS-SEM).

Os resultados demonstram que conteúdos gerados por inteligência artificial (IA) influenciam negativamente as percepções de autenticidade, corroborando pesquisas anteriores sobre a aversão a algoritmos. A autenticidade emergiu como um fator determinante das respostas dos consumidores: ela fortaleceu de forma significativa a atitude perante a marca e o WOM positivo, mas, quando violada, intensificou também o WOM negativo. As análises de subgrupos evidenciaram o papel da divulgação e do reconhecimento da autoria por parte dos consumidores na configuração dos resultados.

O estudo contribui para a literatura de personal branding ao integrar a autoria por IA nos quadros teóricos de autenticidade e oferece orientações práticas para equilibrar eficiência e autenticidade em estratégias de conteúdo impulsionadas por IA.

Palavras-chave: Personal Branding; Inteligência Artificial; Autenticidade; Marketing de Conteúdo; Lealdade do Consumidor

Classificação JEL primária: Marketing (M31)

Classificação JEL secundária: Mudança Tecnológica: Escolhas e Consequências; Processos de Difusão (O33)

Abstract

The rise of social media has made personal branding a vital strategy for professionals, with LinkedIn serving as a central platform for building credibility and trust. At the same time, generative artificial intelligence (GenAI) tools such as ChatGPT are reshaping content creation by enabling efficiency and scalability. While promising, these technologies raise concerns regarding authenticity, trust, and consumer acceptance.

This study investigates the impact of perceived personal brand voice authenticity on personal brand authenticity, and how authenticity in turn shapes perceived personal brand attitude, as well as both positive and negative word of mouth (WOM), emotionality, and loyalty. Type of authorship is further considered as a moderating factor.

A conceptual framework was developed and tested through a survey of respondents (n = 141). Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Results show that content generated by artificial intelligence (AI) negatively influences authenticity perceptions, confirming prior research on algorithm aversion. Authenticity emerged as a key driver of consumer responses: it strongly enhanced brand attitude and positive WOM but, when violated, also intensified negative WOM. Subgroup analyses highlighted the role of disclosure and consumer recognition of authorship in shaping outcomes.

The study contributes to personal branding literature by integrating AI-authorship into authenticity frameworks and offers practical guidance for balancing efficiency with authenticity in AI-driven content strategies.

Keywords: Personal Branding; Artificial Intelligence; Authenticity; Content Marketing; Customer Loyalty

Primary JEL classification: Marketing (M31)

Secondary JEL classification: Technological Change: Choices and Consequences; Diffusion Processes (O33)

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1 Introduction

In recent years, social media has evolved into one of the most influential spaces for communication, networking, and branding. Among various platforms, LinkedIn has gained a central role in professional self-presentation and the cultivation of personal brands. As highlighted by Labrecque et al. (2011), online platforms serve as key catalysts for building personal brands, allowing individuals to strategically manage their identities and engage with audiences. This process, known as personal branding, is increasingly considered a marketing task that can be accomplished by anyone (Shepherd, 2005), and its importance continues to accelerate in today's professional landscape.

At the same time, the digital transformation of marketing has amplified the significance of content creation as a driver of visibility and engagement. Digital content marketing (DCM) has been established as a fundamental strategy for brands to build trust and long-term relationships with their audiences (Rowley, 2008; Holliman & Rowley, 2014). In particular, social media content has been linked to consumer loyalty and engagement (Mathew & Soliman, 2021; Tyrväinen et al., 2023). For personal brands on LinkedIn, content not only conveys expertise and professionalism but also signals authenticity and credibility. Both qualities that research identifies as central for positive brand evaluations and audience trust (Aaker, 1995; Gill & Dawra, 2010).

Parallel to these developments, AI has emerged as one of the most disruptive innovations in marketing. Over the past decade, AI applications have expanded from analytical decision-making to creative tasks, with GenAI tools such as ChatGPT now capable of producing text, images, and other media formats (Grewal et al., 2024; Vaswani et al., 2017). These advancements introduce new opportunities for content creation, enabling efficiency, scalability, and personalization at an unprecedented level (Mittal & Tandon, 2023). In the context of digital marketing, AI can automate routines, personalize brand messages, and even mimic human-like communication styles (Huang & Rust, 2020). However, this potential also brings challenges. Research has consistently shown that consumers evaluate AI-generated content more critically, often perceiving it as less authentic, less empathetic, and less trustworthy compared to human-created content (Brüns & Meißner, 2024a; Graefe & Bohlken, 2020).

Authenticity, therefore, emerges as a key tension point in the discussion of AI-driven content creation. While brand authenticity has long been recognized as a decisive factor for consumer trust and loyalty (Aaker, 1995; Thomson et al., 2006), algorithm aversion suggests that audiences may resist content perceived as authored by machines (Burton et al., 2020). This is particularly relevant for personal brands, where the alignment between communication and personal identity is central. As Pérez (2019) argues, message authenticity enhances

credibility and reduces consumer skepticism, making it a vital element of effective personal branding. The question then arises: can personal brands preserve authenticity and credibility when generating parts of their content with AI?

Despite the rapid adoption of AI in marketing, there is still limited empirical research addressing its implications for personal branding. Existing studies primarily focus on corporate or product brands (Haupt et al., 2024; Overgoor et al., 2019), while the unique dynamics of personal brands with a high degree of identity, self-expression, and trust remain underexplored. Furthermore, emotionality plays a potentially decisive role. Prior research indicates that AI is less favorably perceived in hedonic or emotional contexts (Castelo et al., 2019; Longoni & Cian, 2022), raising concerns for personal branding on LinkedIn, which often relies on personal tone, empathy, and resonance.

Addressing these gaps, the present study examines how different types of authorship (human-authored versus AI-generated) affect perceptions of personal brand authenticity, personal brand voice authenticity, personal brand attitude, WOM, emotionality, and loyalty. By doing so, it contributes to the emerging literature on AI in marketing and sheds light on the mechanisms through which authenticity mediates consumer responses to AI-generated communication.

Based on this rationale, the following research questions are proposed:

RQ1: How does AI-generated content on LinkedIn influence perceptions of personal brand authenticity and personal brand voice authenticity compared to human-authored content?

RQ2: To what extent does perceived authenticity mediate the relationship between authorship type (human versus AI) and consumer responses such as brand attitude, WOM, and loyalty?

RQ3: How does the authorship type impact the perception of personal brand authenticity and subsequent audience behavior?

This thesis thus aims to provide both theoretical and practical insights. On a theoretical level, it extends personal branding literature by integrating AI authorship into frameworks of authenticity and consumer response (Kirkby et al., 2023). On a managerial level, it informs professionals and marketers on LinkedIn about how audiences evaluate AI-generated content, highlighting strategies for balancing efficiency with the demand for authenticity.

Regarding the dissertation structure, it is divided into six chapters. The introduction corresponds to the first chapter, which explains the topic's relevance and the research questions and objectives. The literature review is the second chapter, enhancing the main concepts of the research, which are personal branding, content creation in DCM, and AI in marketing. In chapter three, both the conceptual framework and respective hypotheses are developed. The fourth chapter corresponds to the methodology alongside the description of the study. Chapter five analyzes the data collected during the study, and the results are discussed. Finally, chapter six corresponds to the conclusions and recommendations of the research. Further, theoretical contributions, managerial implications, limitations and future research recommendations are presented in the final chapter.

2 Literature Review

2.1 Personal Branding

2.1.1 Human Branding and Personal Branding

The concept of a human brand appears in branding literature often as an extension of the branding theory from products to people (Thomson et al., 2006). Therewith, the basis for uncertainty is set as various terms refer to the context of branding individuals: human brands, celebrity brands, personal brands, and person-brands (Osorio et al., 2020). The first concept of human brands was defined by Thomson et al. (2006) as “any well-known persona who is the subject of marketing communication efforts” (Thomson et al., 2006). In further research, the definition was expanded to anyone, being already well-known or arising and influenced by any communication actions (Osorio et al., 2020).

Therefore, Fournier & Eckhardt (2019) started capturing the dual-nature and created the concept of a person-brand: “An entity that is at once a person and a commercialized brand offering, wherein both the person and the brand are references using the same brand naming convention.” (Fournier & Eckhardt, 2019). As Thomson (2006) stated, a human brand can be seen as one of several operationalizations of the broader concept of branding, and thus human brands can draw valuable insights from careful and strategic management (Thomson et al., 2006).

Whereas in a comparison to personal brands, a clear distinction between both relies on the concept of the persona as it is described as an individual’s social facade reflecting the role a person has in its life (Osorio et al., 2020). Dion & Arnould (2016) discovered that human brands have a dual nature, joining both the individual and the persona, whereas mainly the persona is associated with offerings having brand value (Dion & Arnould, 2016). This duality is also previously mentioned in the dual-nature defined by Fournier & Eckhardt (2019), constituting that a person is sold as a mixture together with a commercial entity, comparable to a product in the market (Fournier & Eckhardt, 2019). But Osorio et al. (2020) claimed that the dual effect is not recognized by personal brands (Osorio et al., 2020). The term rather stands for the characteristics of a person (Osorio et al., 2020). This view is supported by Gorbatov et al. (2018), who defined a personal brand as “the result of a strategic process of creating, positioning and maintaining a positive impression of oneself, based in a unique combination of individual characteristics, which signal a certain promise to the target audience through a differentiated narrative and imagery” (Gorbatov et al., 2018).

Detailed examination of personal brands by many authors in literature showed that the general focus of personal branding is on the person themselves. Shepherd (2005) agrees that the subject of a personal brand can be any individual (Shepherd, 2005). Moreover, the authors Khedher (2014) and Kucharska & Mikołajczak (2018) indicated that applicable branding

strategies for personal brands contend brand identity, positioning, and image (Khedher, 2014), as well as the marketing mix and brand associations (Kucharska & Mikołajczak, 2018).

A more complete comparison of both approaches can be seen in table 1.

Evaluative criteria	Personal brand	Human brand
Definition	A personal brand is the result of a strategic process of creating, positioning, and maintaining a positive impression of oneself, based on a unique combination of individual characteristics, which signal a certain promise to the target audience through a differentiated narrative and imagery. (Gorbatov et al., 2018)	A human brand is the result of the strategic process of building, leveraging, and sustaining a brand that happens to be a human being. The concept comes from marketing, building upon the branding literature and extending it from products to people. (Thomson et al., 2006)
Subject	Any individual (Shepherd, 2005)	An entity that is at once an individual and a persona transformed into a commercialized brand offering, wherein both the individual and the persona are references using the same brand naming convention. (Fournier & Eckhardt, 2019)
Objective	To manage or coach an individual (Lair et al., 2005)	To manage a brand that is also a real person (Fournier & Eckhardt, 2019)
Branding strategies	Brand identity, brand positioning and brand image, marketing mix, and brand associations (Khedher, 2014; Kucharska & Mikołajczak, 2018)	The same as a personal brand; plus: drivers of brand equity, brand equity measurement, brand expansion, and brand reinforcement

		(Kotler, 1969)
Theoretical approach	Mostly impression management (Gorbatov et al., 2018)	Branding theories adapted from products to people (Shepherd, 2005)

Table 1 - Distinction between personal brands and human brands

One notable issue with this approach is the theoretical challenge and a debate initiated by Kotler (1969), particularly as the scope of marketing gets broadened (Kotler, 1969). In the study of Shepherd (2005), the question was raised whether it is possible to maintain personal branding within a formal marketing framework or if its aspects are too distinct from basic principles of marketing (Shepherd, 2005). However, research showed that early definitions of marketing got extended and that current definitions are used across numerous contexts that were not originally associated with marketing (Shepherd, 2005). Further researchers reacted to the emergence of personal branding. In their studies they concluded that branding can be differentiated by a “small b” approach that relates to product branding only as well as to a “large b” as an extension of branding to services, organizations, and people (Hughes, 2007; Hughes et al., 2008; Speed et al., 2015).

In the realm of social media, the concept of personal branding started to become more popular as articulated by Tom Peters in the article “The Brand Called You.” in 1997 (Labrecque et al., 2011). Thus, the notion gained more awareness within the digital landscape, with social media as well as various online platforms serving as catalysators of personal brands (Labrecque et al., 2011). Presently, the importance continues to accelerate. Literature indicates that personal branding is nowadays a marketing task that can be accomplished by anyone (Shepherd, 2005). As Peters already stated in 1997, the fundamental premise is that a person has the power to be and create someone’s own personal brand (Peters, 1997).

2.1.2 Core Dimensions of Personal Branding

Until now, little importance has been given to the dimensions underpinning the core of a personal brand’s success. Empirical data from various studies identified the need for key components, which include brand authenticity, brand attitude, and brand loyalty (Kirkby et al., 2023), and brand identity (Labrecque et al., 2011).

Following branding theories, brand authenticity and brand attitude are identified as essential dimensions of brand success (Thomson et al., 2006). There is widespread agreement among scholars concerning the minimal distinction between personal and human brands. Although the exact definitions need to be clarified.

Within the Brand Equity Theory by Aaker (1995), the construct of brand authenticity is linked to both brand personality and brand identity, yet a singular, distinct definition of it can be

rarely found (Bruhn et al., 2012). Within marketing research, various associations of the concept of authenticity can be discovered. Positive connotations and associations like “genuineness”, “agelessness”, and “tradition” are frequently attached to the term (Aaker, 1995). The first pillar of the dimension, brand personality, is characterized as “the set of human characteristics associated with the brand” (Aaker, 1995). Whereas the second pillar, brand identity, represents a unique set of all brand associations that are aspired to be cultivated or preserved (Aaker, 1995). In other words, the identity serves to communicate the values a brand embodies, which in turn implies a promise towards its customers (Gill & Dawra, 2010). Although no explicit definition for brand authenticity exists, certain conclusions can be drawn: firstly, brand authenticity is always based on subjective evaluations rather than on attributes stemming from the brand itself. Secondly, the dimension corresponds to various attributes given the absence of a unique definition.

In addition to overall brand authenticity, studies also highlight the role of brand voice authenticity. Pérez (2019) connects the concept to message authenticity as he argues that messages perceived as genuine and aligned with the communicator’s identity increase credibility, mitigate skepticism, and strengthen perceived expertise (Pérez, 2019). Whereas in the context of personal branding, personal brand voice authenticity reflects the consistency and genuineness of the tone, style, and personality expressed through communication (Pérez, 2019). As such, it can serve as a critical antecedent to overall perceptions of personal brand authenticity.

Many studies have established that brand loyalty constitutes the core dimension of brand equity and its underlying theory (Aaker, 1995). In theory, brand loyalty comprises two components: the enduring preference and the point of determined defense (Aaker, 1995). The underlying definition by Aaker (1995) states that the dimension is defined as “an attained state of enduring preference to the point of determined defense” (Aaker, 1995). Gill & Dawra (2010) affirm Aaker’s definitions, pointing out that in conclusion, loyalty encompasses both behavioral and attitudinal dimensions (Gill & Dawra, 2010). The behavioral aspect focuses on the consumers’ actions reflecting repeated consumption, while the attitudinal facet encapsulates values like attitudes, beliefs, and intentions of a consumer towards a brand (Gill & Dawra, 2010).

While loyalty has been widely discussed as a core dimension of brand equity (Aaker, 1995; Gill & Dawra, 2010), further conceptualizations emphasize its nature as a robust commitment. Dick & Basu (1994) propose an integrated framework in which loyalty results from both cognitive and affective antecedents, capturing not only repeated purchasing or following but also strong attitudinal commitment (Dick & Basu, 1994). More recently, Guo & Wang (2024) showed that loyalty can manifest differently in online versus offline contexts, with digital interactions often intensifying uncertainty avoidance and commitment (Guo & Wang,

2024). This implies for personal brands, that loyalty goes beyond simple follower counts as it reflects an enduring and resilient attachment that may be particularly sensitive to questions of authenticity.

According to Keller (1993), brand attitude constitutes one of the three primary categories used to classify brand associations that build up the brand image (Keller, 1993). Within this framework, brand image refers “to the set of associations linked to the brand that consumers hold in memory.” (Keller, 1993). Consequently, Keller (1993) emphasizes that brand attitudes represent an overall evaluation of a brand by consumers, often serving as a foundational element for consumer behavior (Keller, 1993). These attitudes can stem from product-related attributes as well as functional and experiential benefits (Zeithaml, 1988) or from non-product-related attributes and symbolic benefits (Rossiter & Percy, 1987).

But research also shows that perceptions of authenticity and subsequent brand attitudes can be explained through the concept of conceptual fluency (Lee & Labroo, 2004). Lee & Labroo (2004) define the concept as the ease with which a stimulus is processed and linked to meaning in the consumer’s mind (Lee & Labroo, 2004). Thus, when consumers process brand-related communication fluently, they are more likely to form favorable evaluations. Conversely, low fluency can lead to negative attitudes. In personal branding, the alignment between communicated content and the perceived identity of the brand owner plays a decisive role in facilitating such fluent processing.

To date, little importance has been given to the application of the concepts within the context of personal brands online. Existing literature indicates that a personal brand’s identity is based on the pure self-presentation online (Labrecque et al., 2011). Personal brands primarily engage with audiences online through social networking platforms, blogs, and personal web pages, where their branding strategies are predominantly centered on the dissemination of online information (Labrecque et al., 2011).

The brand image component of a personal brand is shaped not only by the information disseminated via social media but also by interactions with other users. As indicated by Keller (1993), certain consumer responses are retained in memory (Keller, 1993), emphasizing that the audience’s reactions and perceptions are critical (Labrecque et al., 2011). Observable reaction encompasses visible behaviors, nonverbal behaviors, and any other forms of perceptible responses or reactions (Ambady et al., 1995). Recent research revealed that strong personal brand identity and image depend upon factors as self-expression, professionalism, self-efficacy, and self-disclosure (Kongsri & Jaroenwanit, 2024).

Having established the theoretical foundation and dimensions of personal branding it becomes evident that the communication of a personal brand largely depends on the creation and dissemination of content. Since personal brands manifest their identity primarily through online

communication, it is necessary to explore how content creation functions as a strategic tool in digital environments. Therefore, the following section discusses content marketing, with a particular focus on DCM, as a critical mechanism for shaping brand perception and fostering engagement.

2.2 Content Creation in Digital Content Marketing

With the development of social media in the past years, content marketing (CM) has become a strong component of a brand's marketing mix. In a highly competitive digital landscape, businesses constantly seek ways to stand out from their competitors and to connect with their target audience. Therefore, DCM has gained prominence as it is a powerful tool for achieving this target, as digital content plays an important role in the commercial setting (Rowley, 2008).

Being one of the pillars, CM measures and more in-depth content creation measures needed to be updated and redefined in the past. Overlapping definitions in research and among practitioners made a unique definition difficult, but the strategic importance of CM became clear (Ho et al., 2020).

2.2.1 Content Marketing and Digital Content Marketing

The roots of CM are historical, but it has still evolved drastically over time and now encompasses a lot of formats and approaches for different industries and objectives. To be more precise, its definition by the American Marketing Association (2025) showcases that it describes a "technique of creating and distributing valuable, relevant and consistent content to attract and acquire a clearly defined audience, with the objective of driving profitable customer action" (Content Marketing, 2025).

According to research, the definition already implies that this marketing strategy follows a customer-centric approach. This can be conducted from the goal of CM as "profitable customer actions" are to be accomplished by any brand. Further, the Content Marketing Institute (as cited in Ho et al., 2020) highlighted that these social media platforms are used to deliver engaging relationships, value for consumers, and measurable success for the brand itself. (Ho et al., 2020)

In literature, different perspectives of CM can be adopted. As Baer (2013) stated, brands use CM for educational, informing, or entertaining purposes for their consumers or to attract new prospects by promoting actions that lead to sales or brand advocacy (Baer, 2013). Further, du Plessis (2022) not only stated in her research in 2015, but also in 2022, that CM is an online marketing technique encouraging user-generated content (du Plessis,

2022). Nowadays, CM is most of the time mentioned in the context of social media or at least digital marketing, which led Ahmad et al. (2016) to the strong association of both CM and social media. As a result, this leads to the term social media CM (Ahmad et al., 2016).

As research from Mathew & Soliman (2021) highlighted, valuable digital brand content on digital platforms impacts long-term benefits for an organization: to these count relationships and brand loyalty (Mathew & Soliman, 2021). Especially in digital marketing, this can lead to better results in customer engagement and brand trust among consumers (Ho et al., 2020).

du Plessis (2022) highlighted that CM's interest in digital marketing can be linked to an interest in online consumer behavior and specific reactions to digital brand content building relationships, loyalty, and trust (du Plessis, 2022). Nevertheless, the relatively new marketing discipline DCM emerged as one of the most successful CM types (Rowley, 2008). In research, the concept gets defined as "creating and sharing relevant captivating and valuable content to increase customer engagement and trust, thereby helping the firms to become a market leader in the industry." (Holliman & Rowley, 2014). But not all researchers agree on a unique terminology and interpretation of the phenomenon. As shown in table 2, various definitions can be found in literature.

Study	Definition of Digital Content Marketing
Rowley (2008)	"Digital content marketing is the management process responsible for identifying, anticipating, and satisfying customer requirements profitability in the context of digital content, or bit-based objects distributed through electronic channels." (Rowley, 2008)
Pulizzi (2013)	Digital Content Marketing is "a commercial process of developing and delivering valuable, authentic and captivating content to attract, acquire and engage a clearly defined and known target audience, resulting in lucrative customer action." (Pullizi, 2013)
Holliman and Rowley (2014)	Digital Content Marketing involves creating, distributing, and sharing relevant, compelling, and timely content to engage customer at the appropriate point in their buying consideration processes, such that it encourages them to convert to a business building outcome.
Järvinen and Taiminen (2016)	Adopted from Holliman & Rowley, 2014

Bicks (2016)	Digital Content Marketing is “the art of communicating with prospective customers without selling products” (Bicks, 2016 as cited in Hollebeek & Macky, 2019) either overtly or directly.
Gordini and Rancati (2014) & Wall and Spinuzzi (2018)	Digital Content Marketing is a strategy for digitally promoting goods or services by producing and disseminating free informational or entertaining content that increases the involvement and confidence of current and potential customers.
Wang et al. (2019)	Adopted from Holliman & Rowley, 2014
Hollebeck and Macky (2019)	Digital Content Marketing is the creation and dissemination of relevant, valuable brand-related content to current or prospective customers on digital platforms to develop their favorable brand engagement, trust, and relationships.
Vieira et al. (2019)	Digital Content Marketing is a strategy focused on digital content creation and investment through spontaneous techniques centered on interactivity and engagement to promote organic search.
Terho et al. (2022)	Digital Content Marketing does not rely on an interruptive advertising approach, but “counts on consumers’ initiative to see trustworthy content that offers value and facilitates two-way conversation.” (Terho et al., 2022)
Gupta and Dutt (2024)	Digital Content Marketing is defined as a “marketing technique focused on delivering valuable, engaging and authentic content to the prospective audience, resulting in positive brand outcomes.” (Gupta & Dutt, 2024)

Table 2 - Definitions of Digital Content Marketing

The summary of all definitions demonstrates that an effective DCM requires a brand’s shift from selling products or services towards offering consumers freely available content. Bicks (2016) makes the significant point in previously shown definitions in table 2, that DCM is about communication and not about generating sales (Bicks, 2016 as cited in Hollebeek & Macky, 2019). Nevertheless, DCM tries to boost a brand’s perception and, therefore, also ultimately sales, but this is achieved by reaching consumer engagement, trust, and relationships with consumers (Blau, 1986). Consequently, perceptions might lead to indirect sales and result in long-term benefits for brands. According to the conducted research, the

information shared needs to be relevant, valuable, informational, entertaining, and authentic (Gupta & Dutt, 2024).

To conclude, it can be said that today's developments in marketing and technology showcase that CM is a fundamental tool for successful and effective digital marketing and contribute to any current inherent marketing strategy.

The focus of content creation, on the other hand, clearly stems from the creation of engaging and attractive content for customers of an organization. Brands' aim on social media is to gain more traffic on their sites by publishing content on their social media channels. By using different platforms, the goal is to put more humans in the funnel of conversion. (Mittal & Tandon, 2023)

For the creation of content, different strategies can be developed and used. Whereas in a study by Koob (2021), the results showed that different context features have a bigger impact on the effectiveness of CM (Koob, 2021). The main link for effective content was found between strategic clarity and strategy commitment. In the research model by Koob (2021), different determinants were tested. To these count the strategizing context, the production context, the distribution context, the promotion context, the marketing performance measurement context, and the marketing organization. (Koob, 2021)

Also, in other research, they encountered that strategic clarity in the strategizing context plays a major role in the effectiveness of CM. In addition, the goal setting theory supports these findings as specific and well-defined challenging goals are expected to result in higher performance. (Koob, 2021)

Therefore, it can be concluded in the first instance that for an effective CM, both a clearly defined strategy and successful communication and understanding within the organization are necessary.

2.2.2 Measures for Effective Content Creation

As found in literature, social media is very different from traditional media that was used in the past. Being defined by unique characteristics, it was named to be a suitable source to publicize information and content (Sun, 2023). The study of Tyrväinen et al. (2023) further showed that the usage of social media platforms increased in the past (Tyrväinen et al., 2023). Ultimately, this means that most consumers now tend to consume most of their information from social media.

However, the fast-changing development has brought up some negative sides. As research showed, the diversity of communication channels and platforms, the ascending amount of social media content, and ever-changing communication channels led to more

conscious consumers in terms of authenticity and credibility of information they consume online (Sun, 2023).

It follows that researchers focused on both the consumption of information on social media, but also on characteristics and measures that the published content needs to fulfill. Overall, six attributes were found in different studies. The first one is called information quality. According to Kahn et al. (2002), the dimension refers to the consumers perception of the presented information and if it is meeting their expectations (Kahn et al., 2002), whereas Sun (2023) added that it is also necessary for brands to exceed these to be successful (Sun, 2023). Additionally, it was discovered that measuring such expectations can be challenging as well as they might change over time (Sun, 2023). It was further demonstrated in the study that for the credibility evaluation of content on social media, different dimensions must be considered (Sun, 2023).

The factor information credibility can thus be defined in terms of topic, source, and lastly, content credibility (Sun, 2023). According to this framework, a topic is a distinctive factor for content's credibility (Sun, 2023). For example, information can be divided into categories like untrusted or credible. On the other hand, the content of entertainment and so-called emotional information are subject of an author's subjective opinion and therefore cannot be evaluated on the appropriateness (Sun, 2023). In contrast, health and scientific information is perceived as professional and has comparatively low engagement (Sun, 2023). Thus, choosing a specific topic in CM has an impact on followers' perception of credibility. This view is supported by Tyrväinen et al. (2023), as their research identified that the definition of information credibility is linked to a consumer's perception of trustworthiness of information resulting from the source, the receiver, and characteristics of the message (Tyrväinen et al., 2023). Whereas the source credibility theory, referred to in Petty et al. (1986), stated that if messages stem from more trustworthy sources, they generate a stronger impact on attitudes of consumers (Petty et al., 1986). Complementing this theory, research discovered that any user must identify a source as credible before the message can reverberate (Tyrväinen et al., 2023). Thus, led to the conclusion that the credibility of information has a beneficial impact on the factor of brand loyalty (Tyrväinen et al., 2023).

The third factor – information usefulness – is a measure that the consumed information presents a benefit for the consumer and its performance (Bailey & Pearson, 1983). The correlation of information and consumers' perceptions also receives in this dimension special interest as it is discovered in research that it is bypassed as long as it is not relevant to any of its consumers (Sasaki et al., 2016). The study of Tyrväinen et al. (2023) revealed that this factor can have a positive influence on brand loyalty (Tyrväinen et al., 2023).

Moreover, positive emotions are supposed to be a reference for the consumers' evaluation of the consumed content online (Bagozzi et al., 1999). Positive emotions get associated with the creation of positive expectations, and especially in the context of social media content, the form of affection demonstrated by the consumers can result in self-brand connections (Hollebeek et al., 2014). In conclusion to these findings, Tyrväinen et al. (2023) added a special role to emotions to be more concrete about their positioning in the context of technology-driven theories (Tyrväinen et al., 2023). Resultingly, Hollebeck et al. (2014) granted the dimension a special role in the context of social media content to generate brand loyalty (Hollebeck et al., 2014).

But it was developed in research that not only the expectations and the perceptions of information get compared to each other, but also the consumer's image according to the image of the source (Sirgy, 1982). This is not all, as the attitudes towards an information source are influenced by the phenomenon of self-congruity (Choi & Rifon, 2012). In conclusion, it can be added that this factor supports the process of locating information that the person perceives as relevant and is again positively impacting brand loyalty (Tyrväinen et al., 2023).

The last attribute interactivity highlights social media's benefit of offering the possibility of real-time communication between all different parties involved. The platforms' high activity levels lead to the result that they present a good alternative for handling communication tasks with clients and customer service (Gautam & Sharma, 2017).

Ultimately, it can be added that the relationship between expectation and perception of information plays a fundamental role for consumers. As research has correctly noted, by meeting expectations and even exceeding them, positive brand loyalty can be fostered.

Furthermore, Koob (2021) raises the key question of how CM can be effective along the content creation process (Koob, 2021). In the research, he states a strong association between both parameters. Conducting the study, the assumption that high-quality content is perceived to be more interacted with was validated (Koob, 2021). Hence, he introduced that consumers look for functional, hedonic, or authenticity content as research proposed that effective content not only needs to meet the consumers' expectations, but also objectives or principles (Koob, 2021).

While digital content marketing provides the strategic framework for how brands create and distribute value, recent technological developments have fundamentally altered the way this process is carried out. In particular, AI has introduced new possibilities for automating, personalizing, and scaling content creation. To understand how these innovations intersect with the principles of CM and personal branding, the next section examines the role of AI in

marketing, with a specific emphasis on its implications for authorship and authenticity in content production.

2.3 Artificial Intelligence in Marketing

2.3.1 Areas of Implication in Marketing

Over the last decade, AI has not only emerged as a significant driver in marketing but also in other business functions. First introduced by John McCarthy in 1956 (Bini, 2018) are now several subfields of AI known. One of them is GenAI, which enables possibilities like human-writing, the creation of other datatypes like images, videos, or audio (Grewal et al., 2024). In comparison to other forms of AI, like analytical AI, the main difference to GenAI is the generation of new content out of past content based on data and already existing information (Vaswani et al., 2017). In marketing, this would mean that AI can be seen as a tool that makes use of any algorithm or statistical model to conduct perceptual, cognitive, and conversational functions that are typical for the human mind (Longoni et al., 2019).

Understanding the development and capabilities of AI is crucial for its proper implementation in marketing activities, as not only in various functions and approaches the influence might be noticed, but also consumers will be affected directly. Therefore, the advancements in technology led to ongoing discussions in research, and thus, no concrete definition can be found.

In academic literature, multiple types of AI intelligences can be found. Ultimately, this viewpoint proves similarities among humans and AI systems: instead of seeing AI as pure thinking machines, intelligences stand for the completion of different tasks as humans would do it (M.-H. Huang & Rust, 2020). It can also be concluded that these systems even mimic human behavior. Overall, these count mechanical, thinking, and feeling AI intelligences (M. H. Huang et al., 2019). For further explanations and definitions, consult table 3.

Type of AI intelligence	Definition	Focus
Mechanical AI intelligence	“Capability to do mechanical and repetitive tasks with relatively limited amounts of learning or adaptation.” (M. H. Huang et al., 2019)	Performance of repetitive tasks for consistent and reliable performance (M. H. Huang et al., 2019)
Thinking AI intelligence	“Capability to analyze and make decisions rationally (or boundedly rationally) and involves learning	Autonomous learning and adaptation from data (M. H. Huang et al., 2019)

	and adapting systematically from data autonomously.” (M. H. Huang et al., 2019)	
Feeling AI intelligence	“Capability to recognize, emulate, and respond appropriately to human emotions.” (M. H. Huang et al., 2019)	Empathetical interaction with people (M. H. Huang et al., 2019)

Table 3 - Definitions of Types of Intelligence

More studies concluded in research that the multiple AI view has two different levels of qualifications. The first one is that to each of the intelligences, there are certain tasks assigned that have already been conducted by the system previously, but they still represent a “fuzzy set” (Varki et al., 2000). Whereas the second qualification is about the third intelligence. It is claimed in literature that, for now, there is no true feeling AI yet (M.-H. Huang & Rust, 2020). In different studies from Huang, he argued that emotional data is too different from cognitive data, which is analyzed in the first two intelligences (M.-H. Huang & Rust, 2020). Concluding the analysis of the framework, it must be noticed that until AI can fully experience emotions, there is a lot of progress necessary.

As digital marketing has been revolutionized a lot by AI in the past few years, there is barely any section that has not been in touch with it. The technology can support various matters, and as tools like ChatGPT are easily accessible, there are no major hindrances in doing so. With the current available solutions, content creation processes could get automated, audience analyses could be conducted, and content could be designed (Wahid et al., 2023).

Especially in DCM, AI is expected to enhance its role in social media content as the systems can perform tasks requiring human-level recognition (Alawneh et al., 2023). Research revealed several benefits for a brand’s content marketing strategy (Wahid et al., 2023). Due to the advancements in the creation of online communication, several touchpoints of AI in the content creation process are already found (Mittal & Tandon, 2023). The study of Mittal & Tandon (2023) further highlighted AI’s potential in digital marketing and concludes that utilizing algorithms to analyze huge amounts of customer data revolutionizes businesses’ way of conducting marketing activities (Mittal & Tandon, 2023).

Huang & Rust (2020) agree that for automating tasks, routines, or data-intensive functions in the content creation process, especially mechanical AI can be used (M.-H. Huang & Rust, 2020). Besides that, AI can support in the completion of other tasks like the automation of social media targeting, retargeting, and posting, or even automating media planning (M.-H. Huang & Rust, 2020).

As of GenAI's capability of matching consumer profiles with companies' marketing materials, a higher engagement and influence on the consumers' behaviors can be achieved (Brüns & Meißner, 2024a). Resultingly, the thinking AI might be the right fit as it brings potential for the content creation and personalization for different customer profiles in various locations and times (M.-H. Huang & Rust, 2020). GenAI's advantage of generating such personalized content is another step towards hyper-personalization in marketing (Brüns & Meißner, 2024a).

Lastly, the third AI system can be used for analyzing real-time engagement and response to communication materials. Therefore, customer responses get tracked, and later, it will be analyzed if any changes according to their reply need to be conducted (M.-H. Huang & Rust, 2020). According to the research of Hartmann et al. (2019), a better understanding of consumers' reasons for their engagement with content can be fostered by analyzing real-time and specific emotions (Hartmann et al., 2019). Thus, a superior experience in terms of interaction can be guaranteed (Hartmann et al., 2019).

In conclusion, AI systems have a significant role in digital marketing due to their different means and opportunities that can be used to optimize strategies. By supporting marketers and creating more effective and efficient workflows, AI can support in facilitating the brand-consumer connection with potential clients (Haleem et al., 2022). As the technology further advances, its impact will grow.

2.3.2. Human-AI authorship in Content Creation

In marketing, the usage of AI has already been taking place for many years. In the past, analytical AI was used to automate decision-making tasks. Whereas now, the development of creative GenAI implements a strong difference (Overgoor et al., 2019). AI-powered tools such as ChatGPT can generate content that can barely be distinguished from human-written content by consumers (Köbis & Mossink, 2021).

To further define the human-AI collaboration, a differentiation between different scenarios needs to be added. The study of Brüns & Meißner (2024) analyzed different options (Brüns & Meißner, 2024a). In general, as a first possibility, brands could choose not to adopt GenAI tools in their content marketing strategy. This would mean that humans are under full control of the entire process, and no automation is done by GenAI. Secondly, GenAI could be adopted to automate selected tasks. This way, humans maintain oversight in the content creation tasks. Lastly, GenAI could be used to automate the entire content creation process, which would mean that human input is fully replaced by AI. (Brüns & Meißner, 2024a)

Another possibility to define human-AI collaboration is the framework of collaborative AI from Huang & Rust (2022). As shown in their research findings, AI's multiple intelligences

view has developed from a rather mechanical tool towards a thinking and feeling intelligence based on how it is nowadays able to mimic human intelligence (M. H. Huang & Rust, 2022). Therefore, a successful collaboration can be achieved by marketers recognizing the strengths of AI, using it for tasks with a lower impact to support marketers, and lastly, to move human intelligence to higher levels when using AI for the automation of tasks (M. H. Huang & Rust, 2022).

The third way of implementing AI in the content creation process is a complete adoption of GenAI in a digital marketing strategy. For the creation of content, this would mean that human input is completely replaced by GenAI and the whole process is automated (Brüns & Meißner, 2024b).

Whereas companies showed a respective interest in the usage of creative GenAI tools as ChatGPT for the generation of their brand's content, the perception of their customers cannot be ignored (Haupt et al., 2024). Several studies showed that consumers perceive GenAI-generated postings negatively, whereas the degree of human-AI collaboration in customer-facing applications played an important role in followers' responses to such content (Haupt et al., 2024).

For more detailed insights into the effects of different authorship types in the content creation process, please refer to table 4.

Study	Effects of Authorship Types
Aldous et al. (2024)	GenAI-generated content scored higher in preferences by consumers.
Brüns & Meißner (2024)	Negative consumer response to brand's GenAI adoption to automate content creation, but the aversion decreases once GenAI is only assisting in the process. Negative attitudinal and behavioral response to brand's GenAI adoption leading to less credibility and less favorable brand attitudes. GenAI-generated content leading to less brand authenticity, triggering negative consumer attitudes and behaviors.
Formosa et al. (2024)	Fewer negative responses on human-assisted content than with AI-assistance.
Graefe & Bohlken (2020)	Higher ratings for human-created content in terms of credibility, readability, or quality.
Haupt et al. (2023)	Negative effect of GenAI-authorship and AI-supported human authorship on consumers' attitude towards a brand, mediated by lower message credibility perceptions.

	Human-AI controlled authorship not creating such negative effects.
Henestrosa & Kimmerle (2024)	AI-authorship is perceived to be less realistic, human-like, intelligent, and competent, and the content receives fewer recommendations, WOM, and less frequent re-reading. Human-generated content receives higher credibility and persuasiveness. Even for identical articles, the GenAI-generated one receives less perceived credibility in comparison to a human-created one.
Kirk & Givi (2025)	Reduced positive WOM and brand loyalty when consumers believe that emotional marketing communication stems from GenAI. Diminished negative effect if GenAI only edits or the explicit GenAI authorship is stated.
Kirkby et al. (2023)	Text disclosed as AI-generated does not be perceived as less authentic, no negative effect on perceived personal brand voice authenticity or brand attitudes. Slight preference for human content in emotional context.
Park et al. (2024)	Difficulties in identifying the authorship type by consumers.

Table 4 - Different Effects on Authorship Types

In sum, it can be stated that among the different studies mentioned in table 4, most discover a negative effect of GenAI-generated content. Whereas the study of Kirkby et al. (2023) leads to the contrary result that GenAI-generated text is not perceived as less authentic or having any negative effects (Kirkby et al., 2023). The researchers themselves published the conclusion that it is only contrary because, compared to other studies, this one was based in specific fields and not in a general, neutral background (Kirkby et al., 2023).

The basis for consumers' predominant negative perceptions of GenAI-generated content is explained by the phenomenon of algorithm aversion throughout literature. In a systematic literature review of Burton et al. (2020), it was found that this theory was already mentioned in the 1950s and can have different causes. To these count that humans perceive AI as generally less trustworthy, less empathetic, and less competent (Burton et al., 2020). Whereas it was conducted that these are individual expectations about algorithms and their capabilities and functionalities (Burton et al., 2020). The outlined study highlighted that the aversion is linked to analytical decision-making and automation of non-human labor (Burton et al., 2020).

As there is widespread agreement among scholars concerning the negative perception of GenAI-generated content, some studies have found evidence on how algorithm

aversion can be overcome. In the analysis of Haupt et al. (2024) on consumers' reactions to AI-generated content, it became obvious that these might fear a loss of control in the identification over the message provider (Haupt et al., 2024). Thus, their research highlights that human-AI collaboration can also be a possibility to diminish negative consequences of GenAI-implication, but only if a hybrid authorship is used (Haupt et al., 2024). Moreover, the research of Graefe & Bohlken (2020) discovered that consumers rated human-generated content higher in terms of credibility, readability, and quality if the authorship was transparent, while being indifferent about the source (Graefe & Bohlken, 2020). According to their findings, algorithm aversion is driven by consumers' subjective source credibility of AI and not by a lack of quality (Graefe & Bohlken, 2020).

Beyond algorithm aversion, recent research introduces disgust as an important emotional mechanism shaping consumer responses to AI-generated content. Chapman & Anderson (2013) describe disgust as a protective reaction that drives avoidance behavior, and this concept has been applied to consumer contexts such as marketing communication (Chapman & Anderson, 2013). Whereas Kirk & Givi (2025) show that when audiences perceive marketing content as authored by AI, particularly in emotional or identity-relevant context, feelings of moral disgust can be triggered (Kirk & Givi, 2025). Resultingly, these reactions not only reduce credibility and persuasiveness but also amplify negative WOM. Thus, disgust serves as an affective pathway through which AI-authorship may damage perceptions of authenticity.

Completing this line of thought, Brüns & Meißner (2024) discovered that the reaction on social media deteriorates when brands adopt GenAI for their social media channels. Their study showcased that the aversion of followers decreases when GenAI-assisted humans are involved in the content creation process (Brüns & Meißner, 2024a). Their studies concluded that depending on the degree of the human-AI collaboration, the reaction of the consumers differs, and their judgements on the brand's authenticity differ as well. For organizations, it is nevertheless important to face technological developments. Therefore, companies need to elaborate on a way of human-AI collaboration that is somehow effective for the company's communication strategy and to maintain a strong consumer-brand relationship (Brüns & Meißner, 2024b). Huang & Rust (2022) make a convincing argument when they write in their research that a deep understanding of GenAI and the collaboration of intelligences in marketing and different stakeholders is necessary (M. H. Huang & Rust, 2022).

Concluding this review, it can be stated that organizations need to conduct a profound analysis on human-AI collaboration in their brand's content marketing strategy, and if efficiency in the content creation process outweighs the brand's authenticity among consumers on social media. Once decisions in favor of AI systems are made, the extent and

impact of the to be performed marketing tasks in replacement of humans need to be clarified, whereas unnecessary replacement needs to be avoided (M. H. Huang & Rust, 2022).

The first aim of the research study reported here is to examine the influence of a type of authorship on consumers' perceptions towards a personal brand and its brand loyalty, as well as WOM. Moreover, consumer perceptions of the personal brand's voice authenticity and the authenticity itself may affect the perceived attitude towards a personal brand.

3 Conceptual Framework and Hypotheses Development

Both the conceptual framework (see figure 1) and the research hypotheses were formulated based on the previous literature review to achieve the research results and conclusions. The purpose of the presented study is to explore the influence of different types of authorship on consumers' perceptions of personal brands on LinkedIn.

The framework investigates how perceived personal brand voice authenticity influences perceived personal brand authenticity, and how authenticity in turn shapes perceived personal brand attitude, both negative and positive WOM, emotionality, and loyalty. Type of authorship is further introduced as a moderating factor for the model.

Each relationship depicted in the model is formulated as a testable hypothesis to ensure conceptual consistency. The following subsections introduce these hypotheses in detail, outlining how authorship type is expected to influence authenticity perceptions and subsequent consumer responses.

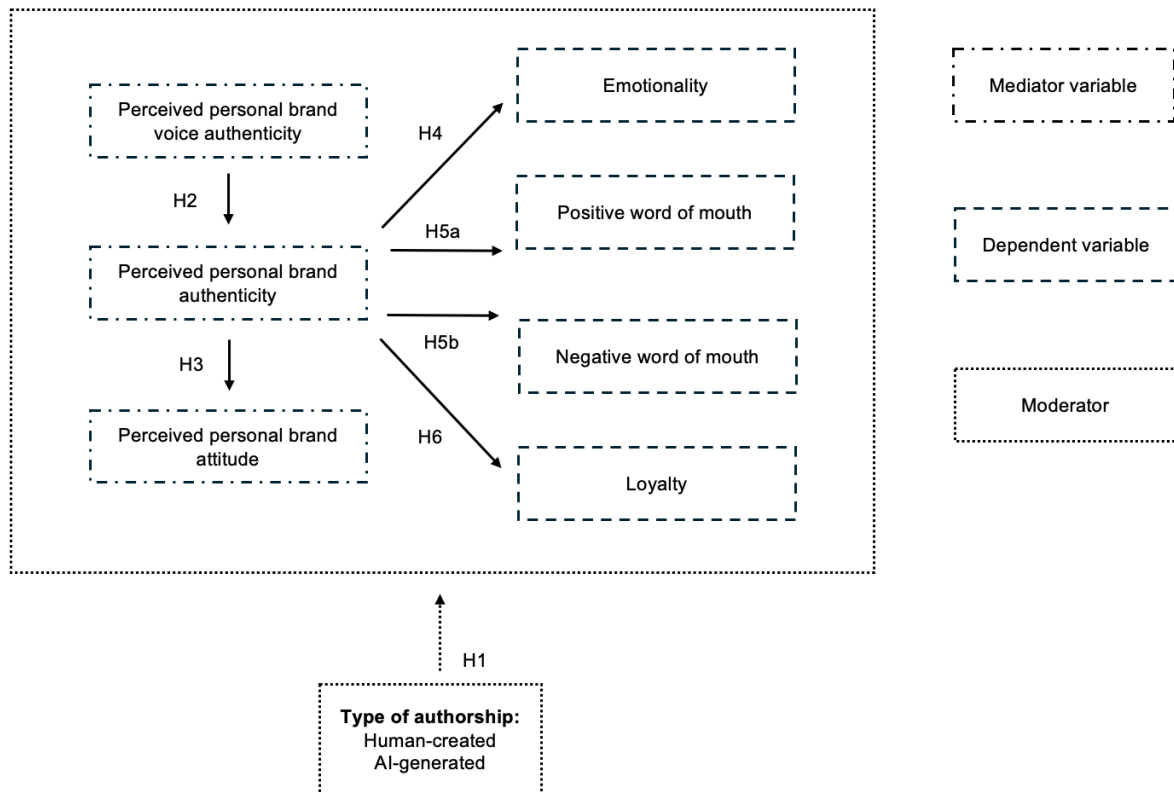


Figure 1 - Conceptual Framework for the research

3.1 Type of Authorship as a Moderator

According to the previous literature review, the impact of AI on consumers' perceptions of personal brands is significantly contingent upon the type of authorship that is used for the creation of marketing material. Various authors have noted a prevailing negative perception among consumers towards content generated by AI (Brüns & Meißner, 2024; Formosa et al., 2024; Haupt et al., 2023; Henestrosa & Kimmerle, 2024; Kirk & Givi, 2025).

In contrast, research by Kirkby et al. (2023) suggests that the framework of studies provides first indications of the expected outcome of the consumers' perceptions of the authenticity of a brand (Kirkby et al., 2023). Thus, in a specific contextual background, the outcome was expected to be more favorable for GenAI-generated content (Kirkby et al., 2023).

The comparison of different studies assessing the perception of AI-generated content and its authenticity within completely distinctive contexts led Kirkby et al. (2023) to conclude that the higher ratings assigned to human-created content indicate a clear relationship with the transparency of the source (Kirkby et al., 2023).

Given the distinctive assumptions in literature, the following hypothesis is proposed:

H1. Type of authorship moderates the relationships in the conceptual model, such that the effects are weaker when the content is AI-generated compared to when it is human-authored.

3.2 Perceived Personal Brand Voice Authenticity and Perceived Personal Brand Authenticity

In literature, it is argued that the notion of brand voice authenticity is posited to function similarly to the concept of message authenticity. It is said that later principle improves the credibility of a message by mitigating skepticism among consumers, thereby increasing the perceived level of expertise and trustworthiness (Pérez, 2019). Within the realm of brand messages, the construct of "authenticity" is embedded in the reflection of the identity and essential nature of any kind of communication material about a brand in question (Pérez, 2019).

Therefore, this study anticipates that consumer perceptions of personal brand voice authenticity will exert a positive influence on the overall authenticity of personal brands itself. In consequence, when a personal brand is considered authentic, it is expected that favorable outcomes for the brand will be ensured.

It is therefore hypothesized that:

H2. Higher perceived personal brand voice authenticity increases perceived personal brand authenticity.

3.3 Perceived Personal Brand Authenticity and Perceived Personal Brand Attitude

It is often found in literature that understanding and quantifying perceptions of authenticity, among other factors, is recognized as essential to explain a consumer's brand attitude.

According to Kirkby et al. (2023), both perceived personal brand attitude and brand attitude are assessments of a brand (Kirkby et al., 2023). However, the latter is posited as a more authentic indicator, positively influencing consumer attitudes (Kirkby et al., 2023).

Thus, in conjunction with the concept of conceptual fluency by Lee & Labroo (2004), these evaluations can be examined to further elucidate the relationship between both parameters. The term refers to “the ease with which the target comes to consumers’ minds and pertains to the processes of meanings” (Lee & Labroo, 2004). The findings indicate two distinctive contexts influencing consumers’ affects and attitudes: first, when a stimulus achieves “fluency” within a given context, it tends to engender a more favorable brand attitude; conversely, when the processing of a stimulus is perceived negatively, it leads to a less favorable evaluation (Kirkby et al., 2023). In this case, the content associated with a personal brand is of particular interest.

On that basis, it is hypothesized that:

H3. Higher perceived personal brand authenticity increases personal brand attitude.

3.4 Perceived Personal Brand Authenticity and Emotionality

The degree to which positive or negative reactions are invoked by the type of source is contingent upon emotionality. Consumer reactions to GenAI-generated content are both cognitive and affective (Castelo et al., 2019). Previous research shows that consumers often experience algorithm aversion (Dietvorst et al., 2015). This aversion is especially highlighted in contexts where decisions are subjective and emotionally laden, as audiences anticipate human empathy and creativity rather than mechanical output (Castelo et al., 2019; Longoni & Cian, 2022).

Emotional responses can further manifest as feelings like disgust when authenticity is perceived to lack (Rozin et al., 2008). If audience sense that content fails to reflect genuine human experience, this will lead to negative affective reactions, which in turn shapes their evaluations of the personal brand.

As authenticity functions as a core driver of emotional resonance, it is therefore hypothesized, that:

H4. Higher perceived personal brand authenticity decreases negative emotional reactions toward the personal brand.

3.5 Perceived Personal Brand Authenticity and Word of Mouth

When individuals experience feelings of disgust in relation to a specific stimulus, they instinctively seek to distance themselves from that source as a form of protective mechanism aimed at mitigating potential harm (Chapman & Anderson, 2013). This principle holds in the context of marketers developing communication material. Consequently, distinguishing the type of authorship can lead to different outcomes, particularly as the integration of GenAI elicits feelings of disgust among consumers (Kirk & Giri, 2025).

One of the consumers' avoidance reactions includes WOM, which encompasses the interpersonal exchange of consumption experiences (Berger, 2014). Numerous studies have shown that this channel is favored by consumers for acquiring information about new services or products, significantly enhancing subsequent consumption likelihood (Kirk & Givi, 2025). By generating WOM, consumers process their own emotions and foster a form of connection with others (Berger, 2014). However, it is imperative to note that disgust can amplify negative WOM, as it leads consumers to focus disproportionately on unfavorable information about a brand.

Thus, as content generated by GenAI already provokes negative perceptions and emotions among most of the consumers, the following hypotheses can be retrieved:

H5a. Higher perceived personal brand authenticity increases positive word of mouth.

H5b. Higher perceived personal brand authenticity decreases negative word of mouth.

3.6 Perceived Personal Brand Authenticity and Loyalty

As previously discussed, the potential avoidance reactions of consumers in response to feelings of disgust can stem from different origins, but however, a second possible outcome needs to be considered. In this context, customer loyalty emerges not only as a metric of repeated purchasing behavior but also as an indicator of a robust commitment (Guo & Wang, 2024). Marketers must recognize that both cognitive and affective antecedents play a significant role in shaping this loyalty, as they facilitate engagement with consumers and foster the transition of consumers into brand advocates (Dick & Basu, 1994).

Based on the impact of the type of authorship leading to distinct behaviors, the following hypothesis can be proposed:

H6. Higher perceived personal brand authenticity increases customer loyalty.

The relationship of the hypotheses is illustrated in the integrated model in figure 1.

4 Methodology

As mentioned previously, the study aims to investigate the impact of the types of authorship on content creation, discovering its influence on perceived personal brand authenticity, personal brand voice authenticity, and attitude, as all as the effects on WOM, emotionality, and loyalty. Furthermore, it examines the mediating role of authenticity dimensions and the moderating effect of content type.

In addition to the overall analysis of the full sample, the study also employs subgroups analyses to provide deeper insights. Respondents were divided into two groups based on whether they perceived the posts presented in the questionnaire as human-authored or AI-generated. This distinction allowed for a comparison of effects across both perception contexts and for testing whether recognition of authorship influenced the hypothesized relationships.

This chapter details the measurement constructs, the research design, and the rationale behind the methodological choices, ensuring the reliability and validity of the results for testing the previously formulated hypotheses (see chapter 3).

For this study, the quantitative research method used was the questionnaire.

4.1 Construct Measurement

From a diversity of articles stemming from the literature review, each construct and individual item was adapted from the original measurement scales for this study.

The questionnaire relies on six constructs, which are represented in the conceptual framework: perceived personal brand voice authenticity, perceived personal brand authenticity, perceived personal brand attitude, both positive and negative WOM, emotionality, and loyalty.

The perceived personal brand voice authenticity, perceived personal brand authenticity, perceived personal brand attitude, and emotionality construct were all adapted from scales developed by Kirkby et al. (2023). Whereas perceived personal brand voice authenticity and personal brand authenticity with both fourteen items form the central mechanism of the model. The construct perceived personal brand voice authenticity further predicts perceived personal brand authenticity, which then predicts perceived personal brand attitude with a total of five items. The construct emotionality being comprised of three items, captures affective reactions and is modeled as an outcome of perceived personal brand authenticity.

Both positive and negative WOM constructs were adapted from the scales of Alexandrov et al. (2013) and comprised three items each, modeled as a consequence of perceived personal brand authenticity.

The loyalty construct was adapted from the scale from Kirk & Givi (2025) and comprised three items, being predicted perceived personal brand authenticity.

Finally, type of authorship is modeled as a moderating variable influencing the relationship between perceived personal brand voice authenticity and perceived personal brand authenticity.

The constructs perceived personal brand voice authenticity, perceived personal brand authenticity, perceived personal brand attitude, emotionality, and loyalty were measured in the questionnaire using a 5-point Likert scale of agreement in which respondents answered from strongly agree (1) to strongly disagree (5) for the variables under analysis. The remaining constructs, positive and negative WOM, were measured using a 5-point Likert scale of likelihood in which participants answered from very likely (1) to very unlikely (5).

Table 5 summarizes all the constructs and respective measurement scales mentioned before. Moreover, Annex A demonstrates all the questions adapted, the source, their respective measurement scales, and the number of items.

Construct	Type of Likert Scale	Source	N° of items
Perceived personal brand voice authenticity	5-point Likert scale of agreement (Strongly agree (1) to strongly disagree (5))	Kirkby et al. (2023)	14
Perceived personal brand authenticity	5-point Likert scale of agreement (Strongly agree (1) to strongly disagree (5))	Kirkby et al. (2023)	14
Perceived personal brand attitude	5-point Likert scale of agreement (Strongly agree (1) to strongly disagree (5))	Kirkby et al. (2023)	5
Positive and negative word of mouth	5-point Likert scale of likelihood (Very	Alexandrov et al. (2013)	6

	likely (1) to very unlikely (5))		
Emotionality	5-point Likert scale of agreement (Strongly agree (1) to strongly disagree (5))	Kirkby et al. (2023)	3
Loyalty	5-point Likert scale of agreement (Strongly agree (1) to strongly disagree (5))	Kirk & Givi (2025)	3

Table 5 - Measurement scales and number of items

4.2 Research Design

This research was designed from previous literature to measure the variables from the previously introduced conceptual model. The survey shown to the participants contains three parts: (1) the information part to introduce some basic terminologies (e.g., personal brand, personal branding); (2) the main question part developed from six constructs; (3) the demographic information collection. The online platform used was Qualtrics (Qualtrics.com), enabling several benefits for researchers as the number of questions and answers is endless, and both logic and open questions are possible.

Regarding the specific research design, respondents were introduced with an explanation of the study's purpose. Then, a brief introduction of basic terminologies followed. The main part of the study employed an experimental design in which participants were sequentially exposed to two different LinkedIn postings. After viewing the first, respondents were asked to identify the type of authorship based on their perceptions and then complete the full set of questions measuring all constructs. The same procedure was repeated for the second posting, ensuring that each participant provided evaluations across both experimental conditions.

With this in mind, the second section of the questionnaire corresponds to the analysis of the constructs measured using matrix table questions. Exposed as statements, all items that constitute the analysis of the constructs were answered by the respondents to indicate their extent of agreement from strongly agree (1) to strongly disagree (5). Whereas for the construct word of mouth, the extent of the respondents' likelihood with very likely (1) to very unlikely (5) was indicated.

Finally, the last section of the questionnaire corresponds to demographic questions, such as gender, age, and education, but also to their social media consumption habits, to develop the sample description.

4.3 Pre-test

The pre-test was conducted to understand if the questionnaire needed to be reanalyzed and changed. The purpose was to analyze whether the storyline of the questions and the scenario given were clear and understandable, or if there were doubts and concerns among the respondents, leading to any confusion. Therefore, the feedback was valuable if there were suggestions for improvement before the final distribution. English was the selected language to reach a broader audience. Furthermore, the pre-test was launched to ensure the questionnaire's perceptiveness.

The pre-test had a total participation of 10 participants. Through the software SmartPLS, a software for variance-based structural equation modeling using the partial least squares path modeling method that enables researchers to analyze data. The proposed scales were analyzed and were all confirmed since Cronbach's alpha values are above 0.70, meaning that all of them are good levels of internal consistency (J. Hair et al., 2013). Among all respondents, no questions or concerns were raised. As there was no need for modifications in the questionnaire, its feasibility was confirmed.

4.4 Data Collection and Procedures

As outlined in section 4.1, the study followed an experimental design in which participants were sequentially exposed to two LinkedIn postings and asked to evaluate the six constructs.

For the present study, the online survey was shared to collect answers from different stakeholders. The respondents' answers were collected anonymously and voluntarily.

From a total of 200 answers, 59 were excluded, which means that the overall collected data corresponds to 141 answers to the questionnaire. More detailed insights in the questionnaire can be found in Annex B.

4.5 Sample Profile

Demographic data was collected through the questionnaire to describe the profile of the collected sample (see table 6).

Leaving a total sample size of 141, yields an effective response rate of 70,50 %. Out of all respondents, 76 are women and 65 are men, with 53.90 % and 46.10 %. Most

respondents are between 25 and 34 years old, representing 56.03 % of the sample.

Moreover, regarding the education level, most of the respondents are master graduates.

In general, the sample profile consists of respondents that are women aged between 25 and 34 years, having a master's degree, and are currently employed.

In table 6, detailed demographic information on the participants is presented.

N = 141	Demographic	Count	%
Gender	Male	65	46.10
	Female	76	53.90
	Non-binary	0	0
	Prefer not to say	0	0
Age	Under 18	0	0
	18 to 24 years	27	19.15
	25 to 34 years	79	56.03
	35 to 44 years	14	9.93
	45 to 54 years	12	8.51
	55 to 65 years	9	6.38
	Older than 65 years	0	0
Education	Less than high school	5	3.55
	High school diploma or equivalent	14	9.93
	Some college, no degree	2	1.42
	Associate degree	4	2.84
	Bachelor's degree	53	37.59
	Master's degree	59	41.84
	Doctorate or professional degree	4	2.83
Employment status	Employed	111	78.72
	Unemployed	2	1.42
	Student	24	17.02
	Retired	0	0
	Others	4	2.84

Table 6 - Demographic information on sample

Out of all respondents, 123 possess a LinkedIn account, with 87.23 %, respectively. Most respondents use the platform daily, representing 33.34 %. Further, regarding their main reasons for opening a LinkedIn account, the majority with 74 of the respondents stated that it was for professional networking purposes.

Regarding their usage and familiarity with GenAI systems, 133 respondents, with 94.33 % respectively, stated that they use them already, of which 96 do so at least once a week (68.09 %) and 62 are familiar with its usage (43.97 %). Whereas 105 confirmed, that processes were more efficient with using GenAI.

In general, the sample profile consists of respondents that have LinkedIn accounts and use the platform daily, as well as they assess GenAI systems at least once a week.

In table 7, more detailed information about the respondents' familiarity with AI systems and their usage of LinkedIn is presented.

N = 141	Demographic	Count	%
Possessing a LinkedIn account	Yes	123	87.23
	No	18	12.77
Frequency of using LinkedIn	Daily	47	33.34
	Multiple times a week	38	26.95
	Once a week	16	11.35
	Once a month	14	9.93
	Less than once a month	14	9.93
	Never	12	8.50
Reason for opening a LinkedIn account	Professional networking	74	52.48
	Job search	24	17.02
	Keeping up with industry news	25	17.73
	Building a personal brand	4	2.83
	Educational purposes	4	2.83
	Others	10	7.11
Usage of AI systems	Yes	133	94.33
	No	8	5.67
Frequency of using AI systems	At least once a week	96	68.09
	Once a week up to several times a month	37	26.24
	Not at all	8	5.67
Familiarity with AI systems	Very familiar	62	43.97
	Somewhat familiar	64	45.39
	Not very familiar	15	10.64
	Not familiar at all	0	0
Changes in efficiency	Yes, for both efficiency and quality.	105	74.47
	No, for neither efficiency nor quality.	6	4.26

	I am not sure.	30	21.27
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Table 7 - Additional demographic information on sample

Overall, the sample can be characterized as predominantly women aged 25 to 34 years, with a master's degree, and being currently employed. Most respondents reported possessing a LinkedIn account and indicated that they use the platform on a daily basis.

In addition, the majority were already familiar with generative AI systems, with almost all participants confirming prior use and many reporting at least weekly engagement.

4.6 Subgroup Analysis Design

But not only the impact of the authorship on the perceived personal brand attributes was measured with the survey. It was also analyzed, whom of the respondents was able to correctly identify the two postings according to their actual authorship.

Out of the 141 valid responses, only 34 were able to indicate the right type of authorship according to the postings presented in the questionnaire. Out of these respondents, 18 are men and 16 are women, with 52.94 % and 47.06 % respectively. Most respondents are between 25 and 24 years old, representing 41.18 % of the sample. Moreover, regarding their educational level, most respondents are master graduates with 35.30 %.

In general, the group consists of respondents that are men aged between 25 and 34 years, having a master's degree, and are currently employed.

From this group of people, 26 possess a LinkedIn Account, with 76.47 %, respectively. Most respondents use the platform daily, representing 29.41 %. Further, regarding their main reason for opening a LinkedIn account, the majority with 14 respondents stated that it was for receiving industry news.

Regarding their usage and familiarity with GenAI systems, 28 respondents, with 82.65 % respectively, stated that they used them already, of which 14 do so at least once a week (41.18 %) and 26 are familiar with its usage (76.47 %). Whereas 24 confirmed, that processes were more efficient with using GenAI.

In general, the profile of the people identifying the authorship correctly consists of respondents that have LinkedIn accounts und use the platform daily, as well as they assess GenAI systems at least once a week.

5 Results and Discussion

For the data analysis, this study employed a PLS-SEM utilizing SmartPLS 4 to evaluate the proposed model. Therefore, the research considers the PLS-SEM as a more appropriate analysis to provide understanding of the individual constructs and the cause-effect relations among all the constructs when a predictive research goal and a relatively complex model are used for a study (J. F. Hair et al., 2014).

Furthermore, the PLS-SEM possesses the advantage of analyzing composite constructs whereas the covariance-based structural equation modeling (CB-SEM) cannot. The assessment of the model of the study was conducted in two steps: the outer model, representing the measurement model, and the inner model, which serves as the structural model. The study implemented various sampling procedures, like bootstrapping and blindfolding utilizing 5.000 resamples. Other than that, the evaluation of the predictive validity involved splitting the sample in two parts – one group of participants who reported that the posting was human-created ($n = 112$) and another group indicating that the posting was AI-generated ($n = 170$).

5.1 Assessment of Measurement Model

The measurement model was assessed through the lens of convergent validity, internal consistency reliability, and discriminant validity. In this evaluation, all constructs were included, as each contained more than two associated items. However, certain items were excluded from the constructs due to their outer loadings falling below the acceptable threshold of 0.70.

5.1.1 Reflective measurement model evaluation

The study specifically examined three fundamental dimensions pertinent to reflective measurement models: convergent validity, internal consistency reliability, and discriminant validity. The results are detailed in table 8.

The perceived personal brand voice authenticity (BVA) construct originally included 14 items. However, several indicators showed low outer loadings (< 0.70) and were therefore excluded from the final model as these are not statistically significant. Following the recommendation by Hair et al. (2013), such items may weaken the construct's convergent validity in reflective measurement models and their elimination therefore can enhance construct validity.

In contrast, Henseler et al. (2016) caution against removing indicators from formative or composite constructs, as doing so may alter the construct's conceptual meaning. Since

BVA was modeled reflectively in this study, removing weak indicators was methodologically appropriate and improved the model's validity.

Moreover, the construct perceived personal brand authenticity (BA) originally incorporated 14 items. In the analysis, some indicators showed low outer loadings (< 0.70) and were therefore excluded from the final model as these are not statistically significant, following both recommendations from Hair et al. (2013) and Henseler et al. (2016).

Further, the present study retained the construct of the perceived personal brand attitude (PBA) indicator as is, but seven indicators were excluded from the construct due to low outer loadings below 0.70 following Hair's et al. (2013) and Henseler's et al. (2016) suggestions.

Furthermore, the construct WOM originally included six items. Throughout the analysis, none of the indicators showed low outer loadings (< 0.70) and were therefore kept in the model, following both Hair's et al. (2013) and Henseler's et al. (2016) recommendations.

In contrast, all remaining outer loadings in the seven reflective measurement models met the threshold of at least 0.7 and are statistically significant ($p = 0.001$). Additionally, the average variances extracted (AVE) for each construct remaining surpassed the threshold of 0.5 for all constructs. Both results reinforcing a high reliability for the indicators.

For the internal consistency reliability, both Cronbach's alphas (α) and composite reliabilities (CR) for all constructs exceeded the required benchmarks of 0.70 (J. Hair et al., 2013) and 0.60 (Henseler et al., 2015) respectively. These findings affirm the internal reliability of the models employed.

Table 8 shows the results obtained regarding the measurement model.

Constructs	Indicators	Outer loadings	α	CR (rho_a)	AVE
Perceived personal brand voice authenticity	BVA5	0.806	0.924	0.925	0.689
	BVA6	0.877			
	BVA7	0.887			
	BVA8	0.874			
	BVA12	0.760			
	BVA13	0.787			
	BVA14	0.797			
Perceived personal brand authenticity	BA5	0.875	0.938	0.939	0.730
	BA6	0.898			
	BA7	0.896			
	BA8	0.874			

	BA12	0.796			
	BA13	0.821			
	BA14	0.816			
Perceived personal brand attitude	PBA1	0.917	0.953	0.955	0.841
	PBA2	0.938			
	PBA3	0.903			
	PBA4	0.909			
	PBA5	0.919			
Positive word of mouth	PWOM1	0.919	0.930	0.930	0.877
	PWOM2	0.941			
	PWOM3	0.949			
Negative word of mouth	NWOM1	0.916	0.891	0.988	0.813
	NWOM2	0.895			
	NWOM3	0.893			
Emotionality	E1	0.926	0.739	0.799	0.789
	E2	0.848			
Loyalty	L1	0.872	0.891	0.907	0.820
	L2	0.936			
	L3	0.908			

Table 8 - Reliability and validity test for the complete data

Following Henseler's, Ringle's, and Sarstedt's suggestion, the Heterotrait-Monotrait (HTMT) ratios (see table 9) shall all be lower than 0.85 with upper confidence bounds (95 %) remaining under one (Henseler et al., 2015).

One HTMT value for the construct BVA and BA exceeded the threshold of 0.85, indicating potential discriminant validity concerns. However, for this construct pair, the theoretical distinction between the constructs was retained, and further analysis within the HTMT interference confirmed acceptable separation as the confidence interval (0.848 – 0.909) did not include 1.0, suggesting statistical acceptable discriminant validity.

The other HTMT results further indicate satisfactory discriminant validity within the data as none of the construct pairs exceed the threshold (range = 0.124 – 0.835).

It is to be noted that the HTMT ratios are indicated in the parentheses, while the diagonal elements in bold represent the square roots of the variance between the constructs and their corresponding measures (AVE).

Table 9 shows the results obtained for the Fornell-Larcker criterion analysis and the HTMT ratios.

	BA	BVA	E	L	NWOM	PBA	PWOM
BA	0.854						
BVA	0.881 (0.946)	0.830					
E	0.614 (0.719)	0.638 (0.754)	0.888				
L	0.180 (0.196)	0.148 (0.172)	0.140 (0.178)	0.905			
NWOM	0.333 (0.338)	0.301 (0.324)	0.232 (0.254)	-0.089 (0.124)	0.901		
PBA	0.792 (0.835)	0.745 (0.792)	0.606 (0.704)	0.196 (0.218)	0.226 (0.213)	0.917	
PWOM	0.775 (0.827)	0.750 (0.809)	0.589 (0.680)	0.093 (0.101)	0.297 (0.292)	0.762 (0.808)	0.937

Table 9 - Fornell-Larcker criterion analysis and HTMT ratios

5.1.2 Composite measurement model evaluation

For the assessment of the formative measurement, the study employed variance inflation factors (VIFs) to identify multicollinearity among the indicators concerning the type of authorship of social media content as well as its impact on the perceived personal brand's voice and overall perception. Hair et al. (2013) state that any factor smaller than ten is considered acceptable and more conservative if less than five. In this model, the VIFs range from 1.524 to 6.625, signifying minimal concern regarding potential multicollinearity (Hair et al., 2013).

See Appendix C for more detailed information about all VIFs.

5.2 Assessment of Structural Model

The structural model is derived from the calculations performed using the PLS algorithm. The model facilitates the examination of path coefficients, which reflect the magnitude of the relationships among the latent variables, and systematically presents the results of the hypothesis tests conducted. To assess the significance of the paths', non-parametric bootstrapping approach is employed.

The results of the SEM analysis for the structural model, utilizing the training sample, are illustrated in figure 2. The Standardized Root Mean Square Residual (SRMR) for the model is 0.091, which is slightly above the commonly recommended threshold of 0.08 for an

acceptable model fit (J. Hair et al., 2013). While this indicates a minor deviation from ideal fit, it not necessarily invalidates the structural model. As SRMR is one of several model fit criteria, the results should be interpreted in conjunction with other indicators such as R^2 estimates, path coefficients, and effect sizes, which together provide a more comprehensive evaluation of model adequacy.

Thus, the assessment of the structural model continues with the examinations of the R^2 estimates, Stone-Geisser's Q^2 value, standardized path coefficients (β), and p-value. First, all path coefficients should be positive and greater than 0.1 and p-values lower than 0.05 (J. Hair et al., 2013). Regarding this, all hypotheses are supported and statistically significant.

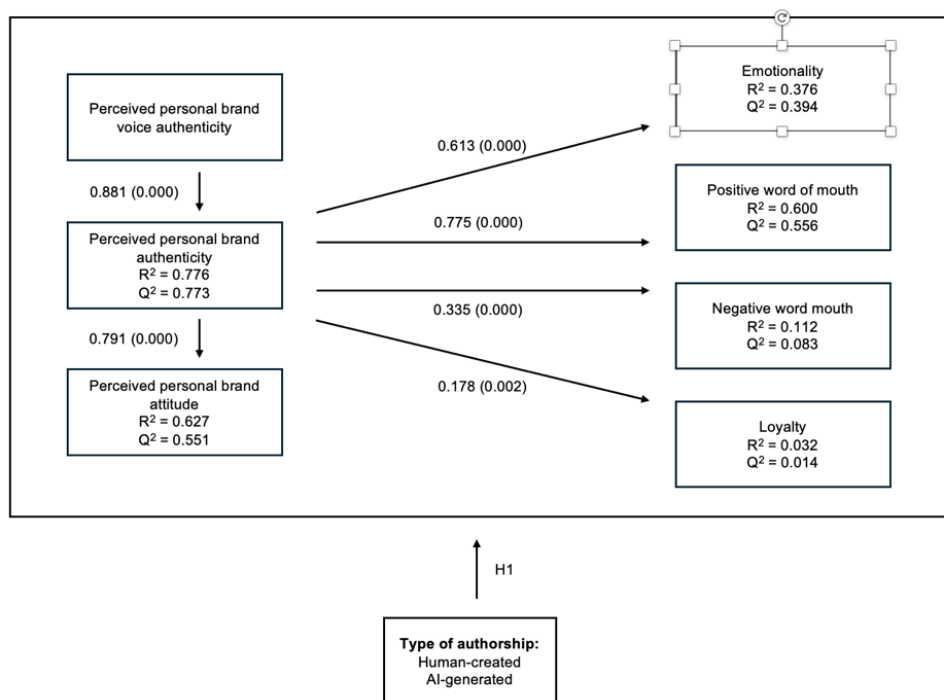


Figure 2 - Structural Model Results

H2 hypothesizes that higher perceived personal brand voice authenticity increases perceived personal brand authenticity. The results ($\beta = 0.881$; $p = 0.000$) have shown that this relationship is significant as the p-value is lower than 0.05 and therefore the hypothesis is supported.

Turning to the remaining hypotheses, H3 states that higher perceived personal brand authenticity has a positively impact on personal brand attitude ($\beta = 0.791$; $p = 0.000$), H4 that higher perceived personal brand authenticity decreases negative emotional reactions toward the personal brand ($\beta = 0.613$; $p = 0.000$), H5a that higher perceived personal brand authenticity increases positive WOM ($\beta = 0.775$; $p = 0.000$), whereas H5b states that higher perceived personal brand authenticity decreases negative WOM ($\beta = 0.335$; $p = 0.000$), and

H6 that higher perceived personal brand authenticity increases customer loyalty ($\beta = 0.178$; $p = 0.002$).

All results show evidence of the statistical significance of all hypotheses mentioned. Furthermore, it means that perceived personal brand authenticity is a central driver of consumer responses, strongly shaping brand attitude and emotional reactions, while also influencing behavioral outcomes such as loyalty and negative WOM.

Taking reference to Hair et al. (2019) the statistical significance is primarily assessed through p-values, but the differences in effect sizes highlight that authenticity's impact is most pronounced on attitudinal and emotional constructs, while behavioral intentions are affected to a lesser extent.

The effect size (f^2) considers small if it is higher or equal to 0.02, medium if its larger or equal to 0.15, and large if it is higher or equal to 0.35 (Cohen, 1988). It is relevant to notice that the effect size of perceived personal brand voice authenticity towards perceived personal brand authenticity suggests a large effect ($f^2 = 3.453$) as well as for perceived personal brand authenticity towards perceived personal brand attitude ($f^2 = 1.673$). However, the effect size of type of perceived personal brand authenticity towards loyalty suggests the weakest effect ($f^2 = 0.033$).

The R square (R^2) is a statistical measure explaining the endogenous variable's variance explained by the exogenous variable(s) and indicates the model's predictive accuracy. The values might range between 0 and 1, and higher values mean higher predictive accuracy than lower levels. Stone-Geisser's Q square (Q^2) is related to the predictive relevance of the structural model, and when results are above 0, there is proof of relevance (Hair et al., 2013).

As stated in figure 2, it is possible to verify that perceived personal brand voice authenticity strongly predicts perceived personal brand authenticity with a path coefficient of 0.881 ($p = 0.000$). The path explains 77.6 % of the variance in perceived personal brand authenticity ($R^2 = 0.776$), underlining a high level of explanatory power. The predictive relevance for this construct is further supported by a Q^2 value of 0.773.

Perceived personal brand authenticity also explains 62.7 % ($R^2 = 0.627$) of the variance in perceived personal brand attitude, with a significant path coefficient of 0.792 ($p = 0.000$). The Q^2 value of 0.551 confirms the model's predictive relevance for this relationship. Furthermore, perceived personal brand authenticity significantly predicts positive WOM ($\beta = 0.775$, $p = 0.000$), explaining 60.0 % of the variance ($R^2 = 0.600$), and confirming predictive relevance ($Q^2 = 0.556$). A smaller but still significant effect is observed on negative WOM ($\beta = 0.335$; $p = 0.000$), explaining 11.2 % of its relevance ($R^2 = 0.112$; $Q^2 = 0.083$). Loyalty is also

significantly influenced by perceived personal brand authenticity ($\beta = 0.178$; $p = 0.002$), although the explained variance is comparatively low ($R^2 = 0.032$; $Q^2 = 0.014$).

Finally, the model accounts for 37.6 % of the variance in emotionality ($R^2 = 0.376$), with a strong and significant effect from perceived personal brand authenticity ($\beta = 0.613$; $p = 0.000$). The corresponding Q^2 value of 0.394 further supports the construct's predictive relevance.

Overall, the results indicate that perceived personal brand authenticity plays a central mediating role in the model, serving as a strong predictor of key outcome variables such as WOM, loyalty, emotionality, and personal brand attitude, while perceived personal brand voice authenticity and type of authorship function as meaningful antecedents.

Table 10 shows all the results mentioned previously.

Relationship	Path coefficient β	p-value ¹	Confidence level		Effect size (f^2)	Results
			LL ²	UL ³		
Perceived personal brand authenticity – Emotionality	0.613	0.000	0.517	0.694	0.603	H4: Supported
Perceived personal brand authenticity – Loyalty	0.180	0.002	0.074	0.298	0.033	H6: Supported
Perceived personal brand authenticity – Positive word of mouth	0.775	0.000	0.520	0.675	1.500	H5a: Supported

¹ $p < 0.05$

² Lower Limit

³ Upper Limit

Perceived personal brand authenticity – Negative word of mouth	0.333	0.000	0.226	0.446	0.126	H5b: Supported
Perceived personal brand authenticity – Perceived personal brand attitude	0.792	0.000	0.742	0.836	1.673	H3: Supported
Perceived personal brand voice authenticity – Perceived personal brand authenticity	0.881	0.000	0.848	0.909	3.453	H2: Supported

Table 10 - Overview of results of structural model

5.3 Multi-Group Analysis: Human-created postings

To further explore the influence of authorship perception, the structural model was analyzed separately for subgroup 1, which comprises respondents who identified the posts as authored by a human. The aim is to assess whether the relationships between the constructs remain consistent within this subgroup.

Out of the 141 valid responses, a total of 282 cases could be generated, of which 111 indicated the postings in the questionnaire as created by humans. From these responses, 46 are men and 65 are women, with 41.44 % and 58.56 % respectively. Most respondents are between 25 and 24 years old, representing 46.85 % of the group. Moreover, regarding their educational level, most respondents are bachelor graduates with 46.85 %.

In general, the group consists of respondents that are women aged between 25 and 34 years, having a bachelor's degree, and are currently employed.

From this group of people, 94 possess a LinkedIn Account, with 84.68 %, respectively. The majority uses the platform multiple times a week, representing 30.63 %. Further, regarding their main reason for opening a LinkedIn account, the majority with 50 respondents stated that it was for networking.

Regarding their usage and familiarity with GenAI systems, 102 respondents, with 91.89 % respectively, stated that they used them already, of which 64 do so at least once a week (57.66 %) and 94 are familiar with its usage (84.69%). Whereas 84 confirmed, that processes were more efficient with using GenAI.

In general, the profile of the people identifying the authorship correctly consists of respondents that have LinkedIn accounts and use the platform multiple times a week, as well as they assess GenAI systems at least once a week.

The results of the SEM analysis for the structural model of human-created postings is illustrated in figure 3. The SRMR for the model is 0.115, which is above the commonly recommended threshold of 0.08 for an acceptable model fit (J. Hair et al., 2013). While this indicates a deviation from ideal fit, it not necessarily invalidates the structural model. As SRMR is one of several model fit criteria, the results should be interpreted in conjunction with other indicators such as R^2 estimates, path coefficients, and effect sizes, which together provide a more comprehensive evaluation of model adequacy.

Thus, the assessment of the structural model continues with the examinations of the R^2 estimates, Stone-Geisser's Q^2 value, standardized path coefficients (β), and p-value. First, all path coefficients should be positive and greater than 0.1 and p-values lower than 0.05 (J. Hair et al., 2013). Regarding this, all hypotheses are supported and statistically significant.

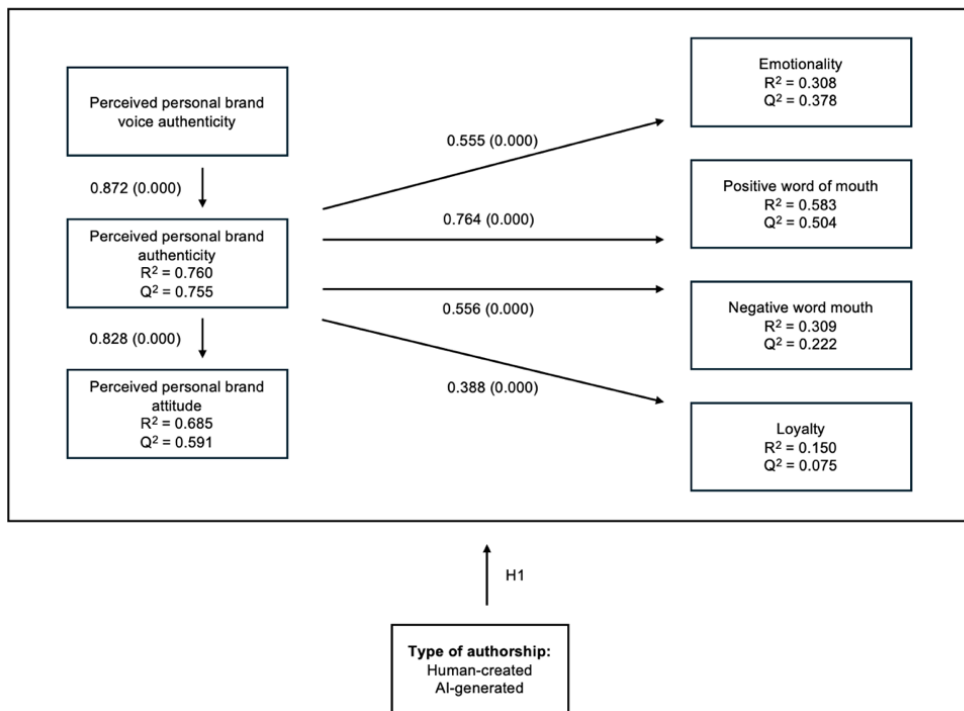


Figure 3 - Structural model for human-created postings

H2 hypothesizes that higher perceived personal brand voice authenticity increases perceived personal brand authenticity. The results ($\beta = 0.872$; $p = 0.000$) have shown that this relationship is significant as the p-value is lower than 0.05 and therefore the hypothesis is supported.

Turning to the remaining hypotheses, H3 states that higher perceived personal brand authenticity has a positively impact on personal brand attitude ($\beta = 0.828$; $p = 0.000$), H4 that higher perceived personal brand authenticity decreases negative emotional reactions toward the personal brand ($\beta = 0.555$; $p = 0.000$), H5a that higher perceived personal brand authenticity increases positive WOM ($\beta = 0.764$; $p = 0.000$), whereas H5b states that higher perceived personal brand authenticity decreases negative WOM ($\beta = 0.556$; $p = 0.000$), and H6 that higher perceived personal brand authenticity increases customer loyalty ($\beta = 0.388$; $p = 0.000$).

All results show evidence of the statistical significance of all hypotheses mentioned. Further, the findings highlight that perceived personal brand authenticity is a central driver of consumer responses, strongly shaping brand attitude and emotional reactions, while also influencing behavioral outcomes. In particular, authenticity demonstrates a strong effect on positive WOM and a clear negative effect on negative WOM, underlining its role in stimulating favorable consumer communication while reducing unfavorable brand-related talk. Loyalty is also significantly affected, although the effect size is smaller in comparison.

Taking reference to Hair et al. (2019) the statistical significance is primarily assessed through p-values, but the differences in effect sizes highlight that authenticity's impact is most

pronounced on attitudinal and emotional constructs, while behavioral intentions are affected to a lesser extent, despite being statistically robust.

The effect size (f^2) considers small if it is higher or equal to 0.02, medium if its larger or equal to 0.15, and large if it is higher or equal to 0.35 (Cohen, 1988). It is relevant to note that the effect size (f^2) of perceived personal brand voice authenticity towards perceived personal brand authenticity suggests a large effect ($f^2 = 3.158$). Similarly, strong effect sizes are observed for perceived personal brand authenticity towards perceived personal brand attitude ($f^2 = 2.179$). Further, another positive effect presents the relationship between perceived personal brand authenticity and emotionality ($f^2 = 0.445$) and negative WOM ($f^2 = 0.447$). The effect on loyalty ($f^2 = 0.177$) is considered medium, while the effect on positive WOM is moderate with $f^2 = 1.399$.

As stated in figure 3, it is possible to verify that perceived personal brand voice authenticity strongly predicts perceived personal brand authenticity, explaining 76.0 % of the variance ($R^2 = 0.760$), with a corresponding Q^2 value of 0.755, indicating strong predictive relevance for the construct. In turn, perceived personal brand authenticity explains 68.5 % ($R^2 = 0.685$) of the variance in perceived personal brand attitude, supported by a Q^2 value of 0.591.

Perceived personal brand authenticity also explains 57.90 % of the variance in positive WOM ($R^2 = 0.583$; $Q^2 = 0.504$), 30.8 % of the variance in emotionality ($R^2 = 0.308$; $Q^2 = 0.378$), and 15.0 % of the variance in loyalty ($R^2 = 0.150$; $Q^2 = 0.075$). The explained variance in negative WOM is 30.9 % ($R^2 = 0.309$), with a Q^2 value of 0.222, supporting the predictive relevance of the construct as well.

Overall, the results indicate that perceived personal brand authenticity plays a central mediating role in the model for human-created postings. It serves as a strong predictor of key outcome variables such as both positive and negative WOM, loyalty, emotionality, and personal brand attitude, while perceived personal brand voice authenticity functions as a highly impactful antecedent.

Table 11 shows all the results mentioned previously.

Relationship	Path coefficient β	p-value ⁴	Confidence level		Effect size (f^2)	Results
			LL ⁵	UL ⁶		
Perceived personal brand authenticity – Emotionality	0.555	0.000	0.170	0.562	0.445	H4: Supported
Perceived personal brand authenticity – Loyalty	0.388	0.000	0.042	0.339	0.177	H6: Supported
Perceived personal brand authenticity – Positive word of mouth	0.764	0.000	0.439	0.711	1.399	H5a: Supported
Perceived personal brand authenticity – Negative word of mouth	0.556	0.000	0.154	0.507	0.447	H5b: Supported
Perceived personal brand authenticity – Perceived personal	0.828	0.000	0.539	0.802	2.179	H3: Supported

⁴ $p < 0.05$

⁵ Lower Limit

⁶ Upper Limit

brand attitude						
Perceived personal brand voice authenticity – Perceived personal brand authenticity	0.872	0.000	0.653	0.847	3.158	H2: Supported

Table 11 - Overview of results of structural model for human-created postings

5.4 Multi-Group Analysis: GenAI-generated postings

The following sections present the structural model results for subgroup 2, which compromise respondents who identified the posts as generated by GenAI. The following results provide insights whether the relationships between the constructs remain consistent within this subgroup.

Out of the 141 valid responses, a total of 282 cases were generated from whose 169 indicated the posting presented in the questionnaire as GenAI generated. Out of the responses, 84 are men and 85 are women, with 49.70 % and 50.30 % respectively. Most respondents are between 25 and 24 years old, representing 62.72 % of the group. Moreover, regarding their educational level, the majority are master graduates with 49.70 %.

In general, the group consists of respondents that are women aged between 25 and 34 years, having a master's degree, and are currently employed.

From this group of people, 152 possess a LinkedIn account, with 89.94 %, respectively. Most respondents use the platform daily, representing 36.69 %. Further, regarding their main reason for opening a LinkedIn account, the majority with 98 respondents stated that it was for networking activities.

Regarding their usage and familiarity with GenAI systems, 164 respondents, with 95.91 % respectively, stated that they used them already, of which 128 do so at least once a week (75.74 %) and 80 are very familiar with its usage (47.34 %). Whereas 126 confirmed, that processes were more efficient with using GenAI.

In general, the profile of the people identifying the authorship correctly consists of respondents that have LinkedIn accounts und use the platform daily, as well as they assess GenAI systems at least once a week.

The results of the SEM analysis for the structural model of AI-generated postings is illustrated in figure 4. The SRMR for the model is 0.116, which is above the commonly recommended threshold of 0.08 for an acceptable model fit (J. Hair et al., 2013). While this indicates a deviation from ideal fit, it not necessarily invalidates the structural model. As SRMR is one of several model fit criteria, the results should be interpreted in conjunction with other indicators such as R^2 estimates, path coefficients, and effect sizes, which together provide a more comprehensive evaluation of model adequacy.

Thus, the assessment of the structural model continues with the examination of the R^2 estimates, Stone-Geisser's Q^2 values, standardized path coefficients (β), and p-values. First, all path coefficients should be positive and greater than 0.1 and p-values lower than 0.05 (Hair et al., 2013).

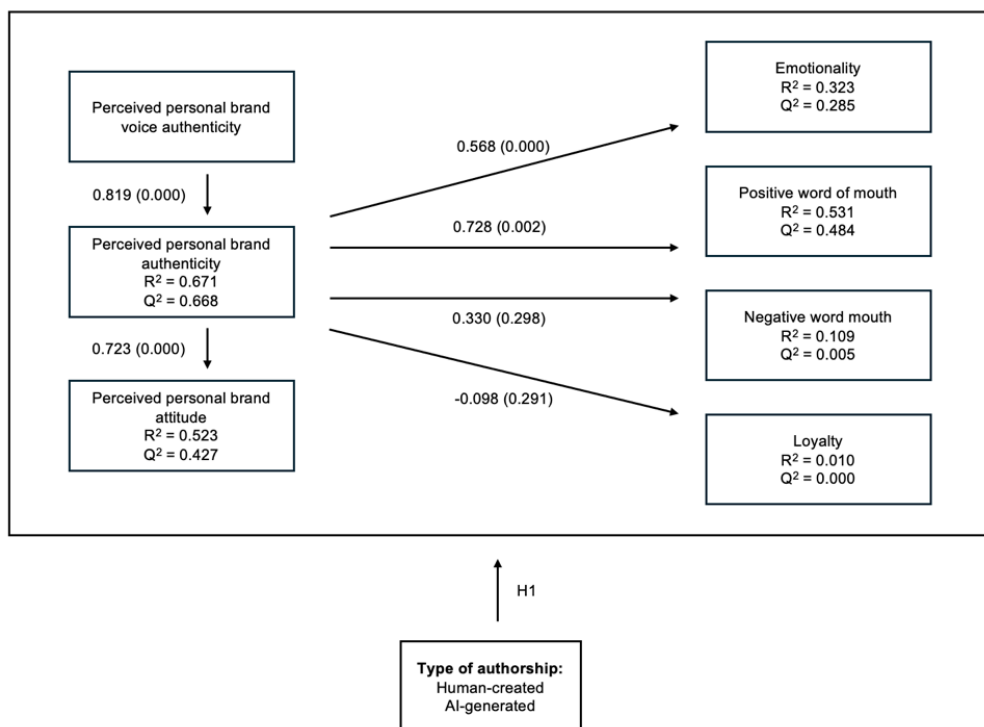


Figure 4 - Structural model for AI-generated postings

H2 hypothesizes that higher perceived personal brand voice authenticity increases perceived personal brand authenticity. The results ($\beta = 0.819$; $p = 0.000$) have shown that this relationship is significant as the p-value is lower than 0.05 and therefore the hypothesis is supported.

Turning to the remaining hypotheses, H3 states that higher perceived personal brand authenticity has a positively impact on personal brand attitude ($\beta = 0.723$; $p = 0.000$), H4 that higher perceived personal brand authenticity decreases negative emotional reactions toward the personal brand ($\beta = 0.568$; $p = 0.000$). H5a suggests that higher perceived personal brand authenticity increases positive WOM. This path is statistically significant ($\beta = 0.728$; $p =$

0.000), providing support for the hypotheses. In contrast, H5b states that higher perceived personal brand authenticity decreases negative WOM. The relationship, however, is not significant ($\beta = 0.030$; $p = 0.298$), so this hypothesis is not supported. Finally, H6 states that higher perceived personal brand authenticity increases customer loyalty ($\beta = -0.098$; $p = 0.291$). This relationship is also not significant, and therefore the hypothesis is not supported as well.

Overall, the results show that several of the proposed hypotheses are supported while others are not. Perceived personal brand voice authenticity continues as a strong predictor of perceived personal brand authenticity, and authenticity itself has a significant impact on brand attitude, emotional responses, and positive WOM.

In contrast, no significant effects were observed for the relationships between authenticity and negative WOM or loyalty. This suggests that while authenticity can stimulate positive engagement and strengthen brand-related attitudes, it may not be sufficient to prevent unfavorable conversations or foster long-term loyalty on its own.

As Hair et al. (2019) emphasize, significance is primarily assessed through p-values, but considering effect sizes and non-significant results provides important nuance: authenticity has its strongest influence on cognitive and emotional evaluations, while its effect on behavioral outcomes appears limited in this study.

The effect size (f^2) is considered small if it is higher or equal to 0.02, medium if it is higher or equal to 0.15, and large if it is higher or equal to 0.35 (Cohen, 1988). It is relevant to note that the effect size (f^2) of perceived personal brand voice authenticity on perceived personal brand authenticity suggests a strong effect ($f^2 = 2.043$), as well as the effect from perceived personal brand authenticity on perceived personal brand attitude ($f^2 = 1.095$).

A similarly large effect is found for the path from perceived personal brand authenticity to emotionality ($f^2 = 0.477$). The effect size for the relationship between perceived personal brand authenticity and loyalty is negligible ($f^2 = 0.010$), and for negative WOM, the effect size remains below the threshold for a small effect ($f^2 = 0.122$), whereas for positive WOM it is supposed to be a large effect ($f^2 = 1.130$).

The R^2 is a statistical measure explaining the endogenous variable's variance explained by the exogenous variables and indicates the model's predictive accuracy. Values closer to 1 indicate stronger explanatory power. Stone-Geisser's Q^2 is related to the predictive relevance of the structural model. When Q^2 values are greater than zero, predictive relevance is established (Hair et al., 2013).

As stated in figure 4, perceived personal brand voice authenticity significantly predicts perceived personal brand authenticity, explaining 67.1 % of the variance ($R^2 = 0.671$), with a corresponding Q^2 value of 0.668, indicating strong predictive relevance. In turn, perceived personal brand authenticity explains 52.3 % of the variance in perceived personal brand attitude ($R^2 = 0.523$), supported by a Q^2 value of 0.427.

Perceived personal brand authenticity also explains 53.1 % of the variance in positive WOM ($R^2 = 0.531$), and the Q^2 value of 0.484 confirms its predictive relevance. Emotionality is similarly well explained ($R^2 = 0.323$; $Q^2 = 0.285$). However, the explained variance in loyalty is negligible ($R^2 = 0.010$; $Q^2 = 0.000$), and the value for negative WOM is moderate ($R^2 = 0.109$; $Q^2 = 0.005$), yet the effect is not significant.

Overall, the results for Group 2 demonstrate that perceived personal brand authenticity remains a key predictor for emotional and attitudinal responses but shows limited impact on loyalty and negative WOM. Perceived personal brand voice authenticity continues to play a vital role as a strong antecedent.

Table 12 shows all the results mentioned previously.

Relationship	Path coefficient β	p-value ⁷	Confidence level		Effect size (f^2)	Results
			LL ⁸	UL ⁹		
Perceived personal brand authenticity – Emotionality	0.568	0.000	0.221	0.435	0.477	H4: Supported
Perceived personal brand authenticity – Loyalty	-0.098	0.291	0.002	0.068	0.010	H6: Not supported
Perceived personal brand authenticity	0.728	0.002	0.423	0.627	1.130	H5a: Supported

⁷ $p < 0.05$

⁸ Lower Limit

⁹ Upper Limit

– Positive word of mouth						
Perceived personal brand authenticity – Negative word of mouth	0.330	0.298	0.034	0.208	0.122	H5b: Not supported
Perceived personal brand authenticity – Perceived personal brand attitude	0.723	0.000	0.426	0.614	1.095	H3: Supported
Perceived personal brand voice authenticity – Perceived personal brand authenticity	0.819	0.000	0.567	0.767	2.043	H2: Supported

Table 12 - Overview of results for structural model for AI-generated postings

5.5 Discussion

The present study aims to explore the influence of different types of authorship on consumers' perceptions of personal brands on LinkedIn. In other words, it investigated whether content created by humans or generated by GenAI affects perceived personal brand voice authenticity, overall personal brand voice authenticity, personal brand attitude, both positive and negative WOM, emotionality, and loyalty.

The findings reinforce the critical role of authenticity in personal branding while extending the understanding of how GenAI intersects with established branding theories.

Prior research has consistently emphasized authenticity as a required basis of favorable consumer responses (Aaker, 1995; Bruhn et al., 2012; Gill & Dawra, 2010).

The hypotheses formulated in Chapter 3 guide the analysis, and the results provide important insights into both theoretical and practical dimensions.

The results highlight several key findings. First, the strong and significant relationship between personal brand voice authenticity and overall personal brand authenticity (H2) further confirms the central role of authenticity in personal branding (Kirkby et al., 2023). This supports theoretical perspectives that message credibility and the perceived alignment between communication and identity are critical in shaping authenticity perceptions (Pérez, 2019). By empirically validating perceived personal brand voice authenticity as a critical antecedent of overall authenticity, the study strengthens theoretical distinctions within authenticity literature,

Moreover, turning to H3, the findings demonstrate that perceived personal brand authenticity positively influences personal brand attitude. This aligns with branding literature that identifies authenticity as one of the most decisive determinants of favorable brand evaluations and consumer attitudes (Gill & Dawra, 2010; Kucharska et al., 2020). In addition, the strong effect size demonstrates that authenticity serves as a stable foundation for consumer judgments, echoing Keller's (1993) conceptualization of brand attitudes as central to consumer decision-making.

As H4 proposed that higher perceived authenticity decreases negative emotional reactions, the findings therewith support this relationship, confirming prior research on algorithm aversion (Castelo et al., 2019; Dietvorst et al., 2015). When consumer perceive a personal brand as authentic, they experience fewer negative emotions, reinforcing the protective role of authenticity in mitigating adverse responses.

The results for hypotheses H5a and H5b reveal the ambivalent nature of authenticity. Supporting H5a, authenticity significantly enhances positive WOM, confirming Berger's (2014) findings that strong perceptions of credibility and genuineness encourage consumers to advocate for brands. However, these findings also show that when authenticity is perceived as violated, negative WOM increases (H5b). This dual outcome joins Chapman and Anderson (2013) and Kirk & Givi (2025), who argue that authenticity violation can trigger strong rejection and moral disgust, leading to amplified criticism. Thus, authenticity can serve both as a catalyst for advocacy and as well as a vulnerability when expectations are unmet.

For H6, the results show that authenticity positively influences loyalty in the full sample and among respondents who believed content to be human created. This finding is in line with Aaker (1995) and Dick & Basu (1994), who identified authenticity and credibility as key antecedents of brand commitment. However, in the subgroup identifying AI-generated content, the effect on loyalty was not significant. This nuance suggests that consumer

recognition of AI authorship weakens authenticity's impact on long-term attachment, complementing disclosure literature (Brüns & Meißner, 2024; Graefe & Bohlken, 2020).

Finally, subgroup analyses reveal important contextual differences. When respondents believed content to be created by humans, authenticity strongly predicted brand attitude, WOM, and loyalty, confirming the stabilizing role of authenticity in traditional branding contexts. By contrast, in the subgroup identifying the content as generated by GenAI, authenticity continued to drive positive WOM and brand attitudes (supporting H3 and H5a) but failed to reduce negative WOM or enhance loyalty (not supporting H5b and H6). These results highlight the boundary conditions of authenticity's effects: while it remains a powerful driver of attitudinal outcomes, its ability to secure behavioral commitments depends on authorship recognition.

In sum, the hypotheses tested confirm the central role of authenticity in personal branding on LinkedIn. While H2, H3, H4, and H5a were consistently supported across analyses, H5b and H6 showed mixed results depending on the subgroup. These findings extend prior literature by showing that AI-authorship introduces vulnerabilities in processes driven by AI. Authenticity emerges not as a uniformly positive construct but as a double-edged factor that can foster both loyalty and advocacy or amplify negative WOM when violated. This contributes to theoretical debates on authenticity (Bruhn et al., 2012; Kirkby et al., 2023) and addresses recent calls for research on AI's role in shaping consumer-brand relationships (Haupt et al., 2024; Longoni & Cian, 2022).

6 Conclusions and Recommendations

The aim of this study was to examine the impact of different types of authorship on personal branding outcomes on LinkedIn, with a particular focus on authenticity perceptions and their influence on brand attitude, WOM, emotionality, and loyalty. The empirical results allow clear conclusions to be drawn, as well as implications for both theory and practice.

Results from the analysis confirm that individuals perceive GenAI-generated content as less authentic, both in terms of overall personal brand authenticity and personal brand voice authenticity. However, these authenticity perceptions remain the decisive drivers of consumer responses. Authenticity strongly enhances brand attitude and positive WOM, but, when violated, also intensifies negative WOM. The findings therefore underline the ambivalent role of authenticity in personal branding, functioning as both a source of consumer advocacy and a trigger of criticism. Importantly, subgroup analyses demonstrated that consumer recognition of authorship further conditions these effects. When respondents identified content as AI-generated, authenticity no longer significantly predicted loyalty or reduced negative WOM, showing that transparency and recognition play a moderating role in shaping outcomes.

6.1 Theoretical Contributions

There is a need for research discussing the perception of different kind of authorship in content creation in marketing. Therefore, the present study brings several theoretical contributions to consider.

First, the results extend the branding literature that identifies authenticity as a decisive determinant of consumer evaluations (Aaker, 1995; Bruhn et al., 2012; Gill & Dawra, 2010). By showing that GenAI-generated content significantly undermines perceived authenticity, the study provides empirical support for research on algorithm aversion (Burton et al., 2020; Castelo et al., 2019) and its application within personal branding on LinkedIn. This represents a valuable extension, as previous studies have predominantly focused on product or corporate brands (Haupt et al., 2024; Overgoor et al., 2019).

The second theoretical contribution takes into consideration that the study reinforces and advances the concept of brand voice authenticity. While Pérez (2019) and Kirkby et al. (2023) conceptualize message authenticity as a precursor to credibility and trust, the strong empirical link identified here between brand voice authenticity and overall authenticity validates these theoretical assumptions in the specific context of AI-mediated communication. This emphasizes that authenticity is not only tied to content but also to style and voice, which function as essential antecedents.

Another contribution takes reference to the ambivalent outcomes of authenticity contribute to a refinement of authenticity theory. Prior literature often frames authenticity as a uniformly positive driver of favorable consumer responses (Kucharska & Mikołajczak, 2018; Labrecque et al., 2011). However, this study shows that authenticity also intensifies negative WOM when perceived as violated, supporting the view that authenticity can act as a double-edged construct (Chapman & Anderson, 2013; Kirk & Givi, 2025). This adds theoretical nuance by acknowledging the risks embedded in authenticity-driven strategies.

Fourth, the non-significant moderating role of emotionality in the link between authenticity and brand attitude challenges earlier work that highlighted the vulnerability of AI in hedonic and affective contexts (Castelo et al., 2019; Longoni & Cian, 2022). The findings suggest that authenticity exerts a consistent influence on consumer evaluations regardless of message framing. This contributes to the debate on the so-called “Word-of-Machine” effect (Longoni & Cian, 2022) by showing that perceptions of authenticity may override emotional tone in shaping brand attitudes.

Finally, the subgroup analyses extend literature on disclosure and transparency in AI communication. Earlier studies argue that transparency in authorship can mitigate negative effects of AI (Graefe & Bohlken, 2020; Brüns & Meißner, 2024). The present study adds that consumer recognition of AI-authorship significantly reduces authenticity’s effect on loyalty and WOM. This demonstrates that disclosure is not only a strategic choice by brands but also an interactive process shaped by consumer awareness, which broadens theoretical perspectives on AI-authorship in digital branding.

6.2 Managerial Implications

With the emerging usage of AI in marketing, its development and capabilities need to be investigated before properly implementing it in marketing activities. Whereas it has already been used for many years, creative GenAI implements a strong difference to previously analytical intelligences (Overgoor et al., 2019). Especially consumers struggle with the distinction from human-created or AI-generated content (Köbis & Mossink, 2021). This results in necessary implications for personal brands as their perceived authenticity based on published content can be affected by customer perceptions.

All aspects mentioned can be accomplished with the right guidance for personal brands and marketers navigating the integration of AI in content creation.

First, personal brands should be cautious in their adoption of GenAI for content creation on LinkedIn. While AI tools can enhance efficiency and support drafting, overreliance on AI risks undermining perceptions of authenticity, which is central to personal

branding. A collaboration in a hybrid approach, in which AI supports but does not replace human input, appears to be a more sustainable strategy.

Second, authenticity must remain the guiding principle of personal branding. Practitioners should ensure that content created with the assistance of GenAI maintains a consistent personal tone, reflecting the brand's identity, and conveying emotional resonance. Techniques such as careful editing, personalization, and integrating lived experiences can help to mitigate authenticity losses caused by AI authorship.

Third, marketers should be aware of the ambivalent outcomes of authenticity. Even when followers perceive a personal brand as authentic, this does not guarantee only positive reactions. Negative WOM remains a risk, particularly when consumers suspect a lack of transparency in the use of AI. Thus, monitoring consumer responses and engaging proactively in online dialogue becomes essential.

For practitioners, these results imply that authenticity is a consistently important driver of consumer responses, regardless of whether content is framed in emotional or rational terms. This highlights the need for personal brands to safeguard authenticity in all communication contexts. Marketers integrating AI into personal branding should therefore focus on ensuring that the brand's identity and voice remain credible across both emotional and informational posts, since audiences evaluate authenticity independently of the message's emotionality.

Finally, disclosure strategies should be considered. While full disclosure of AI use may trigger algorithm aversion in some consumers, research suggests that transparent communication about AI assistance, framed as supportive rather than substitutive, can reduce skepticism (Haupt et al., 2024). Personal brands should therefore experiment with varying levels of disclosure and evaluate their impact on audience trust.

6.3 Limitations and Further Research Suggestions

The present study reached conclusions, theoretical contributions and managerial implications. Therefore, the limitations and further research recommendations should be considered.

Firstly, the sample size ($n = 141$) limits the generalizability of the findings. Future research should replicate the study with larger and more diverse samples, particularly across global markets, to capture cultural differences in AI perception.

Second, the study employed a cross-sectional design, which captures consumer perceptions at a single point in time. A longitudinal design could provide valuable insights into how perceptions of AI-generated content evolve as exposure increases and as GenAI becomes more normalized in society.

Third, the study relied on self-reported survey data, which may be subject to social desirability bias or limited by respondents' actual ability to discern authorship. Experimental designs, eye-tracking studies, or qualitative approaches such as interviews could deepen understanding of how consumers detect and evaluate AI-authorship.

Finally, future research should explore contextual factors in greater depth. Distinguishing between hedonic and utilitarian content types could reveal whether AI-authorship is more acceptable in rational, informational contexts than in emotional, identity-driven ones. While this study found no significant moderating effect of emotionality on the perceived personal brand authenticity and perceived personal brand attitude relationship, future research could investigate under which conditions such effects might occur, for example across different industries or message formats. Similarly, comparative studies across different social media platforms would help to identify platform-specific dynamics of AI adoption in personal branding.

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Annexes

Annex A – Summary of adopted questions and measurement scales, sources, and number of items

Construct	Adapted item	Type of Likert Scale	Source	N° of items
Perceived personal brand voice authenticity	Continuity			
	This text is consistent.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	4
	This text is true to itself.			
	This text offers continuity.			
	This text follows a distinct concept.			
	Originality			
	This text is different.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	3
	This text stands out from other brands.			
	This text is unique.			
	This text clearly distinguishes itself from other brands.			
	Reliability			
	I believe what is said in the text and that it will keep its promise.	5-point Likert scale of agreement (Strongly agree	Kirkby et al. (2023)	3
	This personal brand makes			

	reliable promises.	(1) to Strongly disagree (5))		
	This personal brand is credible.			
	Naturalness			
	This text does not seem artificial.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	3
	This text makes a genuine impression.			
	This text gives the impression of being natural.			
Perceived personal brand authenticity	Continuity			
	This personal brand is consistent over time.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	4
	This personal brand is true to itself.			
	This personal brand offers continuity.			
	This personal brand follows a distinct concept.			
	Originality			
	This personal brand is different.	5-point Likert scale of	Kirkby et al. (2023)	3
	This personal brand stands			

	out from other brands.	agreement (Strongly agree (1) to Strongly disagree (5))		
	This personal brand is unique.			
	This personal brand clearly distinguishes itself from other brands.			
Reliability				
	This personal brand is believable, and I think it will deliver what it promises.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	3
	This personal brand makes reliable promises.			
	This personal brand is credible.			
Naturalness				
	This personal brand does not seem artificial.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	3
	This personal brand makes a genuine impression.			
	This personal brand gives the impression of being natural.			

Perceived personal brand attitude	I find the personal brand appealing.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	5
	I find the personal brand good.			
	I find the personal brand pleasant.			
	I find the personal brand favourable.			
	I find the personal brand likable.			
		5-point Likert scale of likelihood (Very likely (1) to very unlikely (5))		
Word of mouth	Say positive things about this personal brand?			
	Recommend the personal brand to others?			
	Recommend this personal brand to someone else who seeks my advice?			
		5-point Likert scale of likelihood (Very	Alexandrov et al. (2013)	6

	Warn my friends and relatives not to consume content from this personal brand?	likely (1) to very unlikely (5)) 5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))		
	Complain to my friends and relatives about this personal brand?			
	Say negative things about this personal brand to other people?			
Emotionality	The text shows the “personal brand’s benefits” or “creates likability towards the personal brand”.	5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5)) 5-point Likert scale of agreement (Strongly agree (1) to Strongly disagree (5))	Kirkby et al. (2023)	2
	The text “describes quality. Economy or value of performance” or shows “positive or negative emotions”.			

Loyalty	If I knew that a personal brand's content was created by AI, I would be less likely to follow them on social media.			
	Knowing that a personal brand writes their content increases my loyalty toward them.		Kirk & Givi (2025)	3
	I am more likely to recommend a personal brand to others if I believe they create their content.			

Annex B – Questionnaire

Welcome and Thank You for Participating!

Thank you for taking the time to participate in this survey. This questionnaire is part of my master's thesis, which explores how artificial intelligence (AI) influences content creation for Personal Brands on Social Media— especially regarding authenticity, trust, and user perception. Your input is incredibly valuable, as it will help me better understand how different types of content (AI-generated vs. human-written) impact the way we engage with Personal Brands.

The findings of this research aim to contribute to the growing field of AI and marketing, and your honest responses will play a key role in shaping meaningful academic insights.

For any questions that you might have, comments to share, or to indicate your interest in receiving information about the main outcomes and conclusions of the study, please use the following contact details: christina_wolfel@iscte-iul.pt

By clicking "Next", you confirm that you consent to participate in this study.

Thank you for your valuable contribution!

Before you can start, I would like to introduce you to some terminologies, which will be important for your understanding of the questions.

First of all, the term *Personal Brand* refers to the way an individual presents themselves publicly – especially on professional platforms like LinkedIn. It includes how others perceive their personality, values, expertise, and communication style over time.

Therefore, *Personal Branding* describes the strategic process of shaping and managing your public image. It involves intentionally sharing content, opinions, and experiences to build credibility, trust, and visibility as a professional.

Do you have a LinkedIn account?

☐ Yes, I do have a LinkedIn account.

☐ No, I don't have a LinkedIn account.

How often do you use LinkedIn?

☐ Daily

☐ Multiple times a week

☐ Once a week

☐ Once a month

☐ Less than once a month

☐ Never

What was your primary reason for opening a LinkedIn account?

☐ Professional networking

☐ Job search

☐ Keeping up with industry news

☐ Building a Personal Brand

☐ Educational purposes

☐ Others

Have you ever used publicly available generative AI systems like, e.g. ChatGPT or Copilot?

☐ Yes

☐ No

How often do you use publicly available generative AI systems like, e.g. ChatGPT or Copilot?

- ☐ At least once a week
- ☐ Once a week up to several times a month
- ☐ Not at all

How familiar are you with publicly available generative AI systems like, e.g. ChatGPT or Copilot?

- ☐ Very familiar
- ☐ Somewhat familiar
- ☐ Not very familiar
- ☐ Not familiar at all

Did you perceive any changes in terms of efficiency or quality of work while using publicly available generative AI systems?

- ☐ Yes, I did for both efficiency and quality.
- ☐ No, I did not perceive any changes.
- ☐ I am not sure.

To be able to answer the next questions, a brief introduction of a Personal Brand will be given first.

This individual holds a strategic role in innovation communication at a global consulting firm. With a background in psychology and digital transformation, the person translates complex topics like artificial intelligence, the metaverse, and sustainable mobility into accessible narratives.

Formerly in strategy consulting, the individual now focuses on public engagement around emerging technologies, often speaking at events about the societal and ethical dimensions of innovation.

The Personal Brand is defined by clarity, curiosity, and a strong commitment to making innovation understandable and impactful for broader society.

You will now see a LinkedIn posting. After reading the posting, please answer the following questions based on the impressions and cues that shaped your judgement.

There are no right or wrong answers – your personal perception is what matters most!

You will now see a LinkedIn posting. After reading the posting, you will be asked to share your impressions.

30-minute walks improve cognitive performance! 🌱

Dr. Chuck Hillmann's study at the University of Illinois found that young adults' cognitive **#performance** improved after a 20-minute treadmill run at 60% maximum heart rate, for example.

So how can we maintain a good work-life **#balance**?

✓ **Clear boundaries:** Set specific work hours and disconnect from work communications during personal time.

✓ **Regular breaks:** Beyond walking, take brief breaks for meditation, stretching, or simply to step away from your desk.

✓ **Time management:** Organize your tasks with to-do lists, calendars, and time-blocking to lower stress and create more personal time.

✓ **Screen time:** Limit screen use after work to enhance sleep quality and mental health.

✓ **Quality time:** Prioritize spending time with loved ones to maintain strong emotional support and a healthy work-life balance.

True strength lies in the art of balancing work with life's pleasures! 🌱

What helps you the most to balance your work?

Please indicate the type of authorship of the presented posting according to your perception.

☐ This posting is human-created.

☐ This posting is AI-generated.

The Continuity of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This text is consistent.	☐	☐	☐	☐	☐
This text is true to itself.	☐	☐	☐	☐	☐
This text offers continuity.	☐	☐	☐	☐	☐
This text follows a distinct concept.	☐	☐	☐	☐	☐

The Originality of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This text is different.	☐	☐	☐	☐	☐
This stands out from other texts.	☐	☐	☐	☐	☐
This text is unique.	☐	☐	☐	☐	☐
This text clearly distinguishes itself from other texts.	☐	☐	☐	☐	☐

The Reliability of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
I believe what is said in the text and that it will keep its promise.	☐	☐	☐	☐	☐
The text makes reliable promises.	☐	☐	☐	☐	☐
This text is credible.	☐	☐	☐	☐	☐

The Naturalness of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
The text does not seem artificial.	☐	☐	☐	☐	☐
The text makes a genuine impression.	☐	☐	☐	☐	☐
The text gives the impression of being natural.	☐	☐	☐	☐	☐

The Continuity of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand is consistent over time.	☐	☐	☐	☐	☐
This Personal Brand is true to itself.	☐	☐	☐	☐	☐
This Personal Brand offers continuity.	☐	☐	☐	☐	☐
This Personal Brand follows a distinct concept.	☐	☐	☐	☐	☐

The Originality of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand is different.	☐	☐	☐	☐	☐
This Personal Brand stands out from other brands.	☐	☐	☐	☐	☐
This Personal Brand is unique.	☐	☐	☐	☐	☐
This Personal Brand clearly distinguishes itself from other brands.	☐	☐	☐	☐	☐

The Reliability of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand is believable, and I think it will deliver what it promises.	☐	☐	☐	☐	☐
This Personal Brand makes reliable promises.	☐	☐	☐	☐	☐
This Personal Brand is credible.	☐	☐	☐	☐	☐

The Naturalness of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand does not seem artificial.	☐	☐	☐	☐	☐
This Personal Brand makes a genuine impression.	☐	☐	☐	☐	☐
This Personal Brand gives the impression of being natural.	☐	☐	☐	☐	☐

The Perceived Personal Brand Attitude.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
I find the Personal Brand appealing.	☐	☐	☐	☐	☐
I find the Personal Brand good.	☐	☐	☐	☐	☐
I find the Personal Brand pleasant.	☐	☐	☐	☐	☐
I find the Personal Brand favourable.	☐	☐	☐	☐	☐
I find the Personal Brand likeable.	☐	☐	☐	☐	☐

Positive WOM about a Personal Brand: How likely would you be to do any of the following ...

	Very likely	Likely	Neither likely nor unlikely	Unlikely	Very unlikely
Say positive things about the Personal Brand?	☐	☐	☐	☐	☐
Recommend this Personal Brand to others?	☐	☐	☐	☐	☐
Recommend this Personal Brand to someone else who seeks my advice?	☐	☐	☐	☐	☐

Negative WOM about a Personal Brand: How likely would you be to do any of the following ...

	Very likely	Likely	Neither likely nor unlikely	Unlikely	Very unlikely
Warn my friends and relatives not to consume content from this Personal Brand?	☐	☐	☐	☐	☐
Complain to my friends and relatives about this Personal Brand?	☐	☐	☐	☐	☐
Say negative things about this Personal Brand to other people?	☐	☐	☐	☐	☐

Emotionality towards the Personal Brand.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
The text shows the "Personal Brand's benefits" or "creates likability towards the Personal Brand".	☐	☐	☐	☐	☐
The text describes "quality, economy or value performance" or shows "positive or negative emotions".	☐	☐	☐	☐	☐

Loyalty towards the Personal Brand.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
If I knew, that a Personal Brand's content was created by AI, I would be less likely to follow them on Social Media.	☐	☐	☐	☐	☐
Knowing a Personal Brand writes their own content, increases my loyalty towards them.	☐	☐	☐	☐	☐
I am more likely to recommend a Personal Brand to others if I believe they create their own content.	☐	☐	☐	☐	☐

You will now see a second LinkedIn posting. After reading the posting, please answer the following questions based on the impressions and cues that shaped your judgement as you did with the first one. – Don't be surprised, the questions will be the same!

There are no right or wrong answers – your personal perception is what matters most!

You will now see a LinkedIn posting. After reading the posting, you will be asked to share your impressions.

Innovation distinguishes between a leader and a follower! - Steve Jobs. 🍏

I was reflecting on what makes a great **#leader**. Here are some key traits that distinguish exceptional leaders:

✓ **A door opener & protector** - Great leaders don't just create opportunities, they actively support their team through challenges. They enable and protect employees with great ideas, ensuring they feel valued and supported.

✓ **An advocate of equality** - True **#leaders** value contributions over hierarchy. They treat everyone as equals and are always open to ideas, regardless of the source, fostering an inclusive environment where innovation thrives.

✓ **A man of action** - Reliability is a hallmark of **#leadership**. Promises are kept, and actions follow words. A great leader's word is their bond, instilling trust and confidence in their team.

✓ **A true respectful leader** - Discipline, clarity, and direct communication are essential traits. Such leaders prevent uncertainty by providing clear, direct feedback and maintaining an environment of mutual respect.

✓ **An ambitious visionary** - Ambition and vision are critical. Great leaders inspire with their forward-thinking approach and surprise with innovative steps, driving their team toward shared goals and exciting new heights.

✓ **A person with heart** - Kindness and compassion define the human side of leadership. Great leaders connect on a personal level, remembering details about their team members and standing by them during tough times, demonstrating genuine care and support.

THANK YOU, Nicolai Andersen, for being this kind of leader for me & at! 🍏

What makes a good leader for you and who is your favorite leader?

Follow me . for more **#TechforGood** content! 🍏

Please indicate the type of authorship of the presented posting according to your perception.

☐ This posting is human-created.

☐ This posting is AI-generated.

The Continuity of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This text is consistent.	☐	☐	☐	☐	☐
This text is true to itself.	☐	☐	☐	☐	☐
This text offers continuity.	☐	☐	☐	☐	☐
This text follows a distinct concept.	☐	☐	☐	☐	☐

The Originality of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This text is different.	☐	☐	☐	☐	☐
This stands out from other texts.	☐	☐	☐	☐	☐
This text is unique.	☐	☐	☐	☐	☐
This text clearly distinguishes itself from other texts.	☐	☐	☐	☐	☐

The Reliability of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
I believe what is said in the text and that it will keep its promise.	☐	☐	☐	☐	☐
The text makes reliable promises.	☐	☐	☐	☐	☐
This text is credible.	☐	☐	☐	☐	☐

The Naturalness of the Perceived Personal Brand Voice Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
The text does not seem artificial.	☐	☐	☐	☐	☐
The text makes a genuine impression.	☐	☐	☐	☐	☐
The text gives the impression of being natural.	☐	☐	☐	☐	☐

The Continuity of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand is consistent over time.	☐	☐	☐	☐	☐
This Personal Brand is true to itself.	☐	☐	☐	☐	☐
This Personal Brand offers continuity.	☐	☐	☐	☐	☐
This Personal Brand follows a distinct concept.	☐	☐	☐	☐	☐

The Originality of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand is different.	☐	☐	☐	☐	☐
This Personal Brand stands out from other brands.	☐	☐	☐	☐	☐
This Personal Brand is unique.	☐	☐	☐	☐	☐
This Personal Brand clearly distinguishes itself from other brands.	☐	☐	☐	☐	☐

The Reliability of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand is believable, and I think it will deliver what it promises.	☐	☐	☐	☐	☐
This Personal Brand makes reliable promises.	☐	☐	☐	☐	☐
This Personal Brand is credible.	☐	☐	☐	☐	☐

The Naturalness of the Perceived Personal Brand Authenticity.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
This Personal Brand does not seem artificial.	☐	☐	☐	☐	☐
This Personal Brand makes a genuine impression.	☐	☐	☐	☐	☐
This Personal Brand gives the impression of being natural.	☐	☐	☐	☐	☐

The Perceived Personal Brand Attitude.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
I find the Personal Brand appealing.	☐	☐	☐	☐	☐
I find the Personal Brand good.	☐	☐	☐	☐	☐
I find the Personal Brand pleasant.	☐	☐	☐	☐	☐
I find the Personal Brand favourable.	☐	☐	☐	☐	☐
I find the Personal Brand likeable.	☐	☐	☐	☐	☐

Positive WOM about a Personal Brand: How likely would you be to do any of the following ...

	Very likely	Likely	Neither likely nor unlikely	Unlikely	Very unlikely
Say positive things about the Personal Brand?	☐	☐	☐	☐	☐
Recommend this Personal Brand to others?	☐	☐	☐	☐	☐
Recommend this Personal Brand to someone else who seeks my advice?	☐	☐	☐	☐	☐

Negative WOM about a Personal Brand: How likely would you be to do any of the following ...

	Very likely	Likely	Neither likely nor unlikely	Unlikely	Very unlikely
Warn my friends and relatives not to consume content from this Personal Brand?	☐	☐	☐	☐	☐
Complain to my friends and relatives about this Personal Brand?	☐	☐	☐	☐	☐
Say negative things about this Personal Brand to other people?	☐	☐	☐	☐	☐

Emotionality towards the Personal Brand.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
The text shows the "Personal Brand's benefits" or "creates likability towards the Personal Brand".	☐	☐	☐	☐	☐
The text describes "quality, economy or value performance" or shows "positive or negative emotions".	☐	☐	☐	☐	☐

Loyalty towards the Personal Brand.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
If I knew, that a Personal Brand's content was created by AI, I would be less likely to follow them on Social Media.	☐	☐	☐	☐	☐
Knowing a Personal Brand writes their own content, increases my loyalty towards them.	☐	☐	☐	☐	☐
I am more likely to recommend a Personal Brand to others if I believe they create their own content.	☐	☐	☐	☐	☐

To help me better understand the diversity of the participants and analyze patterns across different demographic groups, I would like to end this survey asking a few general questions about yourself.

What is your age?

- ☐ Under 18 years
- ☐ 18 to 24 years
- ☐ 25 to 34 years
- ☐ 35 to 44 years
- ☐ 45 to 54 years
- ☐ 55 to 65 years
- ☐ Older than 65 years

What is your gender

- ☐ Male
- ☐ Female
- ☐ Non-binary
- ☐ Prefer not to say

What is the highest level of education you have completed?

- ☐ Less than high school
- ☐ High school diploma or equivalent
- ☐ Some college, no degree
- ☐ Associate degree
- ☐ Bachelor's degree
- ☐ Master's degree
- ☐ Doctorate or professional degree

What is your current employment status?

- ☐ Employed
- ☐ Unemployed
- ☐ Student
- ☐ Retired
- ☐ Others

Thank you for your participation!

Your responses are greatly appreciated and will help bring this research to life! All answers are treated anonymously and confidential. The obtained data are merely intended for statistical processing and none of the answers will be analysed or reported individually.

Annex C – Variance Inflation Factor (VIF)

	VIF
BA12	2.794
BA13	3.952
BA14	3.800
BA5	4.486
BA6	5.274
BA7	6.625
BA8	5.837
BVA12	2.247
BVA13	2.577
BVA14	2.715
BVA5	3.002
BVA6	5.355
BVA7	5.464
BVA8	5.695
E1	1.524
E2	1.524
L1	1.880
L2	4.750
L3	4.357
NWOM1	2.064
NWOM2	3.477
NWOM3	3.326
PBA1	4.377
PBA2	5.613
PBA3	3.733
PBA4	3.743
PBA5	4.320
PWOM1	3.028
PWOM2	4.391
PWOM3	4.786

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