NOVA IMS Information Management School

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Master Degree Program in

Data-Driven Marketing

Exploring User Emotional Responses to Human and GenAI Influencers

Pedro Francisco Raposo Lopes Soares

Master Thesis

presented as partial requirement for obtaining a Master’s Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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by

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Master's Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Digital Marketing & Analytics

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July, 2025

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisboa, 28 de Novembro de 2024

Pedro Francisco Raposo Lopes Soares

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ABSTRACT

In recent years, GenAI Influencers have emerged and gained new significance on social media and in marketing advertisements, representing various opportunities. However, this does not prove how users feel when observing content made by artificial intelligence, which complicates how brands can use them. A sample of 110 social media users was randomly selected and watched one video featuring either a GenAI or a Human Influencer. We measured users' emotions using the Face Reader, a Neuromarketing tool. Afterward, they completed a questionnaire measuring their perception of the Competence and Warmth of the observed influencer. The results showed that human influencers elicited higher levels of emotional engagement and were perceived as more competent. However, no emotional response mediated the relationship between influencer type and intention to follow. A significant interaction was found: Human influencers were favored when perceived competence was high, while GenAI influencers were more effective when competence was low. Warmth, although a strong predictor of intention to follow, did not interact with influencer type. According to these results, GenAI influencers might still be strategically useful even if they do not generate the same emotional or cognitive evaluations as human influencers. Brands may benefit from using GenAI influencers when innovation or cost-effectiveness are priorities, and human influencers when emotional authenticity and high competence are crucial. These findings emphasize the significance of matching influencer type with campaign goals and contextual factors, and they provide marketers with useful advice on how to customize influencer strategies based on audience expectations and perceived traits.

Keywords:

Neuromarketing; GenAI; Digital Influencers; Consumer Emotions; Social Media

Sustainable Development Goals (SDG):

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1. INTRODUCTION

Nowadays, social media enables unlimited interaction between users and offers multiple ways for brands to reach and engage with consumers (Appel et al., 2020) and recent advancements in Generative AI (GenAI) have revolutionized the marketing industry, creating a landmark, the beginning of a new paradigm that automates content (Peres et al., 2023) which leads to a big economic potential that can generate new opportunities for brands and more.

Influencer marketing has recently transmuted, and many organizations are collaborating with influencers as Generative AI offers plenty of opportunities to reshape advertising research (van Berlo et al., 2024) therefore, GenAI is a unique form of AI that is poised to transform marketing in an entirely new way (Cillo & Rubera, 2024).

What if GenAI could significantly reduce the cost associated with the time-intensive and expensive process of creating visual marketing imagery while maintaining the content's visual appeal and marketing effectiveness? (Hartmann et al., 2023).

Organizations can incorporate generative technology in multiple ways to improve their endorsement strategies since virtual endorsers are especially attractive to companies due to their lower costs or because they are less likely to be involved in a scandal that leads to image repercussions (Hartmann et al., 2023).

Celebrities frequently endorse products, brands, political candidates, or health campaigns (Knoll & Matthes, 2017). The newest steep growth is the use of virtual influencers by brands, which reflects their rising commercial power (Sorosrungruang et al., 2024). Some GenAI Influencers achieve audience reach and engagement rates that make it advantageous for their human counterparts, and this engagement on social media can increase the interest of interest in the brand, which leads to strengthening the bonds with the brand (Sorosrungruang et al., 2024).

Among the leading GenAI influencers, Lil Miquela (@Lilmiquela) counts with over 3 million Instagram followers (School, n.d.) and has endorsed brands like Prada, Calvin Klein, Balmain, Apple, and BMW. In addition, she has released several songs that have accumulated over 2.2M Spotify streams and was chosen by the magazine Time "Most Influential People on the Internet 2018" (Redação, 2023).

Despite this technological promise and the increasing recognition that artificial empathy is crucial to effective AI Powers, there is a lack of research about artificial empathy in the marketing context (Liu-Thompkins et al., 2022). Consequently, there is limited understanding of how brands can effectively utilize GenAI influencers or why and how consumers may respond to them (Sands, Campbell, et al., 2022).

Although some authors have studied this response between the consumers and GenAI influencers, there is still a lack of information about their emotional reaction, users' perception of competence and warmth about them, and their intention to follow and compare all of this with Human Influencer Content. This project explores the research question: **Does GenAI (vs. Human) Influencers' content impact users' intention to follow?**

This study's primary goal is to examine the differences between users' emotional responses and opinions regarding GenAI and human influencers, with an emphasis on how perceived warmth, competence, and emotional response influence the intention to follow. This study's primary goal is to examine the differences between users' emotional responses and opinions regarding GenAI and human influencers, with an emphasis on how perceived warmth, competence, and emotional response influence the intention to follow.

Practically speaking, the results are meant to help brand managers, marketers, and advertisers select campaign endorsers with more knowledge. In a world where brand safety, cost-effectiveness, and adaptability are becoming more and more important, organizations can determine whether GenAI influencers are a viable and effective alternative to traditional influencers by understanding how consumers emotionally respond to them and how they perceive their competence and warmth.

All things considered, this study makes a theoretical contribution by adding knowledge on the cognitive responses to GenAI in marketing, in addition to a practical one by providing data-driven insights for optimizing influencer strategies in an era in which artificial intelligence is challenging the norms of digital interactions.

2. LITERATURE REVIEW

2.1 GENERATIVE ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI), once confined to the realm of science fiction, is now revolutionizing how individuals eat, sleep, work, play, and even manage their relationships (Puntoni et al., 2021).

The development of computer systems or machines that can make decisions and perform tasks resembling human intelligence forms the basis of AI. The main goal is to replicate basic cognitive functions identical to those of humans, including learning, problem-solving, reasoning, perception, and language comprehension (Gill & Kaur, 2023; Samala et al., 2024).

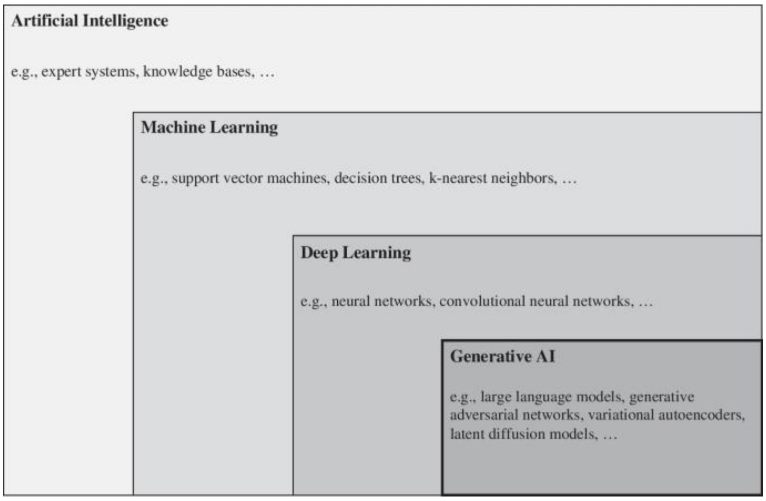

Figure 1 - AI Subjects (Banh & Strobel, 2023)

While Generative AI (Gen-AI) generates content through human-machine interactions, traditional AI depends on explicit programming to carry out tasks. Despite this differentiation, the foundation of Gen-AI lies in fundamental AI technologies such as deep learning algorithms and neural networks.

The term GenAI describes a specific subset of AI models intended to produce new material by identifying relevant patterns and trends in existing data. These models can produce outputs that appear to be original, such as writing, pictures, or other types of media (Fosso Wamba et al., 2024; Gill & Kaur, 2023; Susarla et al., 2023).

GenAI has the potential to revolutionize the delivery, development, and assessment of human learning. Its uses are extensive due to its capacity to produce a wide range of outputs, including text, photos, videos, code, sound, and even intricate creations such as molecules and 3D models (Banh & Strobel, 2023; Yan et al., 2024).

Further, GenAI has the potential to revolutionize marketing by automating content creation, personalization, and customer engagement, in addition to infusing innovation and creativity into companies' worlds (Kumar et al., 2024).

2.2 GenAI Influencers

Influencer marketing has been transformed in recent years by GenAI influencers that are presented in real-time digital environments. Brands are using these synthetic entities as a way to engage consumers and increase sales (Sands, Ferraro, et al., 2022).

According to Kietzmann et al. (2018), five key technological components enable the development and functioning of a GenAI influencer. These include natural language processing, which enables the interpretation of human language details and the extraction of meaningful insights from text. Image recognition capabilities support influencers in interpreting and analyzing visual content such as photos and videos, which improves their ability to understand and respond to visual stimuli. Speech recognition interprets spoken language, allowing the system to process and respond to verbal interactions. Furthermore, problem-solving functions assist in the discovery of hidden insights in user-generated content and direct how the system deals with and analyzes problems. Finally, machine learning enables GenAI influencers to detect and learn from data patterns, increasing adaptability and customization over time.

Although the use of GenAI influencers in marketing is still relatively new, AI influencers who endorse a brand tend to become linked with that brand in the consumer's mind. This suggests that positively perceived AI influencers can lead to more favorable brand perceptions (Thomas & Fowler, 2021).

2.3 Stereotype Concept Model

One of the most popular and significant theoretical frameworks for comprehending stereotypes is the Stereotype Content Model (SCM), developed by and generally acknowledged as the best model for examining stereotype content and how it relates to behavioral tendencies (Fiske, 2018).

Warmth and competence are widely recognized as the two universal dimensions of social perception, as derived from social cognition theories in psychology (Fiske et al., 2007). These dimensions enable individuals to make quick and adaptive judgments about others' intentions (Warmth) and ability to carry those intentions out (Competence), and they are universally applicable across cultures and social groups.

According to Greenwald et al., (2003) a stereotype is defined as a simplified and widely held generalization about members of a particular group of people. Warmth, which includes properties like friendliness and trustworthiness, and competence, which includes assertiveness and skill, are the two main dimensions defined by the SCM (Fiske, 2018).

Since these two dimensions affect how people and groups are perceived and comprehended, they are crucial to social cognition (Kervyn et al., 2012).

Additionally, the positive valence of these two stereotype content dimensions fosters more favorable action tendencies toward members of specific stereotyped categories (Cuddy et al., 2007).

	High Competence	Low Competence
High Warmth	Ingroup, Middle class Pride, Admiration	Older, Disable Pity, Sympathy
Low Warmth	Rich, Professionals Jealous, Envy	Outcast, Homeless Disdain, Disgust

Table 1 - SCM Quadrants (adapted from (Fiske, 2015))

Different emotional reactions can be anticipated for each combination of competence and warmth in the quadrants:

According to the Stereotype Content Model, each combination of perceived warmth and competence evokes distinct emotional responses. Individuals or groups perceived as both highly competent and warm trigger feelings of pride and admiration because they are frequently associated with society's traditional ingroups, such as the middle class. Those perceived as lacking competence and warmth, on the other hand, invoke feelings of contempt and disgust, and are frequently associated with marginalized groups such as the homeless. When competence is high, but warmth is low, the emotional response is typically jealousy or envy directed at successful outsiders, such as wealthy individuals. Finally, individuals or entities perceived as warm but lacking in competence are likely to inspire sympathy and pity, which are frequently associated with benevolent but dependent groups such as the elderly or disabled.

This quadrant is predicted from various studies with the Stereotype Concept Model as Fiske et al., (2002) and Cuddy et al., (2007).

When encountering members of an out-group, we propose that individuals instinctively consider two key questions: Do they intend to harm me? And are they capable of harming me? (Cuddy et al., 2009).

According to Kervyn et al., (2012) consumers have a social relationship with brands that is similar to their relationship with individuals, and the idea that consumers socially interact with brands led to the theory that brand perception can be explained by a social perception framework like the Stereotype Content Model.

Digital influencers have an important effect on personal branding, making them intentional agents whose competence and warmth are evaluated. Similar to this, basic characteristics of person perception, such as warmth and competence, can also be assigned to nonhuman entities when they seem to have humanlike facial features or mental capacities (Crisafulli et al., 2022; Song et al., 2023; Yang et al., 2022).

In the context of influencer marketing, these two evaluative dimensions are critical to how users react to various types of influencers. While human influencers are often judged based on perceived authenticity and relationships with others, GenAI influencers can stimulate a range of emotional responses depending on how competent or warm they appear. Understanding how warmth and competence influence user attitudes is essential for understanding the emotional processes that drive users' behavioural intentions toward GenAI versus human influencers.

2.4 Warmth

Warmth is the most influential personality trait in social judgment and is crucial because intent predicts behavior (Fiske, 2018; Williams & Bargh, 2008).

According to Fiske et al., (2007) the traits of competence and warmth constantly coexist, there is strong evidence that warmth assessments are considerably more significant: warmth is evaluated before competence. It has a stronger impact on behavioral and emotional reactions.

Recent theories and research in social cognition define interpersonal warmth as a collection of traits that reflect the perceived positivity of another person's intentions toward us, such as friendliness, helpfulness, sincerity, trustworthiness, and morality (Fiske et al., 2007).

While coldness indicates hostility, warmth promotes friendliness. "What are this entity's intentions?" is the question that warmth perceptions seek to answer. People or social entities that desire to work together are seen as friendly, approachable, and reliable (Aaker et al., 2012; Cuddy et al., 2011).

2.5 Competence

Similarly, competence refers to the service provider's capabilities and whether they can carry out their intentions to help or harm. Competence includes seeming capable, skilled, competent, agentic, and assertive (Fiske, 2015; Kervyn et al., 2012; Nicolas et al., 2022)

Warmth is the group's socioemotional orientation toward others, while competence is the target group's evaluated competence to perform tasks that are seen as prestigious or high status in a culture, and on the competence dimension, out-groups are seen as differing in their potential to harm the in-group or threaten its goals (Eckes, 2002).

In the competence dimension of the subordinate position, when a group is seen as highly competent, observers typically display passive encouragement behaviors (Li et al., 2020).

2.6 Intention to Follow

According to the theory of planned behavior, an individual's intention to act in a particular way is reflected in their behavioral intentions, which are what motivate behaviors (Ajzen, 1991; Sussman & Gifford, 2019).

According to Venkatesh & Davis, (2000) earlier research, there is a relationship between these two variables, as intention accurately indicates the customer's final behavior (Casaló et al., 2011).

We focus on the intention to follow a brand community account and see its publications, which is crucial for ensuring the community's long-term survival, as it helps maintain traffic levels, keeps users updated with pertinent data, and promotes engagement by allowing them to view content of interest, which is essential for developing and sustaining a community around a specific topic (Casaló et al., 2017).

2.7 CONCEPTUAL FRAMEWORK

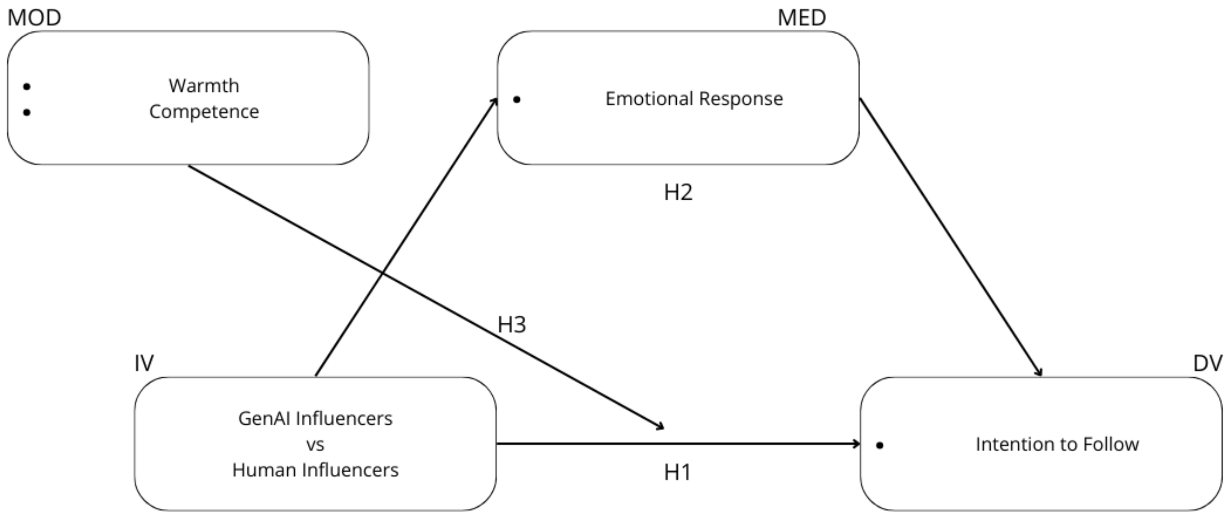

Figure 2 - Conceptual Framework

H1: GenAI (vs. Human) Influencers will impact users' intention to follow.

This hypothesis suggests that the type of influencer—whether it is a generative AI (GenAI) influencer or a human influencer—directly influences the user's intention to follow them on social media. As the presence of AI-generated personas grows in online platforms, it becomes increasingly relevant to understand whether this shift impacts user engagement. The hypothesis is based on the premise that users may respond differently to AI-driven influencers compared to human ones, particularly in terms of perceived authenticity, credibility, and connection. Therefore, H1 investigates whether the mere presence of a GenAI influencer affects users' behavioral intention to follow, regardless of other mediating or moderating factors.

H2: Users' emotional responses mediate the effect of GenAI (vs. human) influencers on users' intention to follow.

This hypothesis suggests that emotional responses serve as a key mechanism that explains how the type of influencer influences users' intention to follow. Rather than a direct effect alone, it proposes that the impact of GenAI versus human influencers operates through the emotional reactions they elicit. Emotions play a central role in shaping how individuals process information, evaluate social figures, and make decisions. If GenAI influencers trigger emotional responses that are different in intensity or valence compared to those triggered by human influencers, these emotions may ultimately determine users' intention to engage with them. Thus, H2 emphasizes the mediating role of affective responses in the relationship between influencer type and behavioral intention.

H3: Perception of warmth and competence moderates the relationship between GenAI (vs. human) influencers and users' intention to follow.

The third hypothesis introduces a moderating effect, arguing that the perceived warmth and competence of the influencer influence the strength or direction of the relationship between the type of influencer and the user's intention to follow. According to the Stereotype Content Model (SCM), warmth (e.g., friendliness, trustworthiness) and competence (e.g., intelligence, skill) are two fundamental dimensions through which individuals assess others. This hypothesis suggests that the effectiveness of a GenAI (vs. human) influencer in generating intention to follow may vary depending on how they are perceived along these dimensions. For example, if a GenAI influencer is perceived as highly warm and competent, the intention to follow may be comparable—or even superior—to that of a human influencer. Conversely, low perceptions in either dimension may reduce the influence of the AI presence. H3 thus explores how social perception shapes the impact of technological agents in social media contexts. Therefore, H3 investigates how social perception influences the intention to follow of users.

The model and hypothesis for this project were developed after thoroughly analyzing all relevant literature on the topic, which was then correlated with the research question and goals.

The purpose of this model is to investigate how consumers' intention to follow generative AI (GenAI) influencers on social media differs from the intention to follow human influencers. It specifically aims to determine whether GenAI influencers cause users to experience different emotional reactions, which in turn affects their intention to follow the influencer.

The model also considers the moderating influence of perceived competence and warmth, investigating whether these perceptions change the direction or importance of the relationship between the consumer's emotional response and the influencer type (human vs. GenAI). In doing so, the model provides a deeper understanding of how consumers interact emotionally with digital influencers and how those interactions influence their social media behavior intentions.

3. METHODOLOGY

In this study, we will use a quantitative data collection method, with most of the data being obtained through the Face Reader, a neuromarketing tool. A randomized experimental design study will be conducted, where individuals will be exposed to a stimulus, an advertiser with a GenAI Influencer or a Human Influencer.

3.1 FACE READER SOFTWARE

FaceReader is a software tool designed to analyze individuals' emotions by categorizing facial expressions on a scale ranging from 0 to 1 (Lewinski et al., 2014) and allows us to measure various metrics for analyzing facial expressions of emotion and includes a comprehensive log of emotional data (Huang & Pricer, 2024)

This software detects faces in images and videos through an algorithm, then synthesizes the face by describing the location of hundreds, usually 500, key facial points (such as the muscles in the cheeks, eyebrows, and lips) and the facial texture of the area delineated by these points (El Haj et al., 2021)

Two calibration methods are available: participant calibration and continuous calibration, with participant calibration being the preferred approach. (Loijens & Krips, n.d.):

FaceReader has an average accuracy of 99% (FaceReader | Facial Expression Analysis, n.d.) and classifies the seven basic universal emotional states (happiness, sadness, anger, surprise, fear, disgust, and neutral) (Huang & Pricer, 2024)

Action Units	Contribution
AU1. Inner Brow Raiser	Sadness, surprise and Fear
AU2. Outer Brow Raiser	Surprise and fear
AU4. Brow Lowerer	Sadness, fear and anger
AU5. Upper Lid Raiser	Surprise, fear and anger
AU6. Cheek Raiser	Happiness
AU7. Lid Tightener	Fear and anger
AU9. Nose Wrinkle	Disgust
AU10. Upper Lip Raiser	Non defined
AU12. Lip Corner Puller	Happiness and contempt (when appear unilaterally)
AU14. Dimpler	Contempt (when appears unilaterally) and boredom
AU15. Lip Corner Depressor	Sadness, disgust and confusion
AU17. Chin Raiser	Interest and confusion
AU18. Lip Pucker	Non defined
AU20. Lip Stretcher	Fear
AU23. Lip Tightener	Anger, confusion, and boredom
AU24. Lip Pressor	Boredom
AU25. Lips Part	Non defined
AU26. Jaw Drop	Surprise and fear
AU27. Mouth Stretch	Non defined
AU43 eyes closed	Boredom

Table 2 - FaceReader Action Units – (*Human Behavior Application | Emotion Analysis*, n.d.)

The videos that were used were searched on YouTube and adapted for the study:

- GenAI Influencer: https://www.youtube.com/watch?v=MXSaZQ2aAAc&t=28s
- Human Influencer: https://www.youtube.com/watch?v=csAXruiBLTs

3.2 QUESTIONNAIRE

For this study, all the questions were measured with a nine-point Likert scale.

Regarding the question about competence, the scale ranges from "Not at All" (1) to "Extremely" (9). For the question about warmth, the scale also ranges from "Not at All" (1) to "Extremely" (9). Additionally, for the question about the intention to follow, the scale ranges from "Strongly Disagree" (1) to "Strongly Agree" (9).

Construct	Measurements Items	Source
Competence (C)	C1. Competent C2. Intelligent C3. Confident C4. Competitive C5. Independent	Adapted from (Levine & Schweitzer, 2015) & (Cuddy et al., 2007)
Warmth (W)	W1. Sincere W2. Good natured W3. Warm W4. Tolerant	Adapted from (Levine & Schweitzer, 2015) & (Cuddy et al., 2007)
Intention to Follow (IF)	IF1. I have the intention to follow to visit Influencers' Instagram account IF2. I predict that I will follow Influencer's Instagram account IF3. I will probably look for new content published in the Influencer's Instagram account	Adapted from (Casaló et al., 2017) & (Rudman & Glick, 1999)

Table 3 - Construct Table

The questionnaire had a total of 15 questions, 5 of them about competence, 4 about warmth, 1 attention-check, 1 manipulation-check (if the influencer showed to them in the video was a human or a GenAI influencer (Sands et al., 2022)), 3 about demographics (age, gender e nationality) and last one was an open question where participants could give their feedback if they wanted.

3.3 Procedure and measure

An experimental study was conducted with a sample of 100 participants to achieve the research objectives and took place at the NOVA Marketing Analytics Lab at NOVA Information Management School. This study was pre-registered on AsPredicted (#204081). Each participant was assigned to a number to identify each case easily it was and utilizing the Face Reader software, 50 participants were randomly shown an advertisement that contained a GenAI influencer's participation, and the other 50 participants watched a similar advertisement with a Human Influencer presence.

After the videos, each participant answered a survey, to understand the perception of the construct’s warmth, competence, and intention to follow.

3.4 Participants

A total of 110 participants voluntarily took part in the study. The data collection started on January 10 of 2025 and finished on December 6 of 2025. There were 56 female participants (51%) and 54 male participants (49%) with ages between 18 years old and 69 years old, with an average of M=28.77 years old. The sample included 107 Portuguese participants, along with one Chinese, one Italian, and one Romanian participant.

Question	Options	Frequency	Percentage
Gender	Female	56	51%
	Male	64	49%

	18	8	7.3%
	19	13	11,8%
	20	18	16,4%
	21	15	13,6%
	22	14	12,7%
	23	4	3,6%
	24	5	4,5%
	25	6	5,5%
	26	1	0,9%
	27	1	0,9%
	29	1	0,9%
	34	1	0,9%
Age	41	1	0,9%
	48	1	0,9%
	51	2	1,8%
	53	3	2,7%
	54	2	1,8%
	55	2	1,8%
	56	2	1,8%
	57	1	0,9%
	58	2	1,8%
	62	1	0,9%
	63	1	0,9%
	66	3	2,7%
	68	1	0,9%

	69	1	0.9%
Nationality	Portuguese	107	97.3%
	Chinese	1	0.9%
	Italian	1	0.9%
	Chinese	1	0.9%

Table 4 - Demographics

4. EMPIRICAL STUDY

4.1 SCALE RELIABILITY ANALYSIS

The analysis of the results from Face Reader and the Qualtrics Questionnaire was done with SPSS. First, we did a Scale Reliability Analysis (Cronbach's Alpha) test of our 3 scales:

Intention to follow:

Item	Cronbach's Alpha	Cronbach's Alpha based on standardized items	Nº of Items
Intention to Follow	0.918	0.920	3

Table 5 - Scale Reliability (Intention to Follow)

Scale reliability was tested, and the alpha was **Excellent** for **Intention to Follow** (α = 0.92), since the minimum threshold for a scale to be considered valid is 0.6, and values above 0.9 are considered excellent."

Competence:

Item	Cronbach's Alpha	Cronbach's Alpha based on standardized items	Nº of Items
Competence	0.840	0.838	5

Table 6- Scale Reliability (Competence)

Scale reliability was tested, and the alpha was **Good** for **Competence** (α = 0.84), since the minimum threshold for a scale to be considered valid is 0.6, and values between 0.8 and 0.9 are considered good.

Warmth:

Item	Cronbach's Alpha	Cronbach's Alpha based on standardized items	Nº of Items
Warmth	0.902	0.903	4

Table 7 - Scale Reliability (Warmth)

Scale reliability was tested, and the alpha was **Good** for **Warmth** (α = 0.9), since the minimum threshold for a scale to be considered valid is 0.6, and values above 0.9 are considered excellent.

4.2 Significant Variables

After this, we've done an independent samples t-test for all variables considering the two groups of observations:

- Group 1: Participants who observed the video of a GenAI Influencer
- Group 2: Participants who observed the video of a Human Influencer

It was possible to observe relevant significance levels in 9 variables:

- Happy
- Lip Corner Puller (AU12)
- Eyes Closed (AU43)
- C_1

- C_3
- C_4
- C_5
- Competence (C)
- W_2

		Mean	Standard Deviation	T-Value	P-Value
Happy	Group 1	0.007	0.014	-1.852	0.035
	Group 2	0.026	0.075		
Lip Corner Puller (AU12)	Group 1	0.051	0.025	-2.155	0.035
	Group 2	0.072	0.079		
Eyes Closed (AU43)	Group 1	0.097	0.036	-1.993	0.05
	Group 2	0.127	0.65		
C_1	Group 1	6.00	1.678	-4.013	0.001
	Group 2	7.24	1.551		
C_3	Group 1	6.42	2.016	-4.288	0.001
	Group 2	7.84	1.398		
C_4	Group 1	5.42	2.043	-6.616	0.001
	Group 2	7.62	1.381		
C_5	Group 1	6.07	2.332	-2.246	0.027
	Group 2	6.95	1.693		
C	Group 1	6.058	1.498	-4.468	0.001
	Group 2	7.196	1.151		
W_2	Group 1	5.44	2.386	-2.286	0.025
	Group 2	6.29	1.410		

Table 8 - Relevant Significant Variables (t-test)

4.3 Marginal Significant Variables

It was possible to observe marginal significant (0.05 =< P =< 0.10) on 4 variables:

- Lip Tightener (AU07)
- Disgusted
- Lip Stretcher (AU20)
- Warmth (W)

		Mean	Standard Deviation	T-Value	P-Value
Lip Tightener (AU07)	Group 1	0.059	0.013	-1.856	0.068
	Group 2	0.69	0.037		
Disgusted	Group 1	0.003	0.006	-1.71	0.093
	Group 2	0.010	0.030		
Lip Stretcher (AU20)	Group 1	0.072	0.010	1.787	0.079
	Group 2	0.058	0.011		
W	Group 1	5.523	1.977	-1.608	0.111
	Group 2	6.027	1.227		

Table 9 - Marginal Significant Variables (t-test)

5. RESULTS AND DISCUSSION

5.1 Significant Variables

The variables that showed statistically significant variations between the GenAI and Human influencer groups are described below:

Emotional Response:

Happy and Lip Corner Puller:

Participants who watched human influencers showed significantly higher levels of the emotion Happy ($M = 0.026$, $SD = 0.075$) than those who watched GenAI influencers ($M = 0.007$, $SD = 0.014$), according to the analysis ($t(108) = -1.852$, $p = 0.035$). Similarly, the human influencer group ($M = 0.072$, $SD = 0.079$) had significantly higher activation of AU12-Lip Corner Puller, which raises the corners of the mouth, than the GenAI group ($M = 0.051$, $SD = 0.025$), $t(108) = -2.155$, $p = 0.035$. These results are consistent with earlier studies showing that AU12 is a significant factor in boosting engagement, especially when happiness is expressed (Gunnery et al., 2013)

Eyes Closed:

Participants who watched human influencers had significantly higher levels of the AU43 - Eyes Closed ($M = 0.127$, $SD = 0.65$) than those exposed to GenAI influencers ($M = 0.097$, $SD = 0.036$), with a p-value of 0.05. According to the literature, AU43 is associated with boredom and indicates a relaxed eye muscle state (Human Behavior Application | Emotion Analysis, n.d.). It suggests that participants may have felt more bored or disengaged while watching the human influencers.

Competence:

Participants who were exposed to human influencers had significantly higher levels of perceived competence (M = 7.20, SD = 1.15) than those who saw GenAI influencers (M = 6.06, SD = 1.50), t(108) = -4.468, p =.001. This suggests that human influencers were perceived as more capable, skilled, and intelligent than their GenAI counterparts. Because competence is a key dimension in social judgment, these findings indicate that, despite technological advancements in GenAI, users continue to attribute higher intellectual abilities to human agents. The difference may also reflect an underlying credibility gap, as previous research has shown that AI influencers are generally perceived as less reliable (Sands, Campbell, et al., 2022).

Warmth (Item 2)

Participants exposed to human influencers perceived them as significantly more good-natured (M = 6.29, SD = 1.41) than those who observed GenAI influencers (M = 5.44, SD = 2.39), t(108) = -2.286, p =.025. This trait, which represents a key component of warmth, aligns with the SCM, which defines warmth as including qualities like kindness, sincerity, and friendliness (Fiske et al., 2002).

5.2 MARGINAL VARIABLES

The variables that showed marginally significant differences between the GenAI and Human influencer groups are described below:

Emotional Responses:

Lip Tightener:

Participants who were exposed to human influencers had slightly higher activation of AU07 - Lip Tightener (M = 0.069, SD = 0.037) than those who observed GenAI influencers (M = 0.059, SD = 0.013), with the disparity approaching statistical significance (t = -1.856, p =.068). AU07 is associated with the contraction of the orbicularis oculi (pars palpebralis) along with the emotional expressions of fear and anger. (Human Behavior Application | Emotion Analysis, n.d.)

Disgusted:

Participants who saw human influencers had slightly higher mean values (M = 0.010, SD = 0.030) for disgust than those who saw GenAI influencers (M = 0.003, SD = 0.006), but the difference was not statistically significant (t = -1.710, p =.093). While not conclusive, this pattern may indicate that users have stronger aversive reactions toward human influencers in certain contexts. It is important to note that disgust is a complex emotion and can be confused with contempt or anger (Landmann, 2023; Langner et al., 2010), which may influence users' interpretations of facial expressions or behaviors based on the influencer's perceived authenticity or intent.

Lip Stretcher:

Regarding AU20 - Lip Stretcher, the results showed that participants exposed to GenAI influencers had slightly higher activation levels (M = 0.072, SD = 0.010) than those who viewed human influencers (M = 0.058, SD = 0.011), with a marginally significant difference (t = 1.787, p = .079). This facial action unit is linked to the risorius and platysma muscles and aids in expressing the emotion of fear. (Human Behavior Application | Emotion Analysis, n.d.)

Warmth

Although the results for the overall warmth construct were not statistically significant, they were close (M = 6.03, SD = 1.23 for human influencers; M = 5.52, SD = 1.98 for GenAI influencers; t (108) = -1.608, p =.111). The results indicate that participants viewed human influencers as warmer than GenAI. The SCM defines warmth as perceptions of friendliness, sincerity, and trustworthiness (Fiske, 2018).

5.3 MEDIATION ANALYSIS

The PROCESS Model 4 (Hayes, 2022) was used to test several mediation models with 5,000 bootstrap samples and 95% confidence intervals to investigate whether emotional expressions or facial action units (AUs) mediated the effect of influencer type (GenAI vs. human) on users' intention to follow.

Mediator	**Path**	**Coefficient**	**Standard Error**	**Confidence Interval (95%)**
Neutral	IV → Neutral → I_F	-0.0439	0.1205	[-0.3324, 0.1924]
Happy	IV → Happy → I_F	-1.0734	1.2166	[-4.2328, 0.4136]
Sad	IV → Sad → I_F	0.1081	0.6958	[-1.316, 1.7218]
Angry	IV → Angry → I_F	-0.0486	0.2188	[-0.486, 0.4467]
Surprised	IV → Surprised → I_F	-0.007	0.0442	[-0.0768, 0.1085]
Scared	IV → Scared → I_F	-0.0765	0.1461	[-0.4619, 0.1242]
Disgusted	IV → Disgust → I_F	0.4402	0.4945	[-0.1299, 1.7193]
Contempt	IV → Contempt → I_F	-0.0049	0.0637	[-0.1901, 0.0852]
Valence	IV → Valence → I_F	0.7874	1.385	[-1.0843, 4.4208]
Arousal	IV → Arousal → I_F	0.0463	0.0845	[-0.0936, 0.2553]
AU1. Inner Brow Raiser	IV → AU01 → I_F	-0.0236	0.1476	[-0.3854, 0.2382]
AU2. Outer Brow Raiser	IV → AU02 → I_F	0.0081	0.101	[-0.0703, 0.3296]
AU4. Brow Lowerer	IV → AU04 → I_F	-0.001	0.0706	[-0.1671, 0.1397]

AU5. Upper Lid Raiser	IV → AU05 → I_F	-0.0094	0.0756	[-0.1456, 0.1664]
AU6. Cheek Raiser	IV → AU06 → I_F	0.0331	0.0954	[-0.0888, 0.2934]
AU7. Lid Tightener	IV → AU07 → I_F	0.0179	0.1137	[-0.1346, 0.316]
AU9. Nose Wrinkle	IV → AU09 → I_F	0.03	0.0996	[-0.18, 0.2296]
AU10. Upper Lip Raiser	IV → AU10 → I_F	0.0002	0.0625	[-0.1581, 0.1102]
AU12. Lip Corner Puller	IV → AU12 → I_F	-0.0268	0.0971	[-0.2441, 0.1499]
AU14. Dimpler	IV → AU14 → I_F	0.0151	0.0626	[-0.1393, 0.1347]
AU15. Lip Corner Depressor	IV → AU15 → I_F	0.0202	0.0534	[-0.066, 0.1552]
AU 17. Chin Raiser	IV → AU17 → I_F	-0.0021	0.0535	[-0.1526, 0.0697]
AU18. Lip Pucker	IV → AU18 → I_F	-0.0301	0.0434	[-0.1366, 0.0363]
AU20. Lip Stretcher	IV → AU20 → I_F	-0.0461	0.0905	[-0.2571, 0.1121]
AU23. Lip Tightener	IV → AU23 → I_F	-0.0803	0.094	[-0.2889, 0.085]
AU24. Lip Pressor	IV → AU24 → I_F	0.0222	0.063	[-0.1457, 0.124]
AU25. Lips Part	IV → AU25 → I_F	0.0109	0.0639	[-0.1316, 0.1407]
AU26. Jaw Drop	IV → AU26 → I_F	0.0181	0.0605	[-0.0916, 0.1587]
AU27. Mouth Stretch	IV → AU27 → I_F	-0.0271	0.0693	[-0.1801, 0.1119]
AU43. Eyes Closed	IV → AU43 → I_F	-0.0364	0.1024	[-0.227, 0.1979]

Attention	IV → Attention → I_F	-0.2091	0.2209	[-0.7876, 0.0135]
Boredom	IV → Boredom → I_F	0.119	0.1849	[-0.1441, 0.5875]

Table 10 - Mediation Analysis of Emotional Response

The coefficients and standard errors provide more information about the possible patterns and directions of the effects, even though none of the mediators attained conventional statistical significance at the 95% confidence level (such as all confidence intervals included zero). Happy (β = -1.0734, SE = 1.2205) and disgusted (β = 0.4402, SE = 0.4945), for example, have relatively large coefficients in absolute value, indicating potentially significant effects that might be obscured by the high variability in the estimates.

Several facial Action Units (AUs) follow this pattern. The estimates were stable despite non-significance, as demonstrated by AU12 (Lip Corner Puller; β = -0.0268, SE = 0.0971) and AU43 (Eyes Closed; β = -0.0364, SE = 0.1024), which both had small coefficients and comparatively low standard errors. These examples indicate that the effects are consistent even though they are probably weak, and more sensitive designs could be used in future research to test their dependability.

The attention variable showed the most notable trend (β = -0.2091, SE = 0.2209, 95%) CI [-0.79, 0.01]). The effect size was moderate and in a significant direction, even though the confidence interval was slightly larger than zero. This could indicate that attention plays a suppressive or buffering role in the association between influencer type and intention to follow.

5.4 Moderation Analysis

A moderation analysis was performed using PROCESS Model 1 by Hayes (2022) to examine whether perceptions of competence and warmth influenced the relationship between influencer type (GenAI vs. Human) and users' intention to follow.
This allowed us to test whether these traits changed the strength or direction of the effect.

5.4.1 Competence

A moderation analysis was performed using PROCESS Model 1 to investigate whether perceived competence mediated the association between influencer type (GenAI vs. human) and users' intention to follow. A 95% confidence interval and 5,000 bootstrap samples were used in the analysis. Before analysis, the moderator (competence) and the independent variable (IV) were both mean-centered. This process investigated whether users' perceptions of the influencer's competence affected the influencer type's effect on intention to follow.

Effect	Path	Coefficient (β)	Standard Error	p-Value	95% Confidence Interval
Direct Effect	IV → I_F	0.0413	0.4344	.9244	[-0.8199, 0.9025]
Moderator	C → I_F	0.2033	0.1552	.1930	[-0.1043, 0.5109]
Interaction	IV × C → I_F	-0.8099	0.3103	.0104	[-1.4252, -0.1946]

Table 11 - Moderator Analysis (Competence)

Competence moderates this relationship, as evidenced by a significant interaction between type of influencer and competence on intention to follow ($\beta = -0.8099$, $p = .0104$) in a moderation analysis using PROCESS (Model 1, 5000 bootstraps, 95% CI).

Competence (C)	Effect of IV on I_F	Standard Error	t-Value	p-Value	95% Confidence Interval
-1 SD	1.2136	0.6568	1.8476	.0674	[-0.0887, 2.5158]
Mean	0.0413	0.4344	0.0951	.9244	[-0.8199, 0.9025]
+1 SD	-1.1309	0.5912	-1.9130	.0584	[-2.3030, 0.0411]

Table 12- Conditional Effect of Moderator (Competence)

Exposure to a GenAI influencer (as compared to a Human Influencer) was marginally significant but positively correlated with intention to follow at low levels of perceived competence (-1 SD) (β = 1.2136, p =.0674). The effect was negative (β = -1.1309, p =.0584) and marginally significant at high competence levels (+1 SD). There was no effect at average competence (β = 0.0413, p =.9244). These results suggest that the effect direction may be reversed depending on users' perceptions of competence.

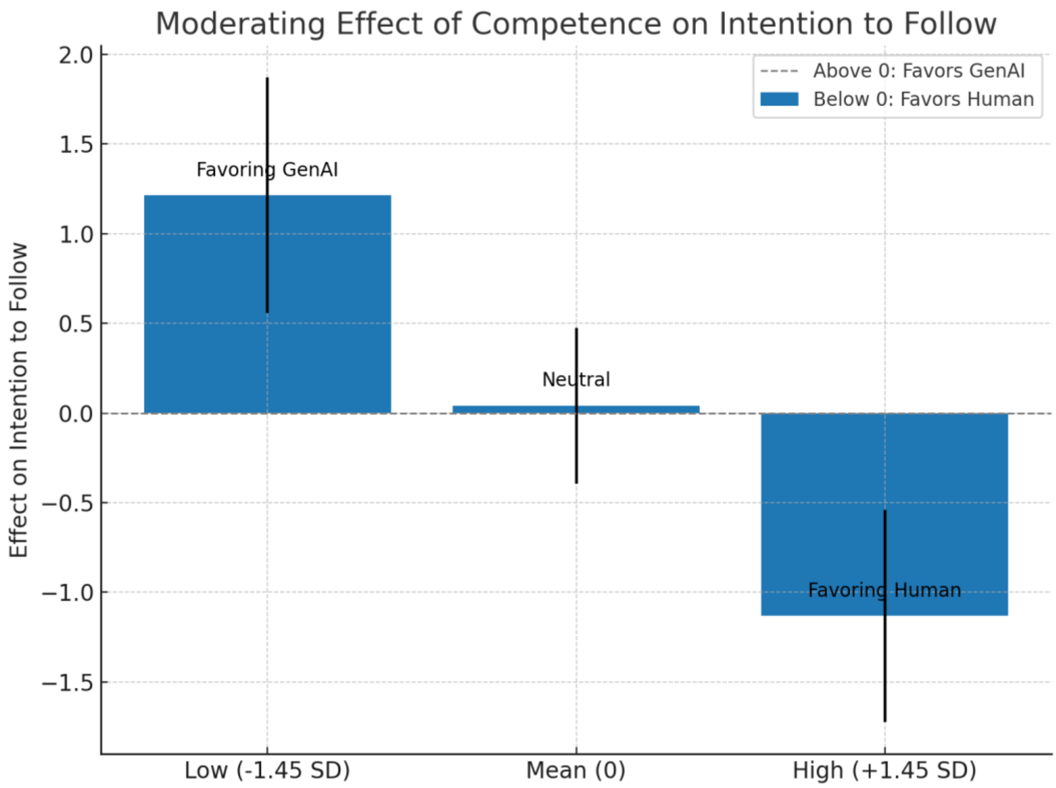

Figure 3 - Interaction Effect of Competence and Influencer Type on Intention to Follow

The conditional effect of influencer type (Human vs. GenAI) on users' intention to follow is shown in Figure 3 for a range of perceived competence levels. The vertical axis shows the magnitude of the influencer type's impact on the dependent variable, while the horizontal axis displays the moderator's (competence) values, which are centered at the mean.

The effect of influencer type on intention to follow is positive (β = 1.2136, p =.0674) at low levels of perceived competence (−1.45 SD below the mean), indicating that users are more likely to follow GenAI influencers than human influencers when perceived competence is low.

On the other hand, the effect becomes negative and significant at high levels of competence (+1.45 SD) (β = -1.1309, p =.0584), suggesting that users prefer human influencers when they believe they are highly competent. The effect is non-significant at mean-centered (average) competence levels (β = 0.0413, p =.9244), suggesting that influencer types do not significantly differ from one another.

The hypothesis that competence moderates the effect of influencer type on intention to follow is supported by these results, which show a significant interaction between perceived competence and influencer type (p =.0104). Human influencers gain from being seen as highly competent, whereas GenAI influencers might be more successful when seen as less competent.

5.4.2 Warmth

To investigate whether perceived warmth influenced the relationship between the type of influencer (GenAI vs. Human) and users' intention to follow, a moderated regression analysis was performed using PROCESS Model 1 (Hayes, 2022). The interaction term (IV × Warmth) was not significant, according to the results (b = -0.0676, SE = 0.2737, p =.8053, 95% CI [-0.6103, 0.4750]). This implies that there was not a significant variance in the influencer type's influence on users' intention to follow across perceived warmth levels. Regardless of the type of influencer, warmth itself had a significant main effect (b = 0.3568, p =.0105), suggesting that higher warmth perceptions were linked to greater intention to follow.

Effect	**Path**	**Coefficient**	**Standard Error**	**p-Value**	**95% Confidence Interval**
Direct Effect	IV → I_F	0.0927	0.4058	.8197	[-0.7119, 0.8973]
Moderator	W → I_F	0.3568	0.1369	.0105	[0.0854, 0.6281]
Interaction	IV × W → I_F	-0.0676	0.2737	.8053	[-0.6103, 0.4750]

Table 13 - Moderator Analysis (Warmth)

In conclusion, perceived warmth emerged as a significant independent predictor, even though it did not moderate the relationship between influencer type and users' intention to follow. This implies that perceived warmth is essential for encouraging user engagement and raising the possibility of being followed, whether an influencer is Human or GenAI. These results highlight how crucial it is to create influencer content that maximizes persuasive effectiveness by enhancing warmth perceptions, particularly for GenAI Influencers.

6. CONCLUSIONS AND FUTURE RESEARCH

The impact of Influencer type on users' emotional responses on intention to follow on social media was investigated in this study. A variety of emotional and perceptual factors were evaluated after participants were randomly assigned to watch a video featuring either a human influencer or a GenAI. The results showed that the two groups' perceptions and emotional responses differed significantly. Participants who watched human influencers showed considerably higher ratings on all Competence subdimensions, as well as significantly higher levels of happiness and smiling-related facial expressions (Lip Corner Puller (AU12)). According to these findings, human influencers might be more successful than their GenAI counterparts at triggering favorable emotional reactions and Competence perceptions.

Although the type of influencer did not significantly influence users' intention to follow (H1), several emotional and perceptual variables revealed significant differences between GenAI and human influencers. The second hypothesis (H2), which proposed a mediation effect through emotional responses, was not supported because none of the tested mediators had a statistically significant indirect effect. However, the third hypothesis (H3) was partially confirmed: competence significantly moderated the relationship between influencer type and intention to follow, implying that perceptions of competence have an important effect on how users respond to GenAI versus human influencers. Warmth, while significant as a main effect, did not interact with influencer type. These findings highlight the complex relationship between emotional responses and social perceptions that impact users' interactions with digital influencers.

To answer the research question "Does GenAI (vs. Human) Influencers' content influence users' intent to follow?", the results indicate that the type of influencer does not significantly predict users' behavioral intentions. However, differences in emotional responses and perceived characteristics, such as competence, influence how users respond to GenAI or human influencers. This suggests that, while influencer type does not directly predict intention to follow, it does interact with competence but not with warmth and emotional responses in significant ways that influence user engagement.

6.1 Theoretical Implications

After completing this research, it is possible to conclude that users' emotional and behavioral responses to GenAI and human influencers are significantly affected by their perceived social traits, particularly competence and warmth. This reinforces theoretical assumptions from the Stereotype Content Model (SCM) and extends them to non-human agents operating in digital contexts.

The results indicate that competence, rather than warmth, moderates the effect of influencer type on intention to follow, implying that when users evaluate GenAI Influencers, practical features might prevail over interpersonal ones. This demonstrates a shift in how traditional social cognition frameworks are implemented in online environments. Furthermore, the linear presumptions of affective influence in digital engagement are called into question by the absence of significant mediation. By challenging the linear assumptions of affective influence in digital engagement, this highlights the need for new theoretical models that better account for emotional responses and consider the unique dynamics.

Notably, competence was found to be a significant moderator: users were more inclined to follow human influencers than GenAI ones when they felt competent. On the other hand, GenAI influencers received higher ratings at lower perceived competence levels, and their positive impact on intention to follow was marginally significant. One interpretation is that GenAI agents gain from a sense of innovation or from decreased user expectations, which could draw attention to traits like entertainment value or creativity. Conversely, because of presumptions of greater authenticity and credibility, human influencers may be more penalized when competence is viewed as low.

Despite being a strong predictor of intention to follow, warmth had no moderating effect on the association between intentions to follow and influencer type. This implies that whether the influencer is a human or a GenAI, warmth consistently and generally shapes user intentions. Although competence distinguishes between different types of influencers, warmth probably plays a role in encouraging emotional connection and trust.

In conclusion, these findings offer some evidence in favor of the study's hypotheses, but they also provide important information for developing existing theoretical frameworks to better comprehend user engagement in the era of GenAI content.

6.2 Practical Implications

In terms of application, this study provides marketers, advertisers, and brands thinking about incorporating GenAI influencers into their communication plans with insightful information. Since virtual endorsers are becoming more and more popular because they are inexpensive and resistant to human-related scandals, it is crucial to comprehend how users react to these entities on an emotional and cognitive level. The results indicate that GenAI and human influencers differ in their emotional engagement and perceived competence, emphasizing the significance of personalizing content strategies depending on the influencer type. When innovation or creative design are crucial, brands may find success with GenAI influencers; however, campaigns that primarily rely on emotional authenticity and high perceived competence may still benefit more from human influencers. Companies should also think about segmenting their influencer strategies according to the competence and warmth expectations of their audience. This way, they can use data-driven insights to match the type of influencer to the objectives of their campaigns. The effectiveness of GenAI implementation depends on how well these virtual agents can replicate not just appearance and communication but also additional social traits that promote favorable customer perceptions as these technologies develop.

To maximize the effectiveness of GenAI influencers over time, companies should also make investments in audience feedback systems and ongoing testing. Finding what appeals most to audience segments can be supported by comparing various content formats, voices, and levels of interactivity. Brands need to remain adaptable and responsive to shifting expectations because user perceptions of GenAI agents are still developing. To preserve trust and prevent possible opposition, it is also crucial to be open regarding how artificial these influencers are. Advertising campaigns being developed should incorporate ethical considerations from the beginning, such as transparency, authenticity, and the psychological impacts of human-AI interaction.

6.3 LIMITATIONS AND FUTURE RESEARCH

Although this study resulted in valuable insights, it is important to acknowledge several limitations. First, although the sample size was adequate for the statistical methods employed, it might not properly represent the variety of perspectives and emotional reactions present in larger populations. A larger and more varied sample could improve the findings' generalizability and reveal deeper effects across demographic groups.

Additionally, while FaceReader offered a non-invasive, computerized way to identify facial expressions, a significant amount of the personalized emotional data could not be analyzed due to the poor quality of some of the recordings. The accuracy of facial recognition may have been limited by problems like low video resolution, poor illumination, and irregular participant positioning, compromising the emotional dataset's reliability and accuracy. Therefore, several emotional responses might have gone undetected or underreported.

Also, there are limitations to using pre-recorded influencer videos, even with efforts to standardize the experiment. These videos may not accurately represent interactive or real-life influencer experiences, which could lower ecological validity and emotional engagement. Furthermore, participants' answers might have been biased due to the influencers chosen. Specifically, the selected human influencer is a divisive figure who frequently provokes strong feelings, both positive and negative. This decision may have influenced the opinions of participants regardless of the influencer type, even though it was made to closely match the human and GenAI videos.

Furthermore, because of existing brand loyalty or aversion, the videos' participation of rival brands Mercedes-Benz and BMW may have unintentionally influenced viewer preferences. Results from these brand associations might be biased, especially when it comes to factors like perceived competence or emotional response. To better control for these external factors and guarantee consistency across conditions, future research should think about utilizing brand-neutral, custom-produced content created especially for the study.

Finally, other potentially important moderators or mediators, like trust, authenticity, or user personality traits, were left out of the model, even though competence and warmth were examined as important social perception variables. By improving data collection conditions, improving video quality for FaceReader-like tools, and expanding the scope of analysis to include more contextual and psychological factors, future research should try to overcome these limitations. A deeper understanding of the changing effects of GenAI influencers on user attitudes and behavior over time may also be possible through longitudinal research or more immersive experimental designs, such as real-time interactions with GenAI influencers.

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APPENDIX A (ETHICS COMMITTEE APROVAL)

This is to certify that
Project No.: **DDMKT2024-12-116412**
Project Title: **Exploring User Emotional Responses to Human and GenAI Influencers**
Principal Researcher: **Pedro Francisco Soares**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 12/11/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of
- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 12/11/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

APPENDIX B (QUESTIONNAIRE)

* Using a nine-point scale ranging from 1 (strongly disagree) to 9 (strongly agree), please **evaluate the extent the following statements** concerning the person present in the video:

	1. Strongly disagree	2	3	4	5. Neutral	6	7	8	9. Strongly agree
I have the intention to follow to visit Influencers' Instagram account	○	○	○	○	○	○	○	○	○
I predict that I will follow Influencer's Instagram account	○	○	○	○	○	○	○	○	○
I will probably look for new content published in the Influencer's Instagram account	○	○	○	○	○	○	○	○	○
Select number 4	○	○	○	○	○	○	○	○	○

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* Considering the video you watched, wich option describes best the influencer that you watched?

○ Human Influencer

○ GenAI Influencer

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* Considering the video you watched earlier, rate on a scale from 1 to 9, where 1 means you completely disagree and 9 means you completely agree, to what extent you consider the main actor in the video:

	1. Not at All	2	3	4	5. Neutral	6	7	8	9. Extremely
Competent	○	○	○	○	○	○	○	○	○
Intelligente	○	○	○	○	○	○	○	○	○
Confident	○	○	○	○	○	○	○	○	○
Competitive	○	○	○	○	○	○	○	○	○
Independent	○	○	○	○	○	○	○	○	○

* Considering the video you watched earlier, rate on a scale from 1 to 9, where 1 means you completely disagree and 9 means you completely agree, to what extent you consider the main actor in the video:

	1. Not at All	2	3	4	5. Neutral	6	7	8	9. Extremely
Sincere	○	○	○	○	○	○	○	○	○
Good natured	○	○	○	○	○	○	○	○	○
Warm	○	○	○	○	○	○	○	○	○
Tolerant	○	○	○	○	○	○	○	○	○

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* Your gender

○ Male

○ Female

○ Non-binary

○ Prefer not to answer

* Age (please insert numbers only)

* Your nationality

○ Portuguese

○ Other

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